Annals of Operations Research
https://doi.org/10.1007/s10479-025-07017-5

ORIGINAL RESEARCH

Intelligent transformation and green development: a double debiased machine learning evaluation of china's IIP initiatives

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Received: 6 March 2025 / Accepted: 17 December 2025

Abstract

In promoting the transformation, upgrading, and green development of traditional industries the Chinese government has been introducing Integration of Informatization and Industrialization Pilot (IIP) initiatives based on intelligent manufacturing and the green economy. As such this study examines the impact of China's IIP policy on the green development of publicly listed manufacturing firms by applying both Difference-in-Differences (DID) and double debiased machine learning (DDML) models to a dataset that spans the period 2007–2022. The evidence suggests that the IIP policy initiative significantly improves firms' green development via the mediating effect of intelligent transformation. Robustness checks, including DDML model regression and Propensity Score Matching-DID (PSM-DID) with nearest neighbour matching, consistently demonstrate significant improvements in environmental efficiency and productivity due to the IIP. Moreover, these effects are notably pronounced in the Yangtze River Economic Belt, heavily polluting industries, and larger firms. This research addresses a gap in micro-level policy analysis, highlighting the potential of intelligent manufacturing to promote sustainable practices. By offering both theoretical and practical insights, the findings guide policymakers and businesses in leveraging informatization and industrialization for green development.

Keywords Intelligent transformation · Double debiased machine learning · Informatization

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1 Introduction

In 2016, major manufacturing countries around the world initiated a new round of industrial layout for the next 5 to 10 years, with the application of advanced technologies in the manufacturing sector becoming a key focus. Germany released its “Digital Strategy 2025,” Japan introduced a future societal vision called a “Super Smart Society” in its fifth Science and Technology Basic Plan, and the Singaporean government unveiled its new “Research, Innovation and Enterprise Plan 2020” (UNDP, 2022). Big data analytics, Internet of Things (IoT) technology, artificial intelligence, industrial internet, and advanced materials are gradually becoming competitive hotspots in manufacturing sectors globally. According to predictions by the German Federal Ministry of Economics and Energy, by 2030, approximately 500 billion devices and machines will be connected through the internet. Concurrently, industry giants such as Siemens, General Electric, and Cisco are significantly increasing their investments in industrial digitalization, with advanced manufacturing technologies becoming crucial for enhancing industrial competitiveness (Federal Ministry for Economic Affairs and Energy, 2020). Since 2014, China has been aggressively promoting the deep integration of informatization and industrialization, with enterprises adhering to specific “Guidelines” designated as pilot projects by the Ministry of Industry and Information Technology (MIIT) (MIIT,2021). This strategic initiative has supported intelligent transformation and digital standardization across sectors, aiming to drive industrial upgrading, economic restructuring, and fundamental changes in development models. In 2024, however, the MIIT revised this enterprise-focused approach and introduced a new policy framework that designates ten pilot cities for integrated “5G+Industrial Internet” applications. This shift marked a transition from firm-level trials to a regionally coordinated, city-level pilot model, emphasizing the advancement of digital infrastructure and the acceleration of AI-driven transformation across key industrial clusters (MIIT, 2024).

Intelligent manufacturing is characterized by the digitalization, networking, and intelligence of production processes. It has become the focal point of this integration, reflecting a growing consensus within the industry. Firms are adopting intelligent manufacturing to align with global technological trends and to enhance their competitiveness in a rapidly evolving industrial landscape. With the rapid development of Chinese manufacturing industry in recent years, China has become the world’s largest manufacturing power. But the manufacturing industry is not strong. There are still many problems in the development of manufacturing industry in China. People must develop new manufacturing, that is, intelligent, service, and green manufacturing. With the increasingly serious problems of environmental degradation and excessive resource consumption caused by industrial development, green manufacturing has attracted growing attention from enterprises (Dangelico et al., 2017; Luo & Jie, 2017; Chen et al., 2025). As the world’s largest carbon emitter and a leading emerging economy, China’s approach to environmental governance has consequently drawn increasing global concern (Dong et al., 2021). In response, promoting the green transformation of the manufacturing sector has become a national strategic priority. In recent years, the Chinese government’s informatization and industrialization integration (IM) strategy has created new opportunities for firms to pursue green upgrades. The effectiveness of intelligent transformation in promoting sustainable growth has been validated in emerging empirical studies (Zhuo & Chen, 2023).

