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Can Industrial Digitalization Promote Regional Green Technology Innovation?

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ABSTRACT

Regional green technology innovation (*RGTI*) carries ecological and technological externalities, serving as a crucial force in aligning economic development with the imperative of environmental preservation. Industrial digitalization (*indig*) exhibits innovative, quality-enhancing, and efficiency-enhancing traits. Yet, the exact effects of *indig* on *RGTI* have not been extensively studied. In this study, based on provincial data from 2013-2019 in China, we investigated the linear and nonlinear relationships, spatial characteristics and underlying mechanisms between *indig* and *RGTI* through a Hansen threshold model and a mediating effect model. The results showed that: i. *indig* fluctuates while *RGTI* increases steadily, both displaying evident spatial agglomeration traits and a unipolar characteristic of regional heterogeneity; ii. *indig* has effectively boosted RGTI at both national and regional levels, with the exception of the northeastern region; iii. There was a single threshold for industrial digitalization and the positive driving trend exhibited a "marginally increasing" characteristic; iv. Two critical elements, namely industrial structure advancement and marketization, have partial intermediary roles. Basing on these results, this study presents several policy recommendations.

Introduction

The new round of the information technology revolution, exemplified by big data and the Internet, has promoted the rapid development of new technologies, intelligent manufacturing upgrades, and other fields. Moreover, countries around the world have embarked on the digital revolution process (Shi, 2022; Xiao & Liu,2022). The digital economy is a new type of industry that utilizes data as a production factor, leverages the Internet as a platform, and integrates digital technology with other domains (Lailag & Chen, 2022; Sui &

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Yao, 2023). From an economic structure perspective, it consists of industrial digitalization and digital industrialization. Industrial digitalization (*indig*) means that digital technology is applied to traditional industries to realize the digitalization-characterized process. Digital industrialization refers to various economic activities that completely rely on digital technologies and data elements, which are collectively referred to as the information industry (Dai & Ma, 2023). Traditional industries are faced with the impact of external shocks, contradictory supply and demand structures, overcapacity, unreasonable factor structures and other difficulties. Industrial digitalization has innovation-driven, quality-enhancing and efficiency-enhancing characteristics. It is an effective way for traditional enterprises to transform, upgrade and improve resource allocation efficiency. Different types of economies, such as developed markets, emerging markets, and frontier markets, exhibit unique contexts and distinct features (Piñeiro-Chousa et al., 2018). According to the China Academy of Information and Communication Technology, in 2021, the proportion of industrial digitalization reached 37.18 trillion yuan, accounting for 81.7% of the digital economy, and 32.5% of GDP. Under the strategy of "Digital China" and "Smart Society", it is increasingly important to promote deep integration of digital technology and real economy. The Chinese economy has undergone an extensive phase of rapid growth, emphasizing the magnitude and pace of economic development, resulting in environmental degradation, elevated carbon emissions, and pollution. In response, the Chinese government introduced a new development paradigm in 2015, encompassing five key elements: "innovation, greenness, coordination, openness, and sharing." This signifies a shift for China from high-speed development to a focus on high-quality development (Hao et al., 2023c; Hao & Deng, 2019), with innovation as the first driving force and a key way to realize green development (Hao et al., 2023d; Mondalet al., 2024; Yanget al., 2024). China's clean energy continues to rapidly develop, and the energy consumption structure has continued to be optimized (Wu et al.,2022; Mao et al.,2023). However, China is still dominated by fossil energy, which accounted for about 84.3% of energy consumption in 2021(Feng et al., 2022; Hao et al.,2022). Among them, coal is the most dominant, accounting for 56% of consumed energy sources, followed by oil (18.5%). In 2020, China established the goals of "carbon peaking" and "carbon neutrality", reflecting China's determination and desire to achieve green economic transformation and high-quality development (Liu et al.,2023; Wu et al.,2024). Regional green technology innovation (RGTI) improves the economic quality (Wang et al., 2018). Particularly in the aftermath of the COVID-19 pandemic, there has been a growing endorsement of the green economy (Piñeiro-Chousa et al., 2022). The RGTI is also of significance in achieving "carbon neutrality" and "carbon peaking". It can balance the dual objectives of economic development and energy transformation, reduce the premium price of green products, and also promote sustainable development (Romero-Castro et al., 2022). Digital technology drives the transformation of production's social relations, the reengineering of those relations, and a comprehensive change in economic and social structures (Knickrehm et al., 2016). It carries significant, disruptive changes to the innovation process (Nambisan et al., 2017). Industrial digitalization is the main driving factor for digital economy development, and is an important starting point for the digital economy to empower high-quality economic development (Qiu et al., 2022). Digital transformation of industries has the ability to empower green and low-carbon development of industries. Industrial digitalization realizes deep integration of digital technology and real economy to provide technological support for *RGTI*.

Existing studies have primarily investigated the relationship between digital economy and technological innovation (Miller & Wilsdon, 2001; Ning et al., 2022). The impact of *indig* on *RGTI* has not been extensively investigated, raising the question: can industrial digitalization effectively promote regional green technology innovation? Complex and changing external dilemmas and internal contradictions have increased the complexity of the impact of digital transformation of traditional industries on *RGTI*. Industrial digitalization is innovation-driven, however, at the beginning of industrial digitalization, a large amount of capital investment is required to build digital facilities and platforms, which will delay the effects on *RGTI*. This paper aimed to explore strategies for optimizing the impact of industrial digitization in fostering regional green technology innovation. Concurrently, it aims to investigate its interrelation with the marketization process and industrial structure. We still need to find out the development levels, characteristics and spatial distribution trends of *indig* and *RGTI*. Industrial digitization displays distinct stage characteristics and exhibits regional variations. This paper aims to further investigate into its non-linear association with regional green technology innovation and analyze its heterogeneous effects across different regions. This paper will provide a deeper understanding of the impact of *indig* of traditional industries on green innovation, and promote green innovation to achieve high-quality economic development by transforming the traditional industrial development mode.

While studies have investigated the environmental impact of the digital economy and explored the implications and influencing factors of *RGTI*, there remains a gap in research specifically examining the nuanced sub-dimensional relationship between industrial digitalization (indig) and *RGTI*. This may undermine the efficacy of targeted innovation policies, management models, and green development practices. The marginal contributions are as follows: i. The overall level of indig, as well as its variations in different regions, is quantified by constructing a comprehensive evaluation system and utilizing the projection pursuit function; ii. The spatial agglomeration characteristics and regional heterogeneities of *indig* and *RGTI* are explored; iii. The linear and non-linear relationships between *indig* and *RGTI* are investigated via OLS and Hansen threshold model, as well as the special driving trend and the regional heterogeneous effects and iv. The potential intermediary mechanisms of two critical factors in the process are tested — industrial structure advancement and marketization.

The rest of the paper is presented as: Part 2 is the literature review and Hypotheses; Part 3 is the research design; Part 4 is the results and analysis; Part 5 is discussion; the last part is the conclusion and recommendation.

Literature review and hypotheses

The digital economy, a concept that was first introduced in the 1990s (Tapscott, 1996), has received a lot of attention. Scholars have studied the definition of digital economy (Mesenbourg, 2001), digital divide (Martin, 2003; Torrent-Sellens et al., 2022), and monopoly effect (Armstrong, 2006). The digital economy is closely associated with rapid progress of the digital technology, which has efficiency-enhancing and quality-enhancing characteristics. Wang et al. (2022) examined the three paths by which the Internet economy impacts eastern Central Europe: human capital, clean technology innovation, and energy structure. Cette et al. (2022) argue that the digital technology will increase labor productivity and total factor productivity of enterprises. Digital technologies can be applied to the financial sector to enable credit risk management of data (Bisht et al., 2022). The digital economy is composed of two main parts: digital industrialization and industrial digitalization. The latter focuses on digital shift or digital technology applications in existing traditional industries, which is all-round transformation of traditional industries. The main advantages of industrial digitization include accelerating economic development (Bjorkdahl, 2020), optimizing industrial environment (Verhoef & Broekhuizen, 2021), improving environmental innovation performance (Hung & Nham, 2023) and corporate performance (Heredia et al., 2022; Peng & Tao, 2022) among others. These advantages are conducive to enterprise development because data is extremely easy to gather and the marginal cost of information exchange is extremely low (Gölzer & Fritzsche, 2017; Reddy, 2023). The green effect of digitalization has been studied in terms of its influencing factors. Researchers argue that this green effect is influenced by the size of the economy (Li & Liao, 2022; Wang & Du, 2022) and the industrial chain (Zhang et al., 2022). Wang et al. (2022) argue that digital transformation significantly affects electric consumption efficiency. Yang & Yee (2022) investigated the three factors that affect process digitization (PDI): differentiation strategy, absorptive capacity, and lean manufacturing.

Innovation means constantly destroying old structures and creating new structures (Schumpeter, 1982). Romer (1986) reported that knowledge has spillover effects.

In addition to digitalization, a nation's innovation can be nurtured by various factors, including public expenditure on education, foreign direct investment (FDI), and entrepreneurial activity (López-Cabarcos et al., 2020). The digital economy enables the change from old to new dynamics, reshaping economic structures such as factor changes, and being knowledge-driven. This has laid the theoretical foundation for studies on digital economy externalities. To influence regional green technology innovation, first, digital technology creates complementarity with links in organizational chains, reconfigures factor resources, triggers production paradigm improvement as well as industry linkage effects, and promotes structural optimization of production sectors (Heo & Lee, 2019; Cao et al., 2024). Digital technology, for example big data, can promote green innovation willingness and green process innovation (Tian et al., 2022). Second, as digital infrastructure continues to improve, it promotes the optimization of the production chain (Kohli & Melville, 2019), changes the traditional information dissemination and enhances the optimization of information dissemination structures (Henfridsson & Bygstad, 2013). Studies have investigated its green effects from the perspectives of its externalities, specifically, the rationality of energy consumption (Ren et al., 2021; Hao et al., 2022; Wang et al., 2022), energy efficiency (Wu et al., 2021; Hao et al., 2023b), carbon reduction feasibility (Hao et al., 2023a; Yi et al., 2022; Zhou et al., 2022; Hao et al., 2023e; Wu et al., 2024), and increasing the export value of green products (Thanh, 2022).

In value chain promotion, the digital shift and upgrading of existing industries, driven by integration with digital technology, are conducive to RGTI in the following ways: i. Green innovation requires more involved information, multi-dimensional and multi-level knowledge synergy, and integration of technology fields. Therefore, it is difficult to carry out green innovation by relying on enterprises' original technology experience and knowledge accumulation in a single technological field (Mubarak et al., 2021; Park,2022). The *indig* can promote industrial chain informatization and transparency, increase labor productivity, thereby improve resource management (Lange et al., 2020), accelerate knowledge integration and reconstruction, promote cross-border industrial integration, expand cognitive domain of enterprises, and thereby promote *RGTI*; ii. Influenced by the green development concept, people began to practice environmental protection behaviors, which promotes the demand side to choose environment-friendly products while *indig* can promote the exchange between the supply and demand sides, reducing information asymmetry; iii. Digital technology applications can effectively change the input structure of production factors of enterprises, and the digital technology itself has green and innovation-driven attributes, which can empower traditional technology of enterprises, such as resource development, and business model among others. These will further reduce technical energy consumption, improve industrial access threshold, and promote *RGTI*. Based on the above analysis, Hypothesis 1 is derived:

Hypothesis 1. Industrial digitalization can promote the improvement of regional green technology innovation level.

Due to high growth and high marginal rewards of the digital shift, it can effectively improve production efficiency, and development of enterprise information networks, which enhances low-cost dissemination of information and information sharing of enterprises (Goldfarb & Tucker, 2019). These can eliminate the spatial limitations of enterprise technology spillover effects, which benefits technological innovations. However, due to high permeability of the digital technology, construction of a large amount of infrastructure is required at the beginning of industrial digitization. Therefore, a lag-effect in play of ecological technology benefits exists, which restricts *RGTI* to a certain extent. With improvement of *indig* and the maturation of information network, the asymmetry of outside information will be further reduced and enrichment of factor inputs will be promoted, which can assist enterprises in enhancing resource utilization cognition, broadening the green innovation of enterprises boundary. Based on the above analysis, Hypothesis 2 is derived:

Hypothesis 2. Industrial digitization has different development stages, and the marginal effect of industrial digitization is increasing.

From the supply side, *indig* offers high technology and high marginal rewards. Upgrading of traditional industries, such as intelligent manufacturing, makes the products more competitive, and factors of production such as technology and data flow into these industries with higher profitability, which has a "crowding out effect" on industries with a low degree of integration with digital technology, such as agriculture and light industry, and "strengthening effect" on some industries with a higher degree of integration. Moreover, traditional industrial interconnection accelerates extension, improves industrial production efficiency and complementary resources level. In turn, the overall competition level of the industry will be improved, and industrial structure optimization will be driven by labor division, model innovation, factor endowment and value transfer. In addition, *indig* diversifies the consumption mode, enhances intelligence and services (Zhao et al., 2022). Simultaneously, industrial structure optimization must break constraints from energy consumption, environmental and other factors. Sticking to the high-end and green direction is the internal requirement of advanced industrial structures. It will meet production side demands as well as internal and external demands of the consumption side, then continuously strengthen *RGTI*, and improve core competitiveness. Based on the above analysis, Hypothesis 3 can be obtained:

Hypothesis 3. Industrial digitalization can improve regional green technology innovation by upgrading the industrial structure.

With its high technology, high payoff, high integration and high synergy, *indig* promotes structural innovation of production factors, empowers the marketization of factors and promotes the marketization process. First, the intelligence brought about by the high technology of *indig* drives the demand for complex labor that cannot realize automated jobs, increases the demand for high-end labor (Staab, 2017), and facilitates production efficiency improvement. Second, high integration and synergy enhances the synergistic effects for each factor, increases the matching speed of various factors. Third, marketization enhances the accu racy of price signals and market information, guides effective allocation of innovation resources, forms an effective market incentive and constraint mechanisms, and promotes enterprises to obtain innovation resources by virtue of their own strength. Gradually, marketization eliminates market barriers, and backward regions improve *RGTI* by learning clean technology. Regions with higher marketization levels tend to have more active economies, which can easily attract the entry of enterprises with clean technologies (Li, 2014), expanding green technology spillover effects and promoting *RGTI.* Based on the above analysis, Hypothesis 4 can be obtained:

Hypothesis 4. Industrial digitalization can improve regional green technology innovation by promoting the process of marketization.

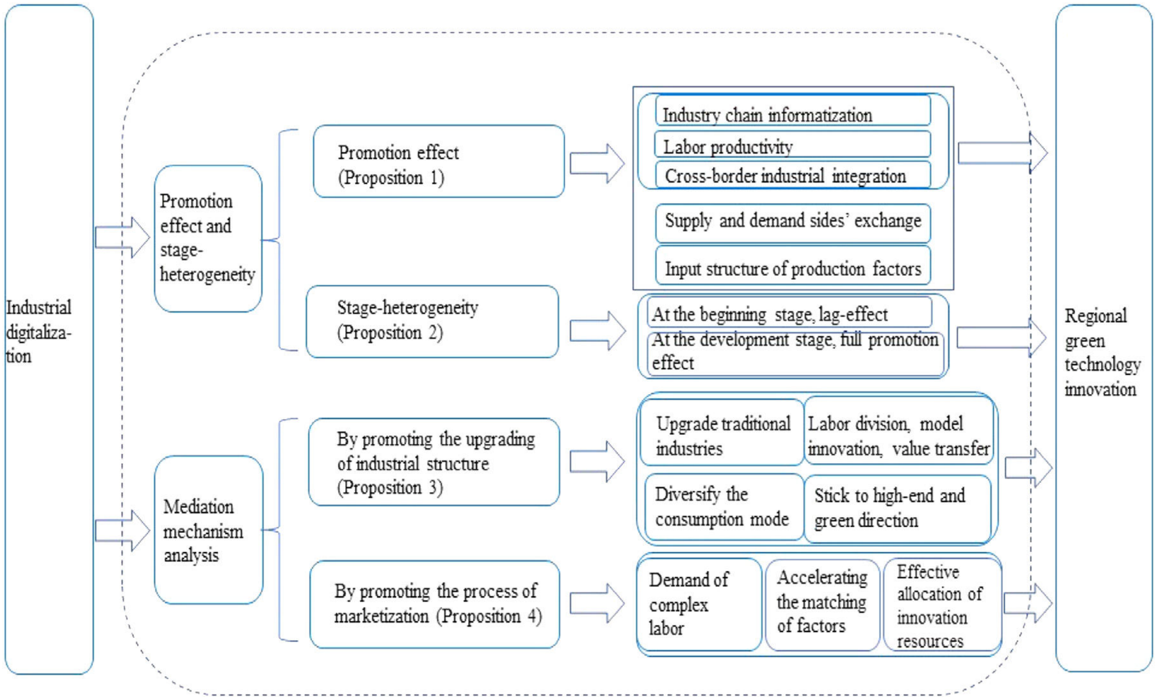

Fig. 1. The diagram of theoretical analysis.

The diagram of theoretical analysis is shown in Fig. 1.

Research design

This section provides an explanation of the research design, incorporating definitions and descriptive statistics for variables, along with the presentation of methods and data sources.

Variable descriptions

Core variables

(1) Core dependent variable: regional green technology innovation (RGTI)

Regional Green Technology Innovation (*RGTI*) is a paradigm of technological innovation aimed at protecting the ecological environment. It considers sustainable economic development, advances in science and technology, and improvements in current processes to enhance resource utilization efficiency, reduce pollutant emissions, and achieve energy conservation synergy. A patent is an important criterion that reflects the original innovation level of a region or country. This indicator is widely recognized by scholars worldwide (Wagner, 2007; Wurlod & Noailly, 2018). Based on the study by Wang & Zhang (2020), we collected green technology patents granted in 30 provinces to represent the *RGTI* level.

Changes in *RGTI* and its percentage across the 4 major regions (east region, central region, west region, and northeast region) of China are presented in Fig. 2. (Specifically, east region refers to Beijing, Tianjing, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; Middle region refers to Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan; West region refers to Sichuan, Guizhou, Yunnan, Shannxi, Gansu, Qinghai, Ningxia, Xinjiang, Chongqing, Inner Mongolia, Guangxi; and northeast region refers to Jilin, Heilongjiang, Liaoning).

According to Fig. 2, for *RGTI*, the eastern region displays a pronounced unipolar characteristic in regional heterogeneity: the gap in RGTI compared to the other three regions is widening rapidly. The number of green patents in the eastern region accounts for more than 50% of the national level, and has an increasing tendency. This indicates that a certain spillover effect of technology exists. The technology's "inertia acceleration effect" will foster the continuous advancement of the entire region, which may cause polarization effects with time and unbalance regional development in the country. The unbalanced *RGTI* level and unipolar characteristic during the study period are reflected in the total number of green patents in each region: east (67011) > central (25284) > northeast (12691) > west (11697).

(2) Core independent and threshold variable: industry digitalization (*indig*) level

Industrial digitalization is defined as the digitalization transformation of industries, which can potentially accelerate economic development, optimize industrial environment, and improve environmental innovation performance. To accurately represent the *indig* level, with reference to the study by Zhao et al. (2020), 13 indicators are selected, considering the following aspects: level of digital finance, industry digital application level, and industry digital convergence level (Table 1). Given the high growth and high marginal rewards of the digital shift, industrial digitization can effectively enhance the production and communication efficiency of enterprises (Goldfarb & Tucker, 2019). Nonetheless, owing to the pervasive nature of digital technology, substantial infrastructure construction should be developed at the onset of industrial digitization. Industrial digitization exhibits distinct stage characteristics, with the initial phase demanding significant funds for digital infrastructure development. This infrastructure construction profoundly influences the widespread adoption of digital technology, consequently impacting the efficacy of industrial digitization in promoting green technology innovation. Consequently, a lag-effect is observed, leading to the selection of industrial digitization as both an independent and threshold variable. The industrial digitization level in each province, city, and autonomous region is assessed using the projection pursuit function. The specific model and data processing steps are outlined below:

① Employ the extremum method for dimensionless processing of the 13 indicators.

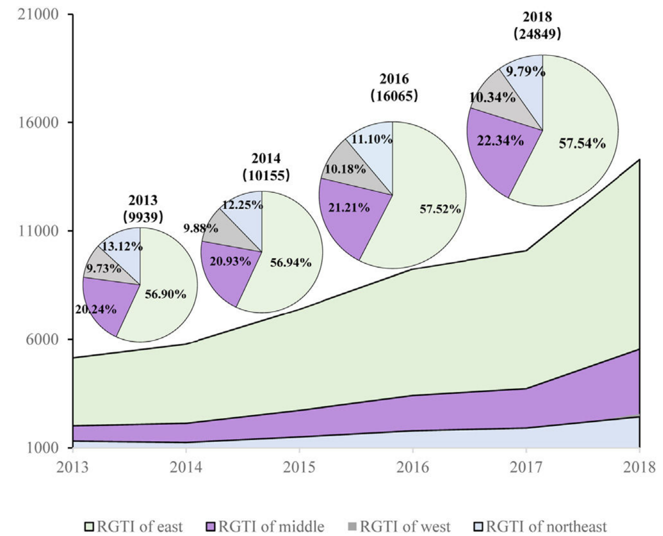

Fig. 2. The number of granted patents of green innovation and the corresponding shares in the four major regions.

② Construct the projection indicator function:

$$Q(b) = S_p \times D_p \tag{1}$$

S_Z denotes the standard deviation of $P(u)_t$ while D_p is the local density of $P(u)_t$;

③ Calculate the optimal projection value in the ideal projection direction:

$$P(u)_t = \sum_{v=1}^{p} b(v)_t \times x(u,v)_t \tag{2}$$

Considering the limitations of traditional methods in solving complex nonlinear optimization problems, an accelerated genetic algorithm (RAGA) is utilized. This algorithm optimizes the projection indicator function using MATLAB programming to achieve global optimization for high-dimensional data:

$$maxQ(b) = S_p \times D_p \tag{3}$$

$$s.t.\sum_{v=1}^{3} b^2(v)_i = 1 \tag{4}$$

Then, the best projection value (z) is calculated, which is the *indig* level value.

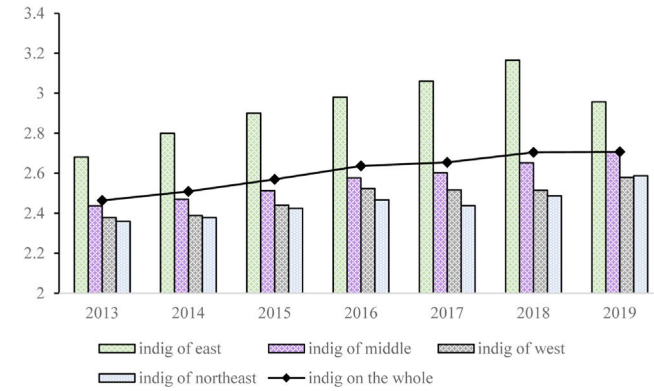

Fig. 3. Industrial digitalization level in the four major regions and on the whole.

indig levels and its changes in the four major regions are shown in Fig. 3.

Based on data shown in Fig. 3, the *indig* level is highly dynamic in the east and progresses significantly. In the other three regions, particularly the western and northeastern regions, its development is slower with a risk of stagnation. There's an imbalance in the characteristics of *indig*. This may be due to slow infrastructure construction and insufficient talent reserves, leading to a slowdown in the momentum of *indig* development, while the high industrial digitization level in the east attracts talents for clustering due to technological spillover effects and the more complete infrastructure. The unbalanced *indig* level during the study period is as: east (2.977) > central (2.565) > west (2.477) > northeast (2.449).

Mediating variables

(1) Advanced industrial structure *(ts)*. First, *indig* has a "crowding out effect" on industries with a low degree of integration with digital technology, such as agriculture and light industry, and a "strengthening effect" on industries with a high integration degree. Second, it also facilitates structural optimization in areas such as cooperative labor division, innovation modes, factor endowments, and value transfer. Third, it can promote consumption pattern renewal. The advanced industrial structure is measured by the ratio of tertiary industry output value to secondary industry output value (Gan et al., 2011). The specific formula is as follows:

$$ts_{ab} = \frac{tio_{ab}}{wio_{ab}} \tag{5}$$

Table 1
Evaluation index system of industrial digitalization level.

Target level	Criterion level	Index level	Data source
Industrial digitization level	Digital finance level	Provincial Digital Financial Inclusion Index	*Peking University Digital Inclusive Finance Index*
	Digital application level of industries	Proportion of the number of enterprises engaged in e-commerce trading activities	*China Statistical Yearbook*
		Number of websites per 100 companies	*China Statistical Yearbook*
		Provincial E-commerce Development Index	*China E-Commerce Development Index Report*
		Number of enterprises implementing the standard of integration of informatization and industrialization	*Ministry of Industry and Information Technology*
		Number of Taobao villages (towns)	*Taobao Village Research Report of China*
	Digital convergence level of industries	Online retail sales accounted for the proportion of total retail sales of consumer goods	*China Statistical Yearbook*
		Enterprise e-commerce sales	*China Statistical Yearbook*
		Enterprise e-commerce procurement volume	*China Statistical Yearbook*
		Courier volume	*China Statistical Yearbook*
		Express business revenue	*China Statistical Yearbook*
		Total exports of hi-tech enterprises	*China Torch Statistical Yearbook*
		Share of technology revenue in operating income in high-tech enterprises	*China Torch Statistical Yearbook*

Table 2
Description of control variables.

Control Variables	Definition	Reference
Government intervention (*gover*)	The share of fiscal spending in GDP represents the level of the government's intervention in the economy. More fiscal spending on science and technology is conducive for technological innovation. Therefore, the ratio of local government general budget fiscal expenditure to GDP represents the level of the government intervention degree (*gover*).	Dong & Wang(2021)
Foreign direct investment (*fdi*)	FDI has a technology spillover and demonstration effect, and has a positive impact on improving innovation capability to a certain extent. The ratio of foreign direct investment to GDP represents the level of foreign direct investment (*fdi*) level in each region.	Zhong & Shao (2022)
Environmental regulation(*er*)	Environmental regulation can improve enterprise environmental awareness and promote RGTI. Considering industrial wastewater, industrial SO_2, and industrial smoke, standardize the three pollutants, find the weight for each pollutant, and the comprehensive index of environmental regulation(*er*)can be obtained.	Li & Du (2014)
Financial scale (*finsize*)	Solomon Tadesse (2002) argues that a good financial system is able to provide the technological innovation system with large-scale input financing needed for technological innovation. It promotes long-term, stable, and sustainable behaviors of technological innovation. The financial scale (*finsize*)is represented by the ratio of added value in the financial industry to regional GDP.	Li & Yang (2018)
Degree of openness (*open*)(used in the robustness test)	Opening up to the outside world will introduce advanced technologies, play a demonstration effect role and promote technological innovation. The proportion of total import and export to regional GDP represents the level of openness (*open*).	
Science and technology investment (*rd*)(used in the robustness test)	The more investment in science and technology, the greater the possibility of RGTI. The proportion of R & D expenditure in GDP in each province represents the level of *rd*.	

Whereby ts_{ab} denotes the advanced industrial structure level in province *b* in year *a*, tio_{ab} is the gross value of tertiary industry in province *b* in year *a*, while wio_{ab} denotes the gross value of secondary industry in province *b* in year *a*.

(2) Marketization level *(mi)*. It is the extent to which the market influences resource allocation. At the beginning of marketization, the pursuit of economic efficiency and restricted efficiency of resource allocation affects *RGTI*. As the marketization level continues to increase, it will guide enterprises to efficiently allocate innovation resources, and attract enterprises with clean technology to enter (Li, 2014). This paper employs the total marketization index, considering factors like marketization extent, speed, and depth. This index was proposed by Fan Gang and has been widely adopted (Fan et al., 2011).

Control variables

The relevant control variables are described in Table 2

Model design

Panel regression model

Based on the analyses above, we established a panel regression model to empirically verify whether *indig* can promote *RGTI* as follows.

$$lnRGTI_{it} = \alpha_0 + \alpha_1 indig_{it} + \alpha_2 gover_{it} + \alpha_3 fdi_{it} + \alpha_4 er_{it} + \alpha_5 finsize_{it} + \mu_i + \varepsilon_{it} \quad (6)$$

Whereby $RGTI_{it}$ is the level of green technology innovation in province *i* in year *t*, $indig_{it}$ is the industrial digitalization level in province *i* in year *t*. Control variables affecting *RGTI* include $gover_{it}$, fdi_{it}, er_{it}, and $finsize_{it}$. Where, $gover_{it}$ denotes government intervention, fdi_{it} is the foreign investment level, er_{it} denotes environmental regulation, $finsize_{it}$ is the scale of financial development.

Dynamic Panel threshold model

Equation (6) explores the direct effects of *indig* on *RGTI*. Given the development stage of *indig*, there may be nonlinear relationships between its development and RGTI. Given the dynamic nature of industrial digitization and to mitigate estimation bias arising from endogeneity, we adopt the approach proposed by Kremer et al. (2013) by employing a dynamic panel threshold model.

$$lnRGTI_{it} = \alpha_0 lnRGTI_{i(t-1)} + \alpha_1 indig_{it} I(indig \le \Upsilon_1) + \alpha_2 indig_{it} I(indig \le \Upsilon_2) + \cdots + \alpha_n indig_{it} I(\gamma_{n-1} \le indig \le \Upsilon_n) + \alpha_{n+1} indig_{it} I(indig \ge \Upsilon_n) + \beta control_{it} + \delta_{it} \quad (7)$$

Whereby $\gamma_1, \gamma_2 \cdots \gamma_n$ denotes the threshold value at different levels, *I* is the indicative function, and *indig* is the threshold variable. Control variables are the same while δ_{it} are the random disturbance terms.

Mediation effect model

To investigate how indig influences RGTI, we explored whether the advanced industrial structure and marketization may act as mediating variables. According to the study by Baron & Kenny (1986), the mediation effect model is constructed based on the panel regression model as follows.

$$lnRGTI_{it} = \alpha_0 + \alpha_1 indig_{it} + \sum control + \mu_i + \varepsilon_{it} \quad (8)$$

$$M_{it} = \beta_0 + \beta_1 indig_{it} + \sum control + \mu_i + \varepsilon_{it} \quad (9)$$

$$lnRGTI_{it} = \gamma_0 + \gamma_1 indig_{it} + \sum control + \mu_i + \varepsilon_{it} \quad (10)$$

M is the mediating variable, including ts_{it}, mi_{it}. Ts_{it} denotes the advanced industrial structure while mi_{it} denotes marketization.

Data sources

The study is based on data for 30 provinces from 2013 to 2019 in China (Taiwan, Hongkong, Macao and Tibet are not included due to data availability). Unless specified, the data sources for this research include the *China Finance Yearbook, Wind Database, China Statistical Yearbook, China Environmental Statistical Yearbook, China Urban Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Research Data Services Platform (CNRDS)*, as well as provincial statistical yearbooks, provincial statistical bulletins, and official websites of provincial statistical bureaus. A descriptive statistic of the variables can be found in Table 3. The results show that there are large gaps in government intervention *(gover)* and financial size *(finsize)* among others, indicating an unbalanced regional development in China.

Analysis and results

Estimation results of different models are presented sequentially.

Table 3
Statistic description of variables.

Variables	Obs	Mean	Std.Dev.	Min	Max
lnRGTI	210	7.772	1.273	3.689	10.44
indig	210	2.658	0.339	2.334	4.173
gover	210	0.267	0.111	0.120	0.658
er	210	0.525	0.541	0	2.585
finsize	210	0.0726	0.0297	0.0306	0.185
fdi	210	0.0189	0.0174	0.000107	0.121
ts	210	1.279	0.699	0.633	5.169
mi	210	6.950	1.974	2.530	11.40
lnRGTI 1	210	8.376	1.310	4.564	11.12
open	210	0.257	0.277	0.0128	1.342
rd	210	0.0169	0.0112	0.00458	0.0631

Table 4
Benchmark regression results.

ln RGTI	(1)	(2)	(3)	(4)	(5)
indig	2.0215***	1.9924***	1.9348***	1.4004***	1.4009***
	(5.08)	(4.97)	(4.74)	(4.04)	(4.02)
gover		1.1455	1.3150	0.3782	0.3971
		(0.85)	(1.04)	(0.25)	(0.26)
er			0.2871	0.3539**	0.3497**
			(1.66)	(2.22)	(2.14)
finsize				15.6430***	15.3705***
				(3.96)	(3.32)
fdi					-0.5954
					(-0.21)
_cons	2.3979**	2.1697*	2.1270*	2.6270***	2.6537***
	(2.26)	(2.01)	(1.94)	(3.03)	(3.09)
N	210	210	210	210	210
R^2	0.480	0.485	0.497	0.587	0.587

Note: t-statistic values in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. The following tables are the same (unless otherwise noted).

Baseline regression results

Analysis of benchmark regression results

Based on the Hausman test to determine whether industrial digitization promotes RGTI, we employed the fixed-effects model. The results are presented in Table 4.

In Table 4, from columns (1) to (5), with the sequential addition of control variables, the coefficients of *indig* on *RGTI* were all significant. The influence of the *indig* coefficient on *RGTI* is (1.4009), significant at level 1% with adding all control variables, indicating that industrial digitalization in China can effectively enhance *RGTI*, consistent with findings by Nin et al. (2023).

For the control variables, the coefficient of *gover* on *RGTI* is (0.3971), which is insignificant, indicating that even though administrative interventions can effectively guide enterprises to achieve technological direction changes, its promotion effects on *RGTI* are not conclusive. The coefficient of *er* is (0.3497), significant at the 5% level, indicating that enterprises promote green technology R&D investment to reduce environmental costs that are due to environmental regulation, which promotes *RGTI*, consistent with the conclusion by Tao et al. (2021). Environmental regulation will force the government to implement environmental governance by putting pressure on government officials. Besides, enterprises will also aim at energy conservation and emission reduction, and carry out technological transformation as well as innovation. The coefficient of the financial scale is significant at the 1% level, indicating that finance can serve the real economy and a good financial environment is conducive for *RGTI*. The coefficient of *fdi* is (-0.5954), which is not significant. It maybe because the introduction of foreign capital results in technological dependence and is harmful for progression of *RGTI.*

Threshold test and analysis of industrial digitalization

(1) Threshold test

Considering the phased characteristics of *indig* development, there might be a nonlinear relationship with *RGTI*, as seen in Table 5.

Single threshold is significant, which was selected to report the regression results.

(2) Analysis of threshold results

Single threshold regression results are presented in Table 6.

In Table 6, there is a single threshold effect between *indig* and *RGTI*. The threshold value for *indig* is 2.35. The *indig* coefficients show that the driving trend has a “marginally increasing positive” characteristic. (1) When *indig* < 2.35, the *indig* coefficient is significantly positive (0.2543) at 1% level. Due to infrastructure construction of digital technology and lag effects of ecological technology benefits, promotion of *indig* on *RGTI* cannot be fully realized. (2) When *indig* > 2.35, impact coefficient of *indig* on *RGTI* is significantly positive (0.4357) at 1% level. Upon reaching maturity, industrial digitalization, accompanied by fully established infrastructure, significantly diversifies the types of production factors and optimizes their structures. Importantly, the promotional impact of industrial digitization on RGTI becomes more pronounced.

Further analysis

Analysis of mediating effects

The transmission mechanism in the process is analyzed in part 3. The development of *indig* can promote *RGTI* and broaden cognitive boundaries of enterprises by industrial structure advancement (*ts*)

Table 5
Test for the threshold effect of industry digitization level.

	Number of thresholds	F-statistic value	P-value	Threshold value			Number of Sampling
				10%	5%	1%	
Industrial digitization (*indig*)	Single Threshold	35.62***	0.0000	11.3615	13.2229	19.0610	600
	Double threshold	9.17	0.1317	10.0495	12.0353	16.3915	600
	Triple threshold	4.49	0.8250	14.1259	15.8463	19.6503	600

Table 6
Threshold regression results.

	indig						
	indig<2.35	indig>2.35	l.green	gover	er	finsize	fdi
Coefficient	0.2543*	0.4357***	0.7276***	1.5213***	0.0943	3.7041*	-0.6183
T-value	1.70	2.98	15.05	3.00	1.25	1.93	-0.42

Table 7
Results of the mediation mechanism test.

	model1 ln RGTI	model2 ts	model3 ln RGTI	model4 mi	model5 ln RGTI
indig	1.401***	0.4424***	1.011***	1.749***	0.7995***
	(8.26)	(5.03)	(6.25)	(9.08)	(4.21)
ts			0.8818***		
			(6.79)		
mi					0.3439***
					(5.60)
Control variable	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
R-squared	0.9545	0.9593	0.9640	0.9756	0.9614
Obs.	210	210	210	210	210
Sobel test	Z=4.041, P=0.0000			Z=4.765, P=0.0000	
Proportion of total effect that is mediated	0.2785			0.4293	
Bootstrap Test	Z=2.82, P=0.005			Z=4.53	P=0.000

and marketization (*mi*). The mediation effect model is used to examine the potential mechanism (Table 7).

Model (1) of Table 7 shows the direct positive effects of *indig* on *RGTI*, and in model (2), the coefficient of *indig* on *ts* is (0.4424), which is significantly positive at the 1% level, proving that industry digitalization may enhance industrial structure advancement. Model (3) adds *ts* into model (1), and the *indig* coefficient is still significant (1.011), with some decrease compared with model (1), but positive at 1% level. Accordingly, the mediating effect size of *ts* is 0.390=1.401-1.011, and accounts for 27.85% of total effect, indicating that *indig* improves *RGTI* by enhancing advanced industrial structure.

Model (4) confirms that the *indig* coefficient on *mi* is (1.5054), significantly positive at 1% level, proving that industry digitization can promote marketization. Model (5) adds the mediating variable of marketization level into model (1), and the *indig* coefficient is still (0.7995), which is significantly positive at 1% level, with obvious decreases compared with model (1). Accordingly, the mediating effect size of *mi* is 0.6015=1.401-0.7995, accounting for 42.93%, indicating that *indig* can enhance *RGTI* by promoting marketization.

Regional Heterogeneity Analysis

Due to factors such as resource endowments and historical influences, the levels of industrial digitization (indig) exhibit variation among different regions in China. To investigate potential spatial heterogeneity in the impact of indig on RGTI, four major regions are taken into account: the east region, central region, west region, and northeast region. The results are in Table 8.

In Table 8, it is shown that *indig* in the eastern region promotes *RGTI* at 1% level, but with the lowest coefficient. This may be because the eastern region has a higher level of industrial digitalization and is in the exploration period, which has a certain blindness for digital inputs (Griliches et al., 1991). *Indig* development will also intensify the financial burden and cause resource mismatch, increasing the price of green technology or green products and limiting green development (Li et al., 2016). Therefore, its marginal effect on *RGTI* is diminishing.

Table 8
Regional heterogeneity.

	East lnRGTI	Central lnRGTI	West lnRGTI	Northeast lnRGTI
indig	1.0730***	3.4832***	3.2047***	1.7822*
	(5.39)	(9.91)	(3.24)	(4.27)
gover	0.2601	2.2996*	0.5648	-1.2721
	(0.16)	(2.22)	(0.33)	(-0.75)
er	0.0887	0.1937	0.7549***	0.5914*
	(0.39)	(0.80)	(5.07)	(3.50)
finsize	9.5965*	9.6535	14.5214**	16.3257*
	(1.98)	(1.26)	(2.82)	(3.70)
fdi	-4.9465*	-10.3881	-18.5149	5.9922*
	(-1.95)	(-0.76)	(-0.98)	(2.99)
_cons	4.6272***	-1.8295	-2.3029	1.9274
	(8.02)	(-1.24)	(-0.90)	(2.43)
N	70	42	77	21
R^2	0.731	0.837	0.698	0.887

Compared to the other two regions, *indig* in the central and western regions significantly promotes *RGTI*. This outcome could be because these regions have more potential promotion space for *indig*: with completed digital infrastructure, the use of digital technology has expanded adaptability of regional resources and enhanced the possibility as well as efficiency of carrying out green innovation activities; in the overall industrial chain, deep integration of digital technology and traditional industries promotes synergistic clustering of industries, and improves the cooperative innovation levels, as well as *RGTI*.

It's noteworthy that the *indig* coefficient for *RGTI* in the northeast region stands at 1.7882, which is positive but only significant at the 10% level. This indicates potential benefits from green dividends due to digitization. However, *RGTI* is limited due to reasons such as beginning of industrial digitalization, underdeveloped infrastructure, and contradictions in supply and demand of talents.

Discussion

Based on Model (1) shown in Table 4, we infer that *indig* enhances *RGTI*, thereby confirming Hypothesis 1. As the industrial digitization progresses, deep integration of digital technology and traditional industries has been enhanced. The extensive penetration and use of digital technology is expected to increase the demand for highly skilled and educated personnel. This will also continuously optimize the human capital structure, and lay the foundation for the proliferation of innovative factors and *RGTI* (Sun & Hou., 2019). Furthermore, deep integration will elevate employee innovation (Wang, 2022) and enhance open innovation by easing the identification, access, matching, and utilization of digital resources (Wu, 2022).

The regression results obtained from the panel threshold model presented in Table 6 reveal a development characterized by distinct phases in industrial digitization. These phases demonstrate increasing marginal effects, thus confirming Hypothesis 2. (1) Specifically, when indig is less than 2.35, the indig coefficient is positive (0.2543) at the 1% significance level. RGTI promotes information sharing effects, including multi-dimensional and multi-level knowledge, as well as the integration of technological domains. Undertaking RGTI solely based on enterprises' past technological experience and knowledge accumulation becomes challenging in such circumstances (Mubarak et al., 2021). *Indig* promotes industrial chain informatization and transparency, accelerates knowledge integration and reconstruction, promotes industrial cross-border integration, and expands the cognitive domain of enterprises, effectively improving the production efficiency. Besides, there are regional imbalances in industrial digitalization. The western region, represented by Xinjiang, Inner Mongolia, and the northeast region are lagging behind in industrial digitalization, and the *indig* degree is low. Due to infrastructure construction of digital technology and lag effects of ecological technology benefits, promotion of *indig* on *RGTI* cannot be fully realized. (2) When *indig* > 2.35, impact coefficient of *indig* on *RGTI* is significantly positive (0.4357) at 1% level. Once industrial digitalization reaches maturity, as indicated by a mature infrastructure, it unlocks a wider range of production tools, arranged in the most efficient manner. Moreover, sophisticated digital technologies optimize traditional business models and resource utilization, leading to improved productivity and innovation. These will further reduce technical energy consumption, improve the industrial access threshold, promote the development of green technology of enterprises, and enhance *RGTI*. Besides, it decreases information asymmetry between enterprises and promotes resource allocation, enabling enterprises to improve their knowledge of resource utilization and efficiently integrate resources. The eastern region, represented by Guangdong and Zhejiang, has been rapidly developing in terms of industrial digitalization. With the national "Beautiful China" development strategy, the environmental protection concept is deeply rooted, promoting the demand side to choose environmentally friendly products. Increased *indig* can further promote supply-side and demand-side communication, which reduces information asymmetry, improves the efficiency of enterprises to change the production mode, and facilitate enterprises to conduct *RGTI*.

Table 7 's mediation effect test results highlight that the advanced industrial structure and marketization processes lays the foundation for industrial digitalization to foster green technology innovation, corroborating Hypothesis 3 and Hypothesis 4. Industrial digitalization can upgrade traditional industries, strengthen the competitiveness of highly integrated industries, and ultimately lead to industrial transformation and upgrading. Of note, *indig* promotes structural innovation of production factors, empowers the marketization of factors and enhances the marketization process owing to its high technology, high payoff, high integration and high synergy. Marketization strengthens inter-regional technology exchanges, which favors regional green technology innovation.

Conclusions, Recommendations and Future research direction

Conclusions and recommendations

Given the dual constraints of energy and environment, promoting regional green technology innovation through industrial digitalization becomes a pivotal strategy to achieve the "dual carbon" goal and foster high-quality economic development. We have empirically analyzed the mechanism and effects (linear & non-linear) of *indig* on *RGTI*. The main conclusions are: i. *Indig* and *RGTI* have positive spatial correlations, with obvious spatial agglomeration characteristics. The *indig* level fluctuates, while the *RGTI* level continuously rises, showing regional heterogeneity and a unipolar characteristic; ii. *Indig* can effectively promote *RGTI,* both at national and regional levels (apart from the northeastern region), and during the research period, the *RGTI* level improved by about 0.4446, which was attributed to *indig*; iii. There is a single threshold for *indig*, with a threshold value of 2.35, and the positive driving trend has a “marginally increasing” characteristic; iv. There are two critical factors with partly intermediary roles —industrial structure advancement (0.2390) and marketization (0.6015). Accordingly, the following policy recommendations were made:

(1) Enhance industrial chain digitalization and intelligent transformation. Smoothen the digital trade circulation system and develop digital service trade. Focus on industrial digitalization and improve service efficiency as well as quality. As an important driver for regional green technology innovation, industrial digitization can optimize the structure of talents, and improve the development vitality of the region as a whole. However, giving full play of its effect requires strengthening digital infrastructure in the whole existing industrial chain. Steadily promote digital industry cooperation, promote digital infrastructure construction and scientific research and innovation.

(2) Due to regional heterogeneity, each region should formulate own corresponding policies to development characteristics. By formulating differentiated policies, the huge potential of industrial digitalization service economy will be released and imbalance of development between regions will be alleviated. Moreover, increasing the allocation of innovation resources and capital investment is essential to stimulate enterprise-led green technology innovation. The low level of industrial digitization in the northeast region cannot promote *RGTI* while in the west and northeast, it is slow and at risk of stagnation. Therefore, it is necessary for relatively backward regions to undertake industry transfer from the eastern and central regions to synergistically build an industrial chain system, ensuring steady introduction of advanced technologies. Due to the high demand of digital technology for talents, it is helpful for backward regions to establish supporting policies to attract short-term talents in key fields and accelerate talent flow.

(3) Promote industrial structure advancement and marketization. Upgrade traditional industries by digital technology, digitalize the traditional operation model, and promote information exchange on supply and demand sides. Besides, optimize the configuration of heterogeneous resources and improve resource utilization efficiency via deep integration in the industrial structure advancement process, promoting the cognitive level of overall industry and improving the innovation boundary of enterprises. Continuous development of marketization is an effective motive force for enhancing green innovation. Enterprises should employ feedback signals from the market in time to alleviate resource mismatches and further promote technological spillovers.

(4) Enterprises should actively develop digital technology and realize digital transformation. The digital economy can promote the progress of green technology, thereby improving the green production efficiency of enterprises. If enterprises build digital platforms, while promoting information sharing and improving technical levels, they can also prevent potential risks and achieve smooth development of enterprises. In addition, the creation of a digital platform enables collaborative development among enterprises, facilitating more precise professional division of labor through the utilization of digital technology.

Limitations and future research direction

The purpose of this empirical study is to investigate the linear and non-linear impact of industrial digitalization on regional green technology innovation. These results indicate that the former can significantly promote the latter. However, this paper investigates the influence of both internal and external factors on green technology innovation, utilizing macro-level data. While a micro-level perspective holds greater sway and significance for companies and enterprises in policymaking, it is crucial to consider the path of industrial digitization for attaining high-quality economic development from a micro standpoint (Ning et al., 2022; Ning et al., 2023). In addition, since both industrial digitalization and regional green technology innovation show certain spatial correlation, whether industrial digitalization as the main body of digital economy has a spatial spillover effect on regional green technology innovation need to be further discussed.

Declaration of competing interest

None.

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Appendix A

Robustness tests of basic regression

(1) Lag period test

indig with one-period lag (*indig1*) and two-period lag (*indig2*) are introduced into the benchmark regression model to mitigate the possible estimation bias caused by reverse causality. In Table A1, coefficients of *indig1* and *indig2* are significantly positive. Thus, the results are robust.

Table A1
Results of lag period test.

	(1)	(2)	(3)	(4)
indig1	2.0423***	1.5485***		
	(5.00)	(4.05)		
indig2			1.9616***	1.7662***
			(4.93)	(4.40)
gover		0.9505		1.1437
		(0.71)		(1.21)
er		0.2995*		0.1984
		(1.96)		(1.69)
finsize		13.0246***		4.9100
		(2.78)		(1.19)
fdi		-2.4013		-4.8354*
		(-0.96)		(-1.87)
_cons	2.4869**	2.4445**	2.8618***	2.6635**
	(2.31)	(2.63)	(2.76)	(2.51)
N	180	180	150	150
R^2	0.446	0.543	0.494	0.553

(2) Replacing the dependent variable

While some studies measure regional green technology innovation using the quantity of granted green patents, others utilize the quantity of green technology applications (Xu & Cui., 2020). Therefore, we adopted the number of green patent applications for the robustness test. In models (1) and (2) of Table A2, the coefficient of indig is positive and significant, indicating that the results are robust.

Table A2
Results of replacing dependent variable.

	(1)	(2)	Non-municipalities1	Non-municipalities2
	ln RGTI 1	*ln RGTI 1*	*RGTI*	*RGTI*
indig	2.5588***	1.8466***	2.0617***	1.4273***
	(5.34)	(4.65)	(4.40)	(3.60)
gover		0.5073		0.4338
		(0.28)		(0.24)
er		0.2602		0.3562**
		(1.60)		(2.37)
finsize		19.4098***		18.9843***
		(3.81)		(3.88)
fdi		1.6920		0.8291
		(0.58)		(0.18)
_cons	1.5733	1.7538*	2.2266*	2.3409**
	(1.24)	(1.76)	(1.81)	(2.38)
N	210	210	182	182
R^2	0.530	0.627	0.471	0.599

(3) Reducing samples

This paper directly removes municipality samples for robustness test, and results are in columns (4) and (5) of Table A2. The coefficients of *indig* on *RGTI* are significantly positive, proving that the results are robust.

(4) Endogenous test

① (Two-stage least squares) regression with instrumental variable

Empirical analyses might encounter endogenous problems due to reverse causality. Regions with high levels of green technology innovation will pursue high-quality economic development, which is matched with characteristics of industrial digitalization with quality and efficiency, green benefits. Regional human capital level with high level of regional green technology innovation is generally higher. Based on employee organization matching theory, digital transformation and upgrading is inseparable from matching high-quality employees (Xiao et al., 2022). Thus, interactions and a reverse causal relationship may exist between industrial digitalization and regional green technology innovation.

Referring to Arellano & Bond (1991), we adopt the two-stage least squares method (2SLS). The first and second-order lag terms of the independent variables serve as instrumental variables for the endogeneity test. Regression results are shown in Table A3. After considering the possible endogenous problems, industrial digitalization still shows a significant positive impact on regional green technology innovation, indicating robust benchmark regression results.

Table A3
The results of 2SLS regression with instrumental variable.

	(1)	(2)	(3)
indig	2.6097***	1.6898***	2.1055***
	(13.06)	(8.36)	(6.54)
Control variable	No	YES	YES
Province FE	No	No	YES
Kleibergen-Paap rk LM	23.753	16.858	17.474
Kleibergen-Paap rk Wald F	2270.253	1133.876	274.908
N	150	150	150

② GMM with instrumental variable

Given the endogeneity problem, the systematic GMM model is used for regression analysis, and the Sargan statistic is selected to test instrumental variable selection reliability of the GMM model (Table A4). The Sargan test result is 0.986, implying that instrumental variable selection is valid. In addition, the Arellano-Bond statistic AR (2)=0.215, thus, estimation results of system GMM model are consistent and valid. After considering the influence of endogeneity, industrial digitalization can promote regional green technology innovation, implying robust results.

Table A4
The results of GMM regression with instrumental variable.

	(1)
	lngreen
L.lngreen	0.9268***
	(0.0409)
Indig	0.2318*
	(0.1375)
Controls variables	YES
Province FE	YES
AR(1)	0.002
AR(2)	0.275
Sargan test	0.740
N	180

Note: Standard errors in parentheses.

Appendix B

Robustness test of panel threshold

Conduct robustness test by adding control variables to the threshold model. Model (1) adds *open*, model (2) adds *rd*, and model (3) adds both to the original threshold model (See Table B). Models (1)-(3) show that *indig* plays an increasing marginal effect on *RGTI*. Therefore, the result is robust.

Table B
Panel threshold robustness tests.

	(1) lngreen b/z	(2) lngreen b/z	(3) lngreen b/z
indig·I(indig<2.35)	0.2105	0.2326	0.1811
	(1.36)	(1.49)	(1.12)
indig·I(indig≥2.35)	0.3905**	0.4174***	0.3652**
	(2.58)	(2.77)	(2.33)
L.lngreen	0.7260***	0.7185***	0.7148***
	(15.03)	(14.01)	(13.93)
gover	1.5990***	1.5491***	1.6378***
	(3.13)	(3.03)	(3.18)
fdi	-0.9087	-0.5477	-0.8390
	(-0.61)	(-0.37)	(-0.56)
er	0.0950	0.0933	0.0937
	(1.27)	(1.24)	(1.24)
finsize	3.4088*	3.5471*	3.1979
	(1.76)	(1.82)	(1.63)
open	-0.3447		-0.3653
	(-1.15)		(-1.21)
rd		6.1447	7.5670
		(0.54)	(0.66)
_cons	0.6070	0.3993	0.6422
	(1.58)	(1.20)	(1.65)
N	180	180	180
R^2	0.853	0.851	0.853

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