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Research article

Intelligent manufacturing and green innovation: Quasi-natural evidence from China

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ABSTRACT

Intelligent manufacturing is an important driving force for improving quality and efficiency and promoting green innovation. Based on the data of Chinese listed companies and taking the Chinese intelligent manufacturing pilot demonstration projects as a quasi-natural experiment, this paper constructs a difference-in-differences (DID) model to explore the effect and mechanism of intelligent manufacturing on enterprise green innovation. The results show that intelligent manufacturing has significantly promoted green innovation in China, and this effect is still valid after considering various robustness tests. Heterogeneity analysis shows that in areas with a good green development foundation and poor information infrastructure, the impact is more obvious. In non-state-owned enterprises and mature enterprises, the impact is more obvious. Mechanism analysis indicates that intelligent manufacturing enhances green innovation through cost management effects, efficiency improvement effects, and employment structure optimization effects. The conclusions provide clear policy implications for developing countries to promote intelligent manufacturing practices and green high-quality development.

1. Introduction

Since the 2008 global financial crisis, various countries have proposed different forms of reindustrialization strategies, such as Industry 4.0, modern industrial strategy, and "Made in China 2025." A core element is the application of intelligent technologies and supporting technologies to efficiently perform a large number of simple, repetitive, and even flexible and precise tasks [1], which will set off a "manufacturing intelligence revolution" in the national economic system. Intelligent manufacturing is based on advanced information and manufacturing technology, which optimizes the production process and improves the design, production, management, and integration level of the entire product life cycle [2] to achieve the intelligence of manufacturing equipment and processes. The entire manufacturing process has the characteristics of automatic learning, automatic perception, automatic decision-making, and automatic execution [3,4]. Davis et al. [5] argued that the widespread application of intelligent technology in the manufacturing industry has led to a profound transformation from automated production to personalized design and production of products as well as enterprise management and services. Kang et al. [6] pointed out that intelligent manufacturing is the integration of advanced information and communications technology and existing manufacturing technologies and has become a new revolution and paradigm in modern manufacturing.

Currently, the total energy consumption in China is gradually increasing, and the pressure on ecological resources and the

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environment is constantly increasing [7–9]. The extensive growth model that investment, resource investment, and external demand previously drove can no longer continue [10]. Green innovation is an important driving force for transforming the mode of economic development and an important support for achieving green sustainable development. Against the backdrop of this transformation of driving forces, intelligent manufacturing, with its outstanding advantages of permeability, diffusion, and spillover, provides a development opportunity for green innovation and has become an important lever for industrialization and green transformation in various countries [11]. However, the new industrialization led by information technology still fundamentally aims at expanding the scale of industrialization and economic aggregate and does not emphasize the green and intelligent technological revolution. The attention to new energy and new resources needs to be improved [10,12]. Large technology investment and high transformation costs characterize green innovation activities. In their decision-making behavior, enterprises may not only give up green innovation because of the associated risks, but they may also seize the development opportunity of intelligent manufacturing to enhance their market power. Therefore, in terms of the impact of intelligent manufacturing on green transformation, there are two perspectives: data-driven innovation and the curse of capability.

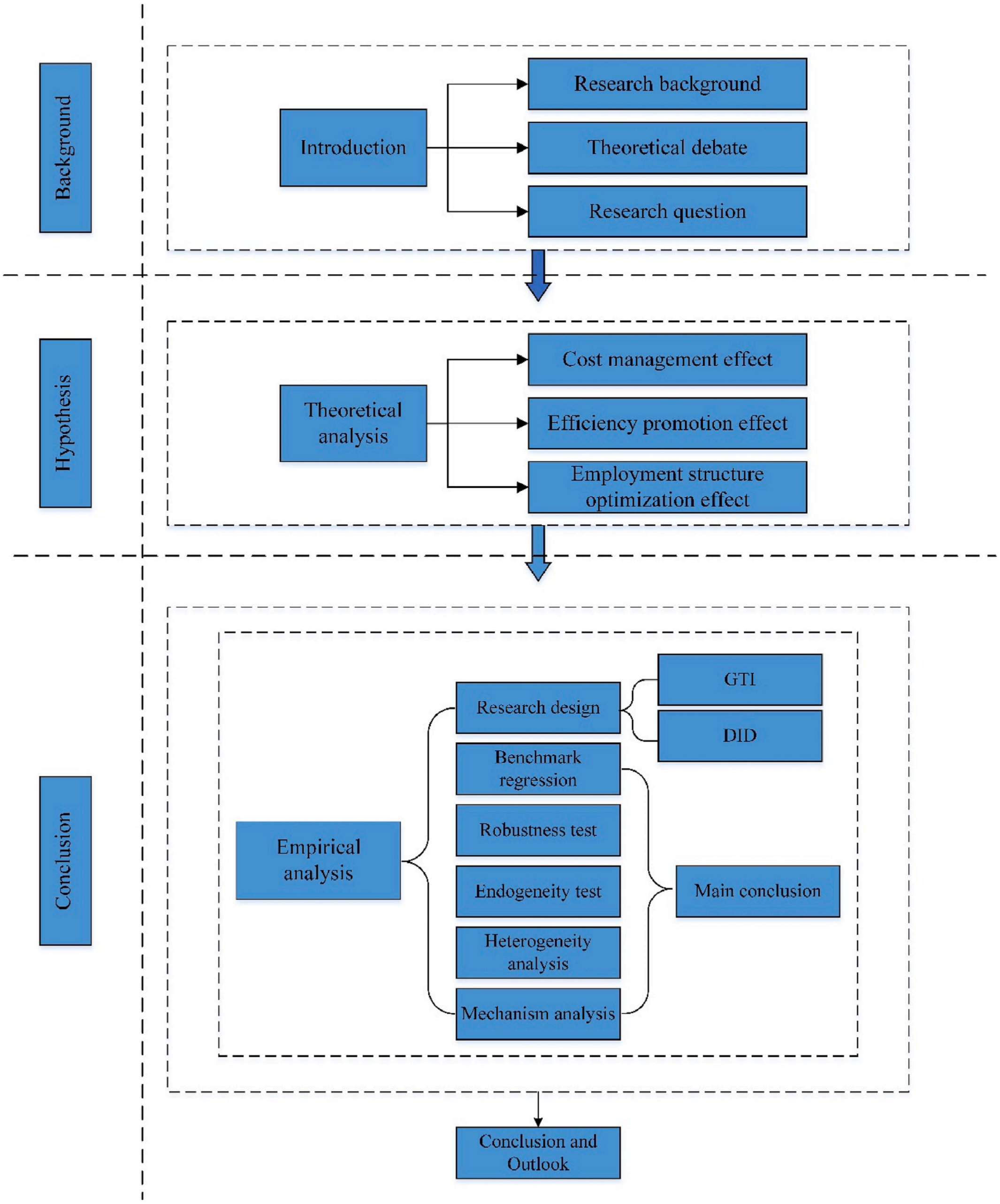

Fig. 1. Research framework.

Specifically, the dynamic capability theory proposes that the technology paradigm shift triggered by intelligent technology can strengthen the dynamic capability of enterprises to identify innovation opportunities, transform innovative thinking, and optimize and reorganize existing green resources through strategic upgrading. The information processing theory proposes that the scalability and openness of intelligent technology can help enterprises identify their own resource needs [13] and effectively improve the efficiency of enterprise resource allocation and information integration capabilities. This joint role promotes green transformation of enterprises. Intelligent manufacturing equipment has been found to have high efficiency and precision and can monitor energy consumption and pollution in real time to regulate excessive pollution through standardized control [14–16]. Additionally, intelligent manufacturing can reduce the cost of renewable energy and provide cleaner manufacturing processes [17]. Gan et al. [18] and Tang et al. [19] found that the construction of robotics and telecommunications infrastructure could significantly improve the level of green innovation. Bernard et al. [20] argued that intelligentization could facilitate the flow of information, technology, research, and data, breaking geographical constraints and enabling the realization of green innovation's full potential. Li et al. [21] and Qiao et al. [22] also found that robotics and information infrastructure significantly reduce air pollution. However, the curse of capability suggests that the application of intelligent technology will lead to information overload [23], not only raising the threshold for enterprise data decision-making, but also squeezing out the necessary resource investment for strategic upgrading. Specifically, with the continuous expansion of information channels, the exponential growth of network connections and information flooding have begun to emerge, making it difficult for enterprises to timely discover and capture valuable information from massive amounts of data. Under this condition, there is an imbalance in the matching between digital technology applications and organizational management capabilities. In addition, the massive resource investment required for the digital materialization process will have a crowding out effect on green upgrading [24], weakening the necessary resource base for green upgrading. The combined effect hinders the green transformation of enterprises. Zhao et al. [25] used provincial panel data from China to study the effect of artificial intelligence on green growth and found that the effect had U-shaped characteristics, with significant regional and industry heterogeneity. Xiong et al. [26] reached a similar conclusion using the Yangtze River Economic Belt as a case study. Zhang et al. [27] and Zhou et al. [28] argued that smart technologies would exacerbate green inequality and air pollution. They cited the potential risks and costs to environmental governance posed by defects in intelligent technology that can impact government decision-making mechanisms, information dissemination mechanisms, and social organization structures. They also cited the potential for significant errors and judgments by environmental decision makers because of data bias [29]. Luan et al. [30] proposed a new explanation from the perspective of the rebound effect.

The marginal contribution is as follows: first, from the research perspective, we bring intelligent manufacturing and enterprise green innovation into the same analytical framework, and systematically investigate the effect of intelligent manufacturing on enterprise green innovation, therefore, it can provide new understanding and enlightenment to improve the refinement of eco-environmental management, improve the efficiency of resource utilization, and promote green and low-carbon green development. Second, in terms of research content, it enriches the research on the effect of intelligent manufacturing on enterprise green innovation, not only enriches the relevant theoretical literatures, but also provides experience for developing countries to develop the application of intelligent manufacturing in the green low-carbon transition. Third, we use various advanced robust estimation methods of DID, dual machine learning model to test the robustness. Most of the existing studies use IFR data to estimate the development level of intelligent manufacturing (Liu et al. , 2020), but Dauth et al. [31] point out that this construction method may cause the error terms in the areas with similar industrial structure to be correlated, so the standard error may be underestimated.

Intelligence and greenery are the future development directions of the manufacturing industry, and how to achieve a balanced development is an important issue that countries urgently need to address. On a theoretical level, the debate surrounding data-driven innovation and the curse of capability provides a good research gap for this paper. On a practical level, China, a major manufacturing country, faces serious environmental protection and resource constraints. This provides a good practical scenario for how to use intelligent manufacturing to achieve green transformation. Therefore, based on the quasi-natural experiment of China's intelligent manufacturing demonstration project, we used microenterprise samples of listed companies to connect the promotion and mode characteristics of intelligent manufacturing with enterprise green innovation and guide enterprise management practices to accelerate the process of intelligent transformation. Fig. 1 shows the research framework of this article.

2. Institutional background and theoretical mechanism

2.1. Institutional background

We divided the development process of intelligent manufacturing in China into three stages. The first stage is the industrialization-driven informatization stage. After its reform and opening up, China initiated the National High-Tech Development Plan (also known as the 863 Program) to promote the development of advanced technologies in the country. The Ministry of Science and Technology was responsible for developing advanced manufacturing systems to upgrade China's manufacturing industry. China has gradually integrated advanced manufacturing technology and the Internet to construct an information network covering the entire country.

The second stage is the integration of industrialization and informatization. In 2007, the central government proposed the strategy of integration, emphasizing informatization to drive industrialization and revitalize the equipment manufacturing industry. In 2010, China realized its informatization goals, and the information industry has become an important pillar of the national economy. However, from the perspective of industry practice, the traditional industrial automation system still dominates industrial production, which has yet to reach a real level of personalized customization as a typical feature of intelligent manufacturing. Compared with developed countries in the same period, China has implemented many beneficial policies but has not yet formed a systematic strategic deployment for intelligent manufacturing.

In the third stage, the "Made in China 2025" policy aims to make the country dominant in global high-tech manufacturing. The country and various regions have launched pilot intelligent manufacturing demonstration projects and supporting measures to create an intelligent manufacturing industry cluster and the atmosphere of a technological breakthrough.

To investigate the effectiveness of intelligent manufacturing models and facilitate the transformation and upgrading of the manufacturing industry in China toward intelligent manufacturing, the Ministry of Industry and Information Technology has focused on key links in manufacturing since 2015. It has prioritized selecting pilot demonstration projects from enterprises that meet the requirements of the two-way integration management system standards in key regions and industries where basic conditions are favorable and demand is pressing. Pilot and demonstration activities have occurred in six areas: process manufacturing, discrete manufacturing, intelligent equipment and products, new forms and models of intelligent manufacturing, intelligent management, and intelligent services. After 3 years of implementation, over 300 pilot enterprises have been selected, covering 92 industry categories and 31 provinces (municipalities and autonomous regions), generating over 100 billion yuan in investment. This has provided valuable practical experience for the development of intelligent manufacturing in China.

2.2. Theoretical mechanism

2.2.1. Cost management effect

Green innovation behavior requires the long-term investment of a large amount of capital and labor. Resource constraints, especially financial constraints, are often the primary problems hindering the green innovation of enterprises. Intelligent manufacturing encourages enterprises to optimize their own organizational structure and promotes their evolution from static organizations to dynamic organisms, which helps to reduce enterprise cost stickiness and total production cost and allows enterprises to devote more resources to green innovation. Enhance the prior tolerance of enterprises to green innovation activities. In this study we mainly analyzed the mechanism of intelligent manufacturing on green innovation from the perspectives of internal agency cost and external transaction cost.

(1) Internal agency cost

The internal agency cost mainly includes sales costs and management costs. From the perspective of sales costs, intelligent manufacturing technology has transformed enterprise sales models [32], a transformation that has created conditions for reducing sales costs. Enterprises achieve collaboration and sharing of information resources in various stages by introducing intelligent high-end equipment, thus reducing the cost of obtaining production information. At the same time, they use digital technology to effectively track the consumption of raw materials and energy as well as the output of waste, and they implement more accurate emission reduction plans (Kusiak, 2017). The application of Internet e-commerce platforms has further accelerated the exchange of product information between enterprises and customers, increasing consumer understanding of products and accelerating the speed of product turnover of enterprises [33], all of which will help enterprises implement precision marketing, reduce sales costs, and promote green innovation.

From the perspective of management costs, intelligence reduces the discretion of managers [34] and the moral hazard that may exist in the principal–agent relationship of enterprises. Managers use intelligent analysis tools to accurately predict changes in market demand and adjust resource inputs in a timely manner [35]. Intelligent technology can also help us timely understand firsthand information such as consumers' green preferences, green environmental protection policies, and trends in industrial clean technology reform [36]. Digital technology subverts the organizational structure of traditional enterprises, alleviates internal information asymmetry, and promotes the development of enterprise organizational structure toward networking and flattening [37]. Various departments can reorganize organizational resources with green innovation as the core through information systems and information platforms, and they can coordinate and complement each other by promoting enterprises' internal governance mechanism and the external environment for the development of the digital economy, thus effectively reducing the internal and external transaction costs in the green innovation process.

(2) External transaction cost

The external transaction cost mainly includes search costs and financing costs. The mechanism by which intelligent manufacturing reduces search costs for enterprises lies in the application of new digital technologies that help break through the boundaries of internal innovation, enhance cooperation (collaboration) innovation capabilities between enterprises [35], shift to open innovation, and promote green innovation activities through knowledge spillovers and transfer. Specifically, with the highly developed division of labor in industries and the increasing complexity of innovation, a new product is often the result of collaborative cooperation among enterprises, suppliers, customers, and other market entities. Compared with internal independent innovation behavior of enterprises, external cooperation is constrained by various cost factors such as search and matching costs, contract costs, and communication and coordination costs [38]. Enterprises' utilization of various information technologies is beneficial for shortening the geographical and technological distance of resource allocation in green innovation; mastering new technologies, concepts, and trends of green innovation at a lower cost; and promoting green innovation in enterprises [39].

The mechanism by which intelligent manufacturing reduces financing costs for enterprises lies in its ability to effectively alleviate information asymmetry in the credit market [40], better promote the matching between financial resource supply and enterprise demand, and provide more financial support for enterprises' green innovation activities. At the same time, the rise of digital finance driven by intelligent manufacturing can effectively compensate for the shortcomings of traditional financing markets, reduce financing costs, alleviate the financial pressure for enterprises to carry out green innovation [41], and stimulate green innovation activities for enterprises.

2.2.2. Efficiency promotion effect

The efficiency promotion effect of intelligent manufacturing is multifaceted and includes the enhancement of R&D efficiency and production efficiency. The application of intelligent technology is conducive to the rational allocation of resources, improving the utilization rate of green R&D investment elements and R&D efficiency while leaving enterprises' inherent resource boundaries unchanged. Specifically, the development of intelligent technology has accelerated the encoding of knowledge [42], expedited the exchange and sharing of data and knowledge elements among various systems, increased opportunities for green integrated innovation among different innovation entities, and fast-tracked the efficiency of green innovation. In addition, intelligent manufacturing promotes the continuous optimization of technological innovation models and mechanisms, providing opportunities and conditions for enterprises to accelerate breakthroughs in key core green innovation, effectively breaking the low-end, lock-in state of green technology in reality [43], and to break through technological bottlenecks and improve innovation speed with shorter practice.

Enterprises' application of digital technology allows them to obtain market and user information through multiple channels, greatly extending the radiation range of their green product sales market [44], and to explore new market opportunities [45]. At the same time, enterprises use advanced and mature digital technology to digitize and green their existing products and services, which helps them speed the innovation process of products and services, cultivate new business projects, and expand new business models based on digital platforms. The new business model can increase enterprises' operating revenue, improve their performance returns, and provide them with financial guarantees to introduce green equipment and carry out green innovative production. The new business model is also conducive to increasing the expected returns of enterprises' green innovation R&D investment, thereby encouraging them to invest more in R&D and stimulating green innovation behavior. From the perspective of technological progress benefits, the use of big data technology can effectively enhance the ability of enterprises to collect, accumulate, and comprehensively analyze data information on energy investment structure, pollution emissions, and green emission reduction technologies; enhance their ability to predict emission reduction; and force enterprises to carry out energy-saving and emission reduction green innovation.

2.2.3. Employment structure optimization effect

The two classic informatization development and labor demand theories are the skill-biased technological change (SBTC) hypothesis and the routine-biased technological change (RBTC) hypothesis. According to SBTC, the improvement of enterprise informatization will increase the demand for high-skilled labor and reduce the demand for low-skilled labor [46]. RBTC holds that the improvement of enterprise informatization levels will replace repetitive and procedural jobs and complement non-repetitive and non-programmed jobs [47]. The excessive demand for highly skilled labor in intelligent manufacturing drives the transformation and upgrading of workers' knowledge and skills, continuously improving the level of human capital, changing the direction of skill development, and achieving dynamic matching between new jobs and knowledge and skill structures (Kusiak, 2017). Enterprises are more likely to integrate advanced technology, knowledge, and green production concepts into their products and services, promoting green innovation activities.

In addition, the boundary extension effect of artificial intelligence requires highly skilled labor with scientific research capabilities and technologically innovative thinking. Organically integrating various data resources to solve the complexity problems of production and service systems enhances the collaborative innovation ability in the green technology research and development process [48]. The application of intelligent technology in enterprises also requires the introduction of information technology-oriented talents.

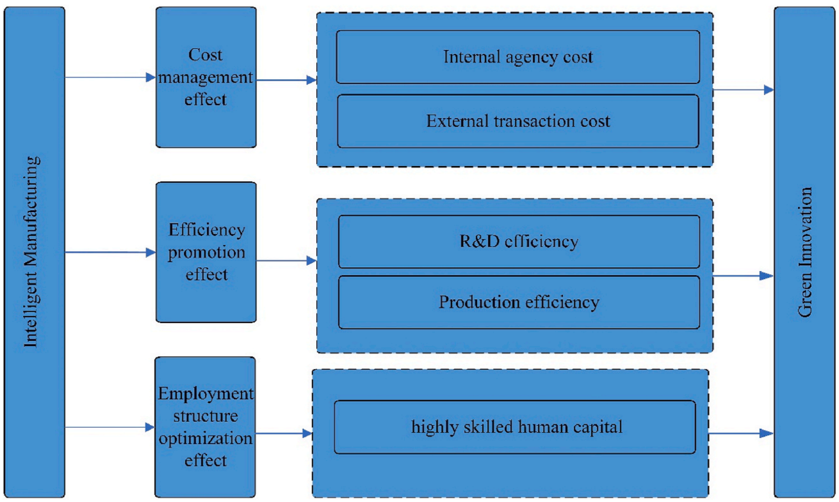

Fig. 2. Impact mechanism.

This will provide important technical and human support for green technology innovation, reduce the risk of failure and innovation costs in the process of green technology innovation—which is conducive to stimulating the enthusiasm of green innovation in enterprises—and improve the efficiency and quality of green value creation in enterprises [49]. Fig. 2 visually demonstrates the impact mechanism.

3. Research design

3.1. Model setting

To examine the impact of intelligent manufacturing on green innovation, we constructed a staggered DID model based on theoretical analysis.

$$GTI_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \gamma X_{i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

where *GTI* is green innovation, *DID* is the intelligent manufacturing index (the core explanatory variable of this paper), *X* is a group of control variables, λ_t is time fixed effect, μ_t is individual fixed effect, ε_{it} is random error, *t* is the time dimension and *i* is the individual dimension.

3.2. Variable selection

(1) Explained variable

In this study we measured the level of green technology innovation using the number of patent applications and acquisitions. A higher number of green patents indicates a stronger green technology innovation capability. This choice of indicator has the advantage of being quantifiable and directly reflects the output of enterprises' green technology innovation activities. Additionally, compared to measures such as R&D investment, patents have a clear technology classification, allowing for analysis of innovation activities based on different technology attributes and the reflection of their different value connotations and contributions. We measured the level of green innovation using the number of green patent acquisitions and tested the robustness of this measure using the number of green patent applications. To address the right-skewed distribution, we added 1 to the number of green invention patents and took the natural logarithm to obtain the core explanatory variable GTI.

(2) Explanatory variable

The central explanatory variable in this study is DID. If enterprise i has been selected as a pilot demonstration enterprise for intelligent manufacturing at time t (including the current year), then DID is set to 1, and 0 otherwise. The coefficient of DID reflects the net effect of intelligent manufacturing on the enterprise's green innovation. A positive value indicates that intelligent manufacturing improves the enterprise's green innovation.

(3) Control variable

To minimize potential endogenous interference resulting from omitted variables, we controlled for factors that impact green innovation based on the work of Yang [50], Lee et al. [51], Amore et al. [52], and Wen et al. [53]. Examples include the following: (a) enterprise size (natural logarithm of total assets per year (Size)), (b) the ratio of revenue to average total assets (Ato), (c) enterprise value (Tobin Q), (d) a dummy variable indicating whether the chairperson and general manager are the same person (Dual), (e) the percentage of shares held by the top 10 shareholders (Top 10), (f) the number of years since the company went public (List Age), (g) the percentage of shares held by institutional investors (Inst), (h) a dummy variable indicating whether the company is audited by one of the Big Four accounting firms (Big 4), (i) and the ratio of net assets to average total assets (ROA).

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
GTI	30,255	0.36299	0.76825	0	6.89972
DID	30,255	0.01061	0.10246	0	1
Size	30,255	22.1162	1.32655	15.5773	28.6365
Ato	30,254	0.66146	0.54894	−0.0479	12.3729
Tobin Q	29,670	2.13361	2.84115	0.67352	259.146
Dual	30,255	0.28405	0.45097	0	1
Top10	30,255	0.5907	0.15495	0.0131	1.0116
List Age	30,255	2.0125	0.94123	0	3.43399
Inst	30,255	0.37476	0.2406	0	3.26727
Big4	30,255	0.05642	0.23074	0	1
ROA	30,254	0.04214	0.07706	−1.8591	0.87959

3.3. Data source

In this study we used a sample of 30,225 annual observations of manufacturing firms listed on the Chinese A-share market from 2010 to 2020. We identified the intelligent manufacturing pilot enterprises based on the list of intelligent manufacturing pilot demonstration projects published by the Ministry of Industry and Information Technology of the People's Republic of China. We obtained the financial data used in this study from the China Stock Market & Accounting Research database. We applied winsorization to the continuous variables at the 1 % and 99 % levels, and the descriptive statistical results are shown in Table 1.

4. Empirical results and analysis

4.1. Benchmark regression

To examine the effect of intelligent manufacturing on green innovation, we employed the staggered DID model. Table 2 shows the benchmark regression results. Column (1) represents the simplified estimation without control variables, whereas column (2) includes control variables. Because macroeconomic policies and cyclical changes in the manufacturing industry may differentially influence the cost stickiness of firms and their willingness to adopt intelligent manufacturing, columns (3)–(5) control for industry fixed effects, city fixed effects, and province fixed effects, respectively. They also control for time fixed effects and individual fixed effects to minimize the bias owing to unobservable or unmeasurable factors at the city and province level.

The results of the benchmark regression (Table 2) demonstrate that intelligent manufacturing significantly enhances the level of green innovation in various circumstances. Specifically, after controlling for time and individual fixed effects, the coefficient of the key explanatory variable is 0.0692 (0.245 * 0.10246/0.36299), which means that for every 1 % increase in the standard deviation of intelligent manufacturing, the green innovation of the enterprise will increase by 6.92 % relative to its average. This indicates that intelligent manufacturing enterprises tend to increase their investments in green innovation activities to meet the requirements of the digital economy and the sustainable development era.

4.2. Robustness test

4.2.1. Modification of the clustering level

The clustering level refers to the assumption that groups of data objects are similar to one another. By varying the dimension of clustering (Table 3), we found that the regression results are consistent with expectations regardless of whether we employed industry clustering, industry–city bidirectional clustering, or industry–city–province clustering.

Table 2
Benchmark regression results.

	(1)	(2)	(3)	(4)	(5)
DID	0.242***	0.245***	0.238***	0.237***	0.237***
	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)
Size		0.0495***	0.0559***	0.0568***	0.0568***
		(0.011)	(0.011)	(0.012)	(0.012)
Ato		−0.0461***	−0.0438***	−0.0430***	−0.0430***
		(0.013)	(0.013)	(0.013)	(0.013)
Tobin Q		0.00125*	0.00111	0.00107	0.00107
		(0.001)	(0.001)	(0.001)	(0.001)
Dual		−0.0159	−0.016	−0.0154	−0.0154
		(0.012)	(0.012)	(0.012)	(0.012)
Top10		−0.122**	−0.106*	−0.114**	−0.114**
		(0.054)	(0.054)	(0.055)	(0.055)
List Age		0.0243	0.0188	0.0157	0.0157
		(0.015)	(0.015)	(0.015)	(0.015)
Inst		−0.0404*	−0.0376	−0.0342	−0.0342
		(0.025)	(0.024)	(0.024)	(0.024)
Big4		−0.100**	−0.103**	−0.109**	−0.109**
		(0.047)	(0.046)	(0.045)	(0.045)
ROA		0.0156	−0.0063	−0.014	−0.014
		(0.041)	(0.040)	(0.041)	(0.041)
time fixed		YES	YES	YES	YES
individual fixed		YES	YES	YES	YES
industry fixed		NO	YES	YES	YES
city fixed		NO	NO	YES	YES
province fixed		NO	NO	NO	YES
N	29866	29278	29278	29278	29278
R-sq	0.744	0.747	0.748	0.750	0.750

Note: We clustered the standard errors in brackets at the enterprise level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. The same applies later.

4.2.2. Replacement of estimation model

Because the majority of enterprises' green patent applications are zero, there is a left truncation characteristic. Therefore, we employed the Poisson pseudo maximum likelihood model and Tobit model, following Faleye et al. [54], to reexamine the effect of intelligent manufacturing on enterprises' green innovation activities. The results appear in columns (1) and (2) of Table 4. The robustness of the results obtained using different models supports the conclusion from the benchmark regression that intelligent manufacturing significantly enhances enterprise green innovation.

In recent years researchers have identified the potential problem of staggered DID as heterogeneous treatment effects, that is, the effect of the same treatment on different individuals may vary, which may be reflected in the length of time after treatment or in the two dimensions of the group that received treatment at different points in time. In this context, the traditional two-way fixed effects estimator, whether static or dynamic, may have potential bias. Therefore, we used the method proposed by Gardner [55], De Chaisemartin and D'Haultfoeuille [56], and Borusyak et al. [57] to reestimate. Fig. 3 shows the results, which indicate that the empirical findings of this study remain robust when the heterogeneous treatment effects are considered.

Furthermore, Bertrand et al. [58] highlighted that the data used in DID estimation often have the problem of serial correlation, which leads to standard error greatly underestimating the standard deviation, resulting in an overestimation of the t statistic and an overrejection of the original hypothesis. To address possible serial correlation, we employed Ma et al.'s [11] approach to build a Gaussian mixture model. Column (3) of Table 4 shows the results, which indicate that the empirical results remain robust.

Finally, considering that the traditional regression model may face the problem of the curse of dimensionality and multicollinearity, we used the double machine learning method to reestimate Chernozhukov's [59] benchmark regression. Columns (1)–(4) of Table 5 show the results of machine learning algorithms such as random forest, lasso regression, gradient boosting, and neural network, respectively. It can be seen that the regression coefficient is still significantly positive, which proves that our basic conclusion is still significant.

4.2.3. Parallel trend test results

The prerequisite for using the DID model is that the sample satisfies the parallel trend hypothesis, meaning that before intelligent manufacturing is implemented, green innovation of the treatment group and control group maintains a parallel changing trend. To verify this, we conducted a parallel trend test following Beck et al. [60]. Fig. 4 shows the results, which indicate that the pre-policy coefficients are not significant, but the interaction coefficients become significant from the year the policy is implemented. The results support the parallel trend hypothesis, and there is no discernible effect prior to the implementation of the policy. The increasing trend of the coefficient after the implementation of the policy suggests that the policy has a certain lag effect. This may be because the policy initially adopted a small-scale pilot demonstration, followed by the dissemination of effective experiences and models through replication and application, eventually expanding the scope of the pilot demonstration. Therefore, the promotion of green innovation by intelligent manufacturing is a dynamic, continuous learning process. As the pilot period extends, local governments' experiences are enriched, and the effects of the measures taken become more evident [61].

Table 3
Modification of the clustering level.

	(1)	(2)	(3)
	industry	industry-city	industry -city-province
DID	0.245***	0.245***	0.245***
	(0.014)	(0.011)	(0.021)
Size	0.0495***	0.0495***	0.0495***
	(0.016)	(0.017)	(0.016)
Ato	−0.0461**	−0.0461**	−0.0461***
	(0.017)	(0.017)	(0.015)
Tobin Q	0.00125	0.00125	0.00125
	(0.001)	(0.001)	(0.001)
Dual	−0.0159**	−0.0159*	−0.0159*
	(0.007)	(0.009)	(0.008)
Top10	−0.122***	−0.122***	−0.122**
	(0.037)	(0.039)	(0.045)
List Age	0.0243	0.0243	0.0243
	(0.026)	(0.027)	(0.025)
Inst	−0.0404**	−0.0404**	−0.0404**
	(0.015)	(0.015)	(0.019)
Big4	−0.100***	−0.100***	−0.100***
	(0.033)	(0.029)	(0.023)
ROA	0.0156	0.0156	0.0156
	(0.027)	(0.037)	(0.037)
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
N	29278	29278	29278
R-sq	0.747	0.747	0.747

Table 4
Results of replacement of estimation model.

	(1)	(2)	(3)
	Tobit	PPML	GMM
L.GTI			0.936***
			−0.0267
DID	0.754***	0.748***	0.618***
	(0.042)	(0.285)	(0.201)
Size	0.182***	0.870***	0.00603***
	(0.004)	(0.088)	(0.002)
Ato	0.00127	0.296**	−0.0278***
	(0.008)	(0.126)	(0.010)
Tobin Q	0.00840***	0.0311***	−0.0009
	(0.002)	(0.005)	(0.001)
Dual	0.0471***	0.662***	−0.008
	(0.010)	(0.206)	(0.012)
Top10	−0.509***	−0.972	−0.0576
	(0.037)	(1.074)	(0.051)
List Age	−0.182***	−0.377**	−0.0178**
	(0.007)	(0.154)	(0.008)
Inst	0.0816***	0.0363	0.0111
	(0.024)	(0.363)	(0.023)
Big4	0.113***	0.226	−0.0266
	(0.020)	(0.254)	(0.025)
ROA	−0.0871	1.363	−0.038
	(0.059)	(1.048)	(0.040)
_cons	−3.072***	−18.58***	
	(0.090)	(2.443)	
sargan			0.814
var(e.y)	0.540***		
	(0.004)		
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
N	29669	29669	24103

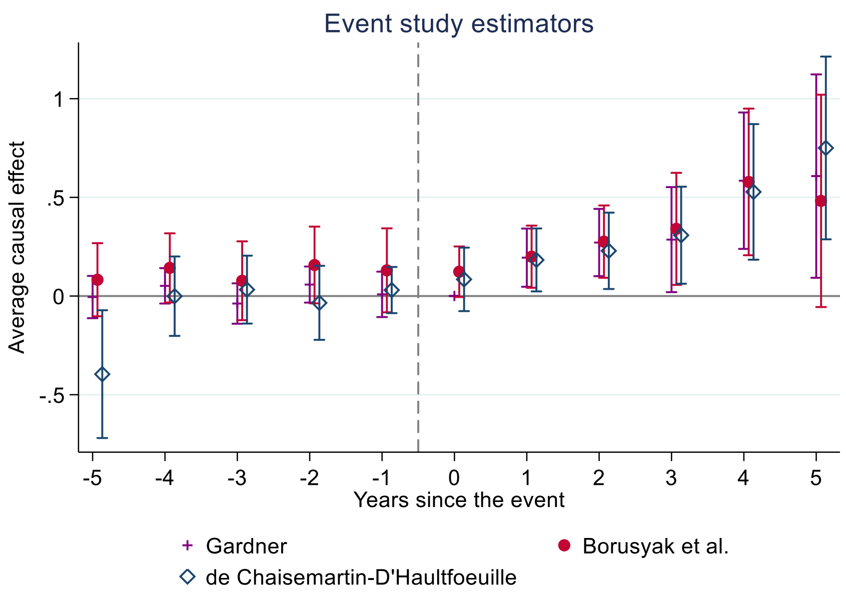

Fig. 3. Heterogeneity robust estimator.

4.2.4. Placebo test

There are two potential issues in using the DID model to assess the impact of intelligent manufacturing on green innovation. One is the possibility of a pseudo-regression problem, where the growth of green innovation in the treatment group is superior in itself regardless of whether or not intelligent manufacturing is implemented. The other is that the level of green innovation gradually deepens over time, at which point the results may not be closely related to intelligent manufacturing and the conclusion may be a

Table 5
Dual machine learning estimation results.

	(1)	(2)	(3)	(4)
	random forest	lasso regression	gradient boosting	neural network
DID	0.196***	0.224***	0.238***	0.251***
	(0.050)	(0.048)	(0.048)	(0.048)
_cons	0.078***	0.005**	0.005**	0.005**
	(0.003)	(0.003)	(0.0026)	(0.0026)
Control variables	YES	YES	YES	YES
Control variable quadratic term	YES	YES	YES	YES
time fixed	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES
N	30255	30255	30255	30255

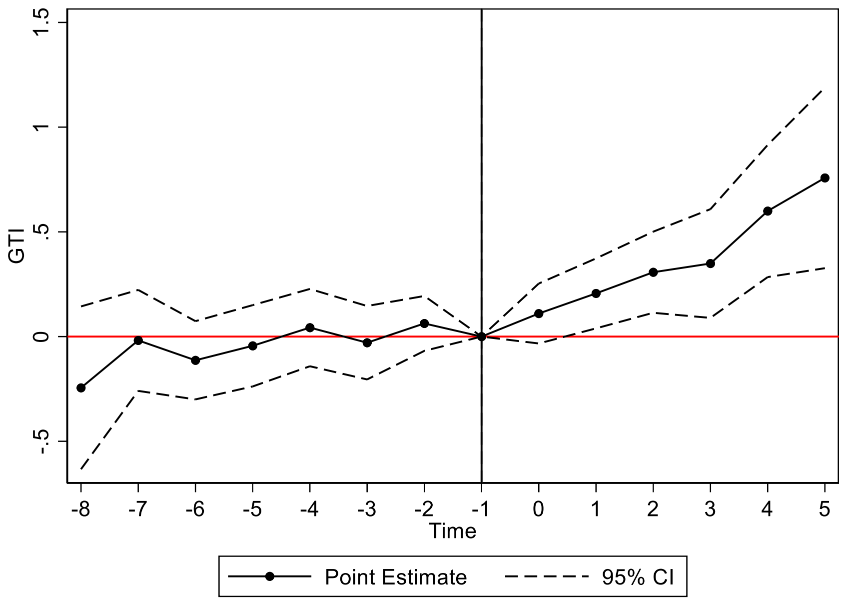

Fig. 4. Parallel trend test results.

random occurrence. To address these concerns, we conducted a placebo test. By randomizing the experimental group, we randomly generated a sample of intelligent manufacturing enterprises, created artificial pilot policy variables, and regressed the sample. We repeated the process 500 times.

Fig. 5 plots the kernel density distribution of the simulated regression coefficients for the randomized experimental group and the control group. It is evident that the regression coefficients for the core explanatory variables are normal distributions with mean values close to zero, indicating that the randomly generated directory of intelligent manufacturing has no effect on green innovation and satisfies the principle of randomness.

4.2.5. Time trend and expected effect

Because non-observational industry-specific factors may affect different enterprises in their respective industries, we added the industry time trend term as an additional control variable to the model for reestimation. The results in column (1) of Table 6 are significantly positive at the 1 % level, indicating that our core conclusion in this study is robust. Considering the potential expected effects of intelligent manufacturing policies, we sequentially incorporated time dummy variables from 1 or 2 years prior to the actual policy shock (2014–2013) in the benchmark regression. The results in columns (2)–(4) of Table 6 show that the regression coefficient of the core explanatory variable DID did not significantly change compared to the benchmark regression, indicating that the regression results without considering the expected effects are still reliable.

4.2.6. Retaining sample and adding control variables

Because the theme of our study is intelligent manufacturing enterprises, we filtered the research sample to include only manufacturing enterprises for empirical analysis. Column (1) of Table 7 shows the results. At the same time, to reduce the impact of macroeconomic factors at the city level on green innovation through non-intelligent manufacturing channels, we referred to Fan et al. [62] and added control variables at city level to mitigate the endogenous bias, including industrial structure (Secind), economic

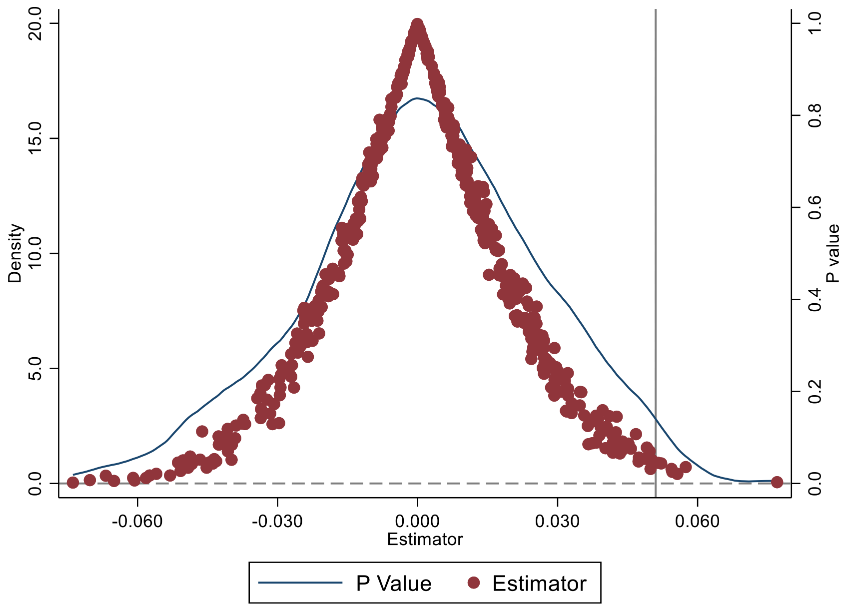

Fig. 5. Placebo test results.

Table 6
Time trend and expected effect test results.

	(1)	(2)	(3)	(4)
	time trend	expected effect		
DID	0.242***	0.205**	0.215***	0.205**
	(0.079)	(0.080)	(0.080)	(0.080)
treat*year2014		0.0894		0.051
		(0.065)		(0.073)
treat*year2013			0.0854	0.0464
			(0.060)	(0.064)
Size	0.0516***	0.0484***	0.0484***	0.0483***
	(0.009)	(0.009)	(0.009)	(0.009)
Ato	−0.0373***	−0.0360***	−0.0361***	−0.0360***
	(0.011)	(0.011)	(0.011)	(0.011)
Tobin Q	0.000272***	0.000329***	0.000329***	0.000328***
	(0.000)	(0.000)	(0.000)	(0.000)
Dual	−0.014	−0.0135	−0.0136	−0.0136
	(0.011)	(0.011)	(0.011)	(0.011)
Top10	−0.139***	−0.138***	−0.138***	−0.138***
	(0.051)	(0.051)	(0.051)	(0.051)
List Age	0.0259*	0.0298**	0.0298**	0.0299**
	(0.015)	(0.015)	(0.015)	(0.015)
Inst	−0.039	−0.0397	−0.0399	−0.0398
	(0.024)	(0.024)	(0.024)	(0.024)
Big4	−0.0935**	−0.0933**	−0.0935**	−0.0934**
	(0.045)	(0.045)	(0.045)	(0.045)
ROA	0.00831	0.0105	0.0106	0.0106
	(0.010)	(0.009)	(0.009)	(0.009)
_cons	−0.675***	−0.650***	−0.650***	−0.650***
	(0.190)	(0.190)	(0.190)	(0.190)
time trend	YES	NO	NO	NO
time fixed	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES
N	30183	30183	30183	30183
R-sq	0.745	0.745	0.745	0.745

development level (PGDP), population density (Density), and human capital (Edu). We obtained the data for these variables from the China City Statistical Yearbook. Column (2) of Table 7 shows the results, which indicate that the coefficient of intelligent manufacturing is still significantly positive regardless of whether the sample of manufacturing enterprises is retained or the control variables are added.

4.2.7. Excluding policy interference

How to eliminate the interference of other policy shocks effectively is difficult in clarifying the effect of intelligent manufacturing policy. During the sample period, other intelligent and information-based policies may also affect green innovation. Based on the aforementioned analysis, we combed the policy shocks that may interfere with the results of this study, including two types: the pilot zone of integration of informatization and industrialization (PZIII) policy and the big data experimental zone (BDEZ) policy. We controlled for the two types of policies in the model. Table 8 shows the results.

The results in columns (1)–(3) demonstrate that intelligent manufacturing significantly promotes green innovation in enterprises. This finding is consistent with the conclusions of the benchmark regression model, indicating the robustness of the results.

4.2.8. Endogeneity test

First, this paper constructs a PSM-DID model to solve the possible sample self-selection problem. The control variables were selected as the characteristic variables, and the propensity score was calculated by Logit regression model and matched with 1:1 nearest neighbor. The impact of intelligent manufacturing on green innovation is re-tested based on the matched samples, and the results are shown in column (1) of Table 9.

Second, the Heckman two-stage model is used to solve the problem of possible sample selection bias. In the first stage, the Probit model is used to calculate the inverse mills ratio (IMR), and it is included in the regression model. The results are presented in column (2) of Table 9.

Finally, in order to solve the possible reverse causality problem, this paper takes the fiber density of each province as the tool variable of intelligent manufacturing, the interactive term between the provincial dimension of cable density and the number of Internet users in the previous year was used as the tool variable of intelligent manufacturing. The results are presented in column (3) of Table 9. It can be seen that after accounting for possible endogeneity, the estimated coefficient is still significantly positive, which is consistent with the benchmark result.

Table 7
Retaining manufacturing sample and adding control variables.

	(1)	(2)
	retaining manufacturing sample	adding control variables
DID	0.227***	0.236***
	(0.082)	(0.084)
Size	0.0823***	0.0489***
	(0.019)	(0.012)
Ato	−0.0574**	−0.0522***
	(0.026)	(0.014)
Tobin Q	0.00345	0.00155**
	(0.002)	(0.001)
Dual	−0.0119	−0.0192
	(0.016)	(0.013)
Top10	−0.140*	−0.124**
	(0.0825)	(0.0597)
List Age	−0.0198	0.0265*
	(0.02)	(0.0159)
Inst	−0.0376	−0.033
	(0.031)	(0.0262)
Big4	−0.0892	−0.105**
	(0.0719)	(0.0474)
ROA	−0.0323	−0.0576
	(0.0682)	(0.048)
Secind		0.15
		(0.139)
PGDP		−0.0108**
		(0.0046)
Density		0.00471
		(0.0044)
Edu		0.0009
		(0.0056)
_cons		−0.651**
		(0.27)
time fixed	YES	YES
individual fixed	YES	YES
N	18920	27361
R-sq	0.741	0.754

Table 8
Results of excluding policy interference.

	(1)	(2)	(3)
	PZIII	BDEZ	PZIII and BDEZ
DID	0.233***	0.231***	0.232***
	(0.079)	(0.079)	(0.079)
PZIII	−0.0488		−0.0614**
	(0.031)		(0.031)
BDEZ		0.014	0.0164*
		(0.008)	(0.009)
Size	0.0471***	0.0470***	0.0471***
	(0.012)	(0.012)	(0.012)
Ato	−0.0487***	−0.0484***	−0.0484***
	(0.014)	(0.014)	(0.014)
Tobin Q	0.00156**	0.00156**	0.00156**
	(0.001)	(0.001)	(0.001)
Dual	−0.019	−0.0188	−0.0192
	(0.013)	(0.013)	(0.013)
Top10	−0.119**	−0.118**	−0.119**
	(0.057)	(0.057)	(0.057)
List Age	0.0266*	0.0268*	0.0268*
	(0.015)	(0.015)	(0.015)
Inst	−0.0356	−0.0364	−0.0359
	(0.025)	(0.025)	(0.025)
Big4	−0.0979**	−0.0979**	−0.0981**
	(0.047)	(0.047)	(0.047)
ROA	−0.0496	−0.0498	−0.0498
	(0.047)	(0.047)	(0.047)
_cons	−0.595**	−0.603**	−0.600**
	(0.251)	(0.251)	(0.251)
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
N	28906	28906	28906
R-sq	0.752	0.752	0.752

4.3. Heterogeneity test

4.3.1. Heterogeneity of regional green development foundation

The green development foundation plays a crucial role in facilitating the green innovation of enterprises. This can be attributed to the fact that high-quality energy-saving and emission-reduction technologies and funding provided by green infrastructure serve as an excellent platform for enterprises to engage in green research and development, ultimately improving the efficiency of their green innovation efforts by reducing technical barriers and transaction costs. However, because of differences in the construction level of green infrastructure and resource endowment, we examined the heterogeneity of the effect of green development foundations on the green innovation of intelligent manufacturing enterprises. Specifically, we followed the approach of Ma et al. [11] in measuring the green total factor productivity (TFP) as a proxy for the green development of prefecture-level cities and divided the sample into two groups based on the median. Columns (1) and (2) of Table 10 show the results.

The results of this study show that the positive impact of intelligent manufacturing on green innovation is more pronounced in regions with strong green development foundations. This is consistent with our expectations, which suggests that the availability of financial support and green infrastructure as well as the concentration of high-tech enterprises and technological resources create favorable conditions for green innovation activities. In particular, the intelligent manufacturing infrastructure of green-intensive systems enhances the development and application of new information technologies, leading to improvements in manufacturing efficiency and product quality as well as reduced resource consumption and improved ecological environments, ultimately contributing to sustainable social and environmental development.

4.3.2. Heterogeneity of regional informatization foundation

The development of information infrastructure, which encompasses technologies such as mobile internet, big data, and artificial intelligence, has the potential to significantly enhance the transformation of intelligent manufacturing in enterprises. By providing support for logistics, business flow, capital flow, technology flow, and information flow, improved information infrastructure can facilitate the interaction between enterprises and markets within a region and improve the efficiency of internal and external communication. This can lead to the reduction of information asymmetry; the saving of human, material, and financial resources; and the reduction of transaction and external knowledge acquisition costs. Additionally, enhanced information infrastructure can facilitate the coordination capacity of various departments within an enterprise, leading to improvements in production efficiency and the integration of external green innovation resources. In this study we used the number of Internet users per 100 in prefecture-level cities as a proxy variable and divided the sample into two groups according to the median. Columns (3) and (4) of Table 10 show the results

Table 9
Endogeneity test results.

	(1)	(2)	(3)
	PSM	Heckman	IV
DID	0.244***	0.530***	1.384***
	(0.081)	(0.063)	(2.913)
Size	0.0498***	0.236***	0.115***
	(0.012)	(0.009)	(0.018)
Ato	−0.0509***	−0.0209	−0.0245**
	(0.014)	(0.016)	(0.012)
Tobin Q	−0.000646	0.0104	0.00497***
	(0.003)	(0.007)	(0.002)
Dual	−0.0162	0.0524***	0.0145
	(0.012)	(0.018)	(0.021)
Top10	−0.126**	−0.962***	−0.371***
	(0.056)	(0.071)	(0.071)
List Age	0.0226	−0.333***	−0.209***
	(0.015)	(0.013)	(0.013)
Inst	−0.0368	0.0988**	−0.0275
	(0.025)	(0.045)	(0.051)
Big4	−0.101**	−0.0167	0.102*
	(0.047)	(0.036)	(0.055)
ROA	0.0142	0.0448	−0.424***
	(0.042)	(0.119)	(0.125)
/mills		−1.566***	
		(0.067)	
Cragg-Donald Wald F statistic			19.22
Kleibergen-Paap Wald rk F statistic			28.22
Kleibergen-Paap rk LM statistic			28.16
_cons		−4.727***	−1.644***
		(0.182)	(0.374)
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
N	28973	29368	27670
R-sq	0.747		−2.843

Table 10
Heterogeneity between green development and informatization foundation.

	(1)	(2)	(3)	(4)
	high GTFP	low GTFP	high informatization	low informatization
DID	0.255**	0.199*	0.134	0.347***
	(0.109)	(0.113)	(0.093)	(0.129)
Size	0.0479***	0.0477***	0.0441***	0.0502***
	(0.017)	(0.017)	(0.015)	(0.019)
Ato	−0.0407**	−0.0620**	−0.0354**	−0.0713***
	(0.016)	(0.026)	(0.018)	(0.024)
Tobin Q	0.00206***	−0.00061	0.00154**	0.00124
	(0.001)	(0.002)	(0.001)	(0.003)
Dual	−0.0166	−0.0223	−0.0274*	−0.00413
	(0.016)	(0.021)	(0.017)	(0.020)
Top10	−0.111	−0.12	−0.051	−0.193**
	(0.071)	(0.091)	(0.075)	(0.086)
List Age	0.0221	0.0331	0.0719***	−0.0367
	(0.018)	(0.025)	(0.020)	(0.024)
Inst	−0.0632**	0.00618	−0.0487	−0.0234
	(0.032)	(0.041)	(0.032)	(0.041)
Big4	−0.169***	−0.00184	−0.119*	−0.063
	(0.058)	(0.073)	(0.064)	(0.064)
ROA	−0.0673	−0.019	−0.0983	0.0156
	(0.062)	(0.076)	(0.062)	(0.073)
_cons	−0.628*	−0.599*	−0.637**	−0.518
	(0.346)	(0.356)	(0.322)	(0.401)
time fixed	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES
N	16748	11851	16667	12013
R-sq	0.737	0.776	0.782	0.704

of this analysis.

The results show that in regions with inadequate information infrastructure, the impact of intelligent manufacturing on green innovation is more pronounced. The reason may be that information technology has facilitated the flow of innovative elements across time and geographical boundaries, leading to the concentration of resources in cities with strong information bases. Additionally, the information infrastructure, which includes technologies, may overlap with functions of intelligent manufacturing and thus mitigate its impact on green innovation. These findings suggest that, in cities with strong information infrastructure, the marginal effect of intelligent manufacturing on green innovation may decrease, providing policy guidance for local governments to promote informatization and intelligent construction in a way that avoids duplication and misallocation of resources.

4.3.3. Heterogeneity of enterprise ownership

The ownership attribute of state-owned enterprises (SOEs) may affect their response to policy incentives, such as those promoting intelligent manufacturing and green innovation. As important pillars of the national economy, SOEs are expected to balance economic and social benefits and to play a greater policy demonstration role in the promotion of green development. Additionally, SOEs may have political connections that give them advantages in terms of access to funds, policy support, and resource allocation. In contrast, non-state-owned enterprises (NSOEs) may have a weaker resource base and be more reliant on policy support, with a greater marginal benefit from positive policies. NSOEs may also have stronger risk preference and higher risk return, allowing for more efficient resource utilization and greater transformation into green innovation outputs.

In this study we investigated the heterogeneous effect of intelligent manufacturing on green innovation of SOEs and NSOEs. The results, presented in columns (1) and (2) of Table 11, indicate that the impact of intelligent manufacturing on the green innovation of NSOEs is more pronounced. Further research is necessary to determine how to utilize the demonstration effect of SOEs effectively in promoting green innovation.

4.3.4. Heterogeneity of enterprise growth stage

According to the life cycle theory, the profitability, scale, investment and financing strategies, growth, and innovation willingness of firms can vary significantly depending on their stage in the life cycle. Based on Dickinson's [63] research and using the cash flow portfolio method, we divided firms into three stages: recession, maturity, and growth. We then analyzed the impact of intelligent manufacturing on green innovation for firms in each stage separately. Columns (3)–(5) of Table 11 show the results.

The results suggest that intelligent manufacturing has the most significant effect on green innovation for mature firms, followed by growing firms, whereas the effect on declining firms is less apparent. The reason may be that mature firms have more financial resources, a higher tolerance for risk, and a greater awareness of environmental issues compared to growing and declining firms. As a result, mature firms may be more likely to invest in green innovation to gain a competitive advantage in the market through the development of differentiated products and the improvement of the added value of green science and technology products. In contrast, growing firms may face financial constraints and incomplete information disclosure, leading to a reduced willingness to invest in green

Table 11
Heterogeneity results of enterprise ownership and growth stage.

	(1)	(2)	(3)	(4)	(5)
	SOE	NSOE	growth	maturity	recession
DID	0.266**	0.168*	0.202**	0.288***	0.0592
	(0.125)	(0.090)	(0.102)	(0.107)	(0.250)
Size	0.0648***	0.0318	0.0331**	0.0536**	0.0493**
	(0.015)	(0.021)	(0.016)	(0.024)	(0.024)
Ato	−0.0618***	−0.00962	−0.0607***	−0.0649*	−0.0427**
	(0.017)	(0.025)	(0.020)	(0.035)	(0.021)
Tobin Q	0.00257***	0.000269	0.000419	−0.00318	0.00216
	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)
Dual	−0.0313**	−0.00012	−0.0267	−0.025	−0.0307
	(0.015)	(0.026)	(0.020)	(0.023)	(0.022)
Top10	−0.0758	−0.226**	−0.135	−0.0521	−0.0128
	(0.068)	(0.108)	(0.085)	(0.100)	(0.106)
List Age	0.0292*	0.112***	0.019	7.37E-05	0.0776
	(0.018)	(0.039)	(0.021)	(0.038)	(0.051)
Inst	−0.0307	−0.112**	−0.0545	0.0231	−0.0641
	(0.031)	(0.046)	(0.038)	(0.046)	(0.058)
Big4	−0.132*	−0.11	−0.114	−0.124	−0.039
	(0.069)	(0.068)	(0.071)	(0.088)	(0.043)
ROA	−0.0238	−0.293**	−0.0784	−0.14	−0.01
	(0.051)	(0.129)	(0.090)	(0.097)	(0.074)
_cons	−0.984***	−0.428	−0.215	−0.711	−0.938*
	(0.322)	(0.472)	(0.338)	(0.514)	(0.536)
time fixed	YES	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES	YES
N	18665	10178	12926	9302	4436
R-sq	0.726	0.797	0.763	0.816	0.823

innovation technologies. Declining firms, meanwhile, may lack the motivation to make green investments because of internal and external difficulties and a lack of innovation incentives.

5. Mechanism analysis

We conducted a thorough analysis of the relationship between enterprise intelligent manufacturing and green innovation through robustness testing and rich heterogeneity analysis. We also examined the theoretical mechanisms behind this relationship, with a focus on the cost management and efficiency promotion effects of intelligent manufacturing on green innovation. We used empirical analysis to investigate the specific channels through which intelligent manufacturing affects green innovation.

To analyze the cost management effect, we examined the internal operating cost and external transaction cost. We measured the internal operating cost using the proportion of sales and management expenses to business income. Columns (1) and (2) of Table 12 show the results. We evaluated the external transaction cost using the company's overseas business income as a proxy for search cost because the geographic and cultural distances often result in significant search costs for businesses seeking information about potential customers [64]. The introduction of digital technology can increase the availability of information, speed up the collection and processing of information, and thus reduce the cost of information search, market development, and information asymmetry. Column (3) of Table 12 shows the results. We also used financing constraints as a proxy for the external financing cost of the enterprise. Column (4) of Table 12 shows the results.

Empirical results show that the coefficient of intelligent manufacturing on sales cost is significantly negative, indicating that intelligent manufacturing reduces sales costs in the business process and promotes green innovation, forming a path of intelligent manufacturing–reducing sales costs–promoting green innovation. The regression coefficient of intelligent manufacturing on management cost is also significantly negative, indicating that intelligent manufacturing reduces management costs in the management process, forming a path of intelligent manufacturing–reducing management costs–promoting green innovation. However, the coefficient of intelligent manufacturing on search cost is significantly positive, indicating that intelligent manufacturing does not reduce the overseas search costs of enterprises. The possible reason is that the pilot project's focus is to promote the transformation and upgrading of domestic manufacturing to intelligent manufacturing, with relatively insufficient expansion of overseas business. As a result, there is no path of intelligent manufacturing–reducing search costs–promoting green innovation. Finally, the regression coefficient of the financing constraint of intelligent manufacturing is significantly negative, indicating that intelligent manufacturing also reduces the financing cost of the enterprise in the management process, forming a path of intelligent manufacturing–reducing financing costs–promoting green innovation.

Aiming at the path of efficiency promotion effect of intelligent manufacturing on green innovation, we described R&D efficiency and production efficiency. Specifically, we used the stochastic frontier analysis model to measure technical efficiency as a proxy variable of R&D efficiency. Technological progress, closely related to R&D activities, is a key driver of TFP growth. Investment in R&D and information and communication technology can enhance the ability of an enterprise to absorb external knowledge and judge external information value, thus providing technical support for the enterprise's strategic adjustment and improving its adaptability to the environment. Column (1) of Table 13 shows the results. We used the growth rate of business income and markup to measure production efficiency in terms of quantity and quality. Columns (2)–(4) of Table 13 show the results.

The empirical results show that the regression coefficient of intelligent manufacturing on technical efficiency is significantly positive, indicating that intelligent manufacturing promotes R&D efficiency and then promotes green innovation, forming a path of intelligent manufacturing–promoting R&D efficiency–promoting green innovation. The regression coefficients of intelligent manufacturing on the growth rate of income and markup are all significantly positive, indicating that intelligent manufacturing leads to improvements in enterprises' quantity and quality of main income and profit sources, forming a path of intelligent manufacturing–promoting efficiency–promoting green innovation.

The introduction of artificial intelligence technology has a heterogeneous impact on the employment structure of enterprise labor [65]. Specifically, we measured the optimization of enterprise employment structure from three dimensions: the proportion of technical department employees, the proportion of graduates or above, and the proportion of R&D personnel. Columns (1)–(3) of Table 14 show the results.

According to the test results, the regression coefficient of technical personnel is significantly positive, indicating that artificial intelligence has increased the number of technical department employees, thereby promoting green innovation, forming a path of intelligent manufacturing–increasing the number of technical department employees–promoting green innovation. The regression coefficient of highly educated talents is significantly positive, indicating that artificial intelligence has increased the number of highly educated talents in enterprises, thereby promoting green innovation and forming a path of intelligent manufacturing–increasing the number of highly educated talents–promoting green innovation. The number of employees in the R&D department is significantly positive, indicating that artificial intelligence has increased the number of R&D employees, thereby promoting green innovation and forming a path of intelligent manufacturing–increasing R&D personnel–promoting green innovation.

6. Conclusions and policy recommendations

Based on the micro-data of listed companies from 2010 to 2020, this article empirically explores the impact of intelligent manufacturing on green innovation on the basis of clarifying the theoretical mechanism. The main research conclusions are as follows: (1) Intelligent manufacturing significantly promotes the level of green innovation. This impact is more obvious in areas with good green development foundations and incomplete information infrastructure, as well as non-state-owned enterprises and mature

Table 12
Results of mechanism analysis: cost management effect.

	(1)	(2)	(3)	(4)
	sales cost	management cost	search cost	FC
DID	−0.0972*	−0.0992**	0.179**	−0.00672***
	(0.058)	(0.044)	(0.090)	(0.002)
Size	0.893***	0.696***	0.0991***	0.000837
	(0.066)	(0.016)	(0.013)	(0.001)
Ato	0.553***	0.225***	0.0744***	0.00241**
	(0.120)	(0.045)	(0.027)	(0.001)
Tobin Q	−0.0417***	0.00756***	0.00365***	−0.00163***
	(0.011)	(0.002)	(0.001)	(0.000)
Dual	−0.0125	−0.00509	0.00129	−0.000956
	(0.028)	(0.010)	(0.007)	(0.001)
Top10	0.233	0.0206	0.0523	−0.0159***
	(0.251)	(0.058)	(0.058)	(0.004)
List Age	0.0574	0.0711***	−0.0329**	0.0160***
	(0.050)	(0.012)	(0.013)	(0.001)
Inst	0.123*	−0.0193	0.0226	−0.00329***
	(0.073)	(0.020)	(0.017)	(0.001)
Big4	0.475***	0.0703	0.126**	−0.00311
	(0.184)	(0.051)	(0.052)	(0.004)
ROA	−0.455**	−0.611***	−0.0721**	0.0119***
	(0.185)	(0.080)	(0.036)	(0.003)
_cons	−2.312	3.089***	−2.140***	1.306***
	(1.481)	(0.354)	(0.293)	(0.030)
time fixed	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES
N	27438	27697	27697	28906
R-sq	0.848	0.952	0.766	0.968

Table 13
Results of mechanism analysis: efficiency promotion effect.

	(1)	(2)	(3)	(4)
	technical efficiency	income growth rate	income	markup
DID	0.0701**	0.643**	0.422*	0.0780**
	(0.032)	(0.297)	(0.215)	(0.039)
Size	0.0595***	0.675	0.801***	0.125***
	(0.017)	(0.741)	(0.108)	(0.019)
Ato	0.584***	0.461	0.910***	0.176***
	(0.049)	(0.335)	(0.179)	(0.030)
Tobin Q	−0.00381	−0.104*	0.0288***	−0.00576**
	(0.005)	(0.060)	(0.009)	(0.003)
Dual	−0.0204	0.136	0.0147	−0.00163
	(0.016)	(0.173)	(0.050)	(0.013)
Top10	0.136	1.542	0.970***	0.0692
	(0.093)	(2.630)	(0.346)	(0.087)
List Age	0.0179	0.829	−0.340***	−0.0443
	(0.039)	(0.787)	(0.074)	(0.031)
Inst	−0.00171	−1.663	0.253***	0.0103
	(0.049)	(1.105)	(0.092)	(0.028)
Big4	−0.0101	0.557	−0.12	−0.114**
	(0.055)	(1.048)	(0.371)	(0.055)
ROA	1.234***	6.297***	−0.392*	−0.181**
	(0.111)	(2.369)	(0.206)	(0.073)
_cons	−1.870***	−16.42	−17.33***	−0.507
	(0.369)	(15.980)	(2.436)	(0.420)
time fixed	YES	YES	YES	YES
individual fixed	YES	YES	YES	YES
N	17134	27577	27697	20886
R-sq	0.229	0.129	0.952	0.875

enterprises. (2) Intelligent manufacturing affects green innovation through three channels: cost management effects, efficiency improvement effects and employment structure optimization effects. In response to the above empirical conclusions, this article puts forward the following countermeasures and suggestions:

First, promote the deep integration of digital and intelligent technology with manufacturing equipment and production process.

Table 14
Results of mechanism analysis: Employment structure optimization effect.

	(1)	(2)	(3)
	technical staff	Highly educated talents	R&D personnel
DID	0.109***	0.438**	0.174**
	(0.036)	(0.206)	(0.068)
Size	0.664***	0.531***	0.490***
	(0.010)	(0.056)	(0.023)
Ato	0.116***	−0.451***	−0.0058
	(0.016)	(0.096)	(0.033)
Tobin Q	0.0119***	0.0377**	0.0298***
	(0.003)	(0.019)	(0.005)
Dual	0.00161	0.0616	−0.0243
	(0.012)	(0.068)	(0.021)
Top10	0.0552	1.178***	−0.201
	(0.055)	(0.325)	(0.124)
List Age	0.0684***	−1.110***	−0.360***
	(0.024)	(0.140)	(0.055)
Inst	−0.0282	0.571***	0.0852
	(0.028)	(0.160)	(0.054)
Big4	−0.0406	−0.368*	0.0332
	(0.036)	(0.191)	(0.071)
ROA	−0.248***	1.109***	−0.264***
	(0.061)	(0.367)	(0.097)
_cons	−9.105***	−5.567***	−9.401***
	(0.211)	(1.229)	(0.497)
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
N	19190	14452	11859
R-sq	0.91	0.9	0.951

Through the construction of intelligent workshop and intelligent factory, the intelligent complete set production line for the specific scene and the modular production unit combining the new technology and process will be developed, promoting the application of new technological innovations such as digital twinning and artificial intelligence. Second, deepen the application of intelligent technology. To further promote the digital transformation of various sectors of the main body. To guide leading enterprises to play a leading role, relying on the industrial Internet, integrated industrial software to drive the industry chain upstream and downstream enterprises synchronous implementation of intelligent manufacturing, and fully take into account the different levels of enterprise input costs and transformation effects of the relationship between the typical application scenarios, according to the characteristics of industry attribute, scale and volume, technology advantage, regional difference, resource endowment, property right attribute and so on, promote a batch of digital equipment and services that meet the needs of enterprises. Third, we will continue to improve the infrastructure. On the one hand, we will continue to promote the large-scale deployment of new network infrastructure such as industrial Internet, Internet of Things and 5G, encourage industries to build their own industrial Internet platforms around resource allocation, supply chain coordination, product life cycle management, etc. The development of intelligent manufacturing and the construction of the Industrial Internet require powerful computing power to support the huge data capacity and the complexity of algorithms, and accelerate the construction of computing power infrastructure such as industrial data centers and intelligent computing centers.

First, explore regional intelligent manufacturing development paths with unique characteristics according to local conditions, formulate differentiated digital transformation plans, promote local innovation and improve policy systems, and guide the accumulation of various resources, such as taking advantage of local energy advantages and relying on hydropower and wind power to focus on green and intelligent production according to local conditions; Facing the "Belt and Road" initiative, accelerate the internationalization process of equipment manufacturing enterprises, etc. Second, under the top-level design of national intelligent manufacturing, guide the cross-regional coordinated development of provinces (autonomous regions and municipalities), promote cross-regional cooperation in key technological innovation, supply and demand docking, and talent training in intelligent manufacturing, and encourage local, industry organizations and leading enterprises, etc. to jointly promote advanced technologies, equipment, standards and solutions. Third, strengthen the construction of information infrastructure and popularize digitalization in underdeveloped areas, provide appropriate fiscal and financial support, strengthen guidance, supervision, tracking and detection, and solve the problem of unbalanced spatial development caused by digital barriers.

Grasp the gradual characteristics of the impact of intelligent manufacturing on green innovation, and accelerate the release of the green effects of the digital economy. First, promote the innovation of digital technology and enable the whole digital industry chain to save energy and reduce emissions. At the same time, promote the application of digital technology in data centers and 5G network management, accelerate the promotion and application of energy-saving 5G base stations, strengthen automation and intelligent energy consumption management, and reduce the energy consumption of new digital infrastructure; finally, optimize the energy structure for the development of the digital economy, adjust the power structure, increase the use of clean energy in the development process of the digital economy, and increase the proportion of renewable energy in energy supply.

7. Discussion and limitations

In this study we demonstrated the heterogeneity of the impact of intelligent manufacturing on green innovation through both theoretical and empirical analyses and arrived at several significant conclusions that future researchers can further refine and expand upon. One avenue for future research is to examine the long-term dynamic impact of intelligent manufacturing on green innovation performance. Another is to analyze the impact of intelligent manufacturing on green innovation for small and medium-sized enterprises using representative microdata because the sample of listed companies in this study may not be fully representative of these enterprises. Finally, on the basis of this study, it is also possible to further investigate the impact of emerging technologies such as artificial intelligence and the Internet of things (IoT) on green innovation.

Data availability statement

The datasets are available from the corresponding author on reasonable request.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

All authors read and approved the final manuscript.

CRediT authorship contribution statement

Xiaoxi Cao: Formal analysis, Data curation, Conceptualization. **Shutong Liu:** Writing – review & editing, Writing – original draft, Visualization, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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