In view of the above this study sets out a research agenda that is reflected by two central questions: Firstly, to what extent the Integration of Informatization and Industrialization Pilot (IIP) policy enhance green development within manufacturing firms; and secondly, is there a role for intelligent transformation as a mediating factor between IIP policy and green development? In other words, this study aims to assess whether the IIP policy enhances green development within these firms and to explore the mechanisms by which intelligent transformation facilitated by the IIP contributes to this development. This evaluation is conducted using a Double Debiased Machine Learning model, focusing on the period following the policy's pilot implementation in 2014 and the following years.

The contribution of the paper is three-fold: Firstly, it is one of the very few studies that explore the environmental benefits of digital business model innovations from the perspective of green development (Han & Zhang, 2022). Prior research on the integration of informatization and industrialization has predominantly focused on the policy analysis of intelligent manufacturing pilot demonstration projects (IMDP) (Wei et al., 2024). Historically, such studies have generally been conducted at urban or provincial levels (Wei et al., 2024), with many failing to address the micro-level implications within individual companies. Therefore, this paper leverages a unique setting of multiple informatization and industrialization integration policies, utilizing Python and manual data collection methods to compile data from publicly listed Chinese manufacturing companies spanning the years 2007 to 2022. This approach allows for a comprehensive analysis of the micro-level impacts of these policies on the green development within these firms.

In addition, previous studies predominantly utilized the difference-in-differences (DID) approach to assess policy impacts (Dey et al., 2023; Mikalef et al., 2021; Skare et al., 2023), often overlooking model misspecification and the challenges posed by high-dimensional data. Therefore, a second contribution and innovation of this paper lie in its application of machine learning for automated data processing and model training. Compared to the DID model, machine learning techniques are more effective at handling high-dimensional data. Traditional statistical methods, when faced with many features, typically require dimensionality reduction or variable selection, which can result in a loss of information. Machine learning, especially advanced algorithms like random forests and deep neural networks, can manage thousands of variables without significantly increasing error. This capability is crucial for uncovering potential causal relationships within complex policy effects, thereby enabling a more accurate identification and interpretation of the causal links between the Integration of Informatization and Industrialization Pilot (IIP) policy and green development in firms.

Prior research on enterprise intelligent transformation often utilized single variables, such as text mining's keyword frequency counts (Qi et al., 2020), or solely the ratio of intangible assets (Yang et al., 2024). However, relying on single variables may introduce errors and biases. This paper's significant third contribution rests in the use of multiple factors for intelligent transformation, employing entropy methods for a novel measurement approach, which is then integrated into this study's mechanism analysis. Our research implements dynamic adjustments of weights in the analysis of intelligent transformation mechanisms, enhancing the precision in reflecting the significance and contributions of diverse sub-variables. The objectivity and wide applicability of this method not only yield theoretical innovations but also provide practical insights. By minimizing the influence of subjective human factors, this study offers a scientific and systematic method for quantifying intelligent transformation, promoting in-depth exploration within the domain.

This study's main findings robustly demonstrate the Integration of Informatization and Industrialization Pilot (IIP) significantly enhances the green development of manufacturing firms in China. The parallel trend tests confirm compliance with pre-implementation conditions, and subsequent analyses post-implementation indicate a modest but positive effect on green development. The DID regression and PSM-DID regression employing nearest neighbour matching consistently show significant improvements in the environmental efficiency and productivity of firms resulting from the IIP. Furthermore, robustness checks using Green Total Factor Productivity as the dependent variable, along with comprehensive DDML analyses, confirm the policy's substantial impact across various models and settings, adjusting for potential biases, including endogeneity issues addressed using the Terrain Ruggedness Index as an instrumental variable. The mechanism analysis utilizing the DDML model underscores that intelligent transformation acts as a critical mediator, significantly boosting the policy's effectiveness. Additionally, heterogeneity analysis reveals that the IIP policy particularly benefits firms in the Yangtze River Economic Belt, heavily polluting industries, and larger firms, suggesting that customized policies could further optimize environmental outcomes. Overall, this study provides readers with theoretical and practical guidance on understanding the impact of the IIP policy on green development within manufacturing firms and the role of intelligent transformation in this process.

The rest of this paper is organized as follows. Section 2 reviews the existing literature and develops the hypotheses in the context of the Integration of Informatization and Industrialization Pilot (IIP) and its impact on green development within manufacturing firms. Section 3 outlines the methodology and model design used to evaluate these hypotheses whilst Sect. 4 presents the empirical results. Section 5, which discusses the results and Sect. 6 concludes with an overview of the study's findings and policy implications.

2 Literature review and hypotheses development

2.1 Theoretical considerations

2.1.1 Technology diffusion theory

Technology diffusion theory underscores the significance of comprehensively grasping the factors that facilitate or impede AI implementation to ensure sustainable development and adoption. Guided by this theory, the analysis explores how initiatives like the IIP impact the adoption and integration of technology within manufacturing sectors, ultimately influencing their environmental progress and operational effectiveness (Novak, 2020; Xie et al., 2021).

Driving Force Theory provides a critical lens for understanding how external forces, such as policy interventions, shape firms' behaviour toward intelligent transformation and green development. As shown in Fig. 1, the IIP policy influences the process of industrialization, which in turn activates various driving forces—technological advancement, institutional pressure, market competition, and environmental awareness—that encourage firms to invest in intelligent transformation. This includes intelligent investment, application, and innovation, which are key components of the proposed mechanism. By incorporating Driv-

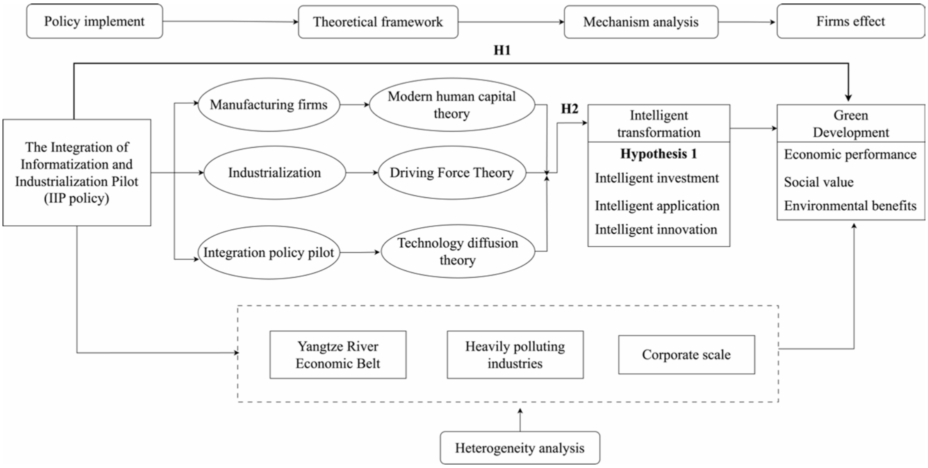

Fig. 1 Conceptual framework

ing Force Theory, this study highlights how these factors interact to promote the adoption of green practices in manufacturing firms. The theory thus plays an essential role in explaining why certain firms respond more actively to policy stimuli and provides a theoretical basis for identifying effective strategies to support sustainable industrial transformation.

2.1.2 Driving force theory

In physics, the term “driving force” typically describes the force acting in a vehicle’s propulsion. In business, it refers to the internal and external influences propelling a company towards specific goals. These forces guide business operations towards targeted outcomes. Driving force theory, applied in various disciplines like management science, sociology, economics, and environmental science, investigates the multifaceted influences on industry development. For instance, Chen et al. (2021) explored the dynamics between multi-stage international mergers and acquisitions and knowledge network restructuring. Similarly, Pichlak (2021) analysed the motivators for technological eco-innovation, and Qin et al. (2019) studied the drivers of agricultural intensification. This framework proves crucial in this research by showing that the growth and advancement of industries, especially through policies like the integration of informatization and industrialization, are shaped by several factors including market trends, competitive dynamics among companies, and emerging opportunities. Studying these elements with the driving force theory is vital for creating effective strategies that foster the growth of green practices within the manufacturing industry.

2.1.3 Modern human capital theory

Modern human capital theory suggests that highly skilled workers, possessing advanced knowledge and professional skills, are more equipped to facilitate the intelligent transformation of companies (Galor & Moav, 2000). This skilled workforce is crucial for enabling widespread green innovation activities essential for improved environmental results. This theory is critical for examining how sophisticated human capital can effectively aid in implementing the IIP policy, promoting sustainable development and environmental accountability in manufacturing enterprises.

In Fig. 1, these theoretical approaches collectively form a comprehensive basis for evaluating the complex effects of the Integration of Informatization and Industrialization Pilot (IIP) policy on the ecological advancement of manufacturing firms, exploring how technological advancements, industry dynamics, and skilled human capital intersect to influence industry outcomes.

2.2 IIP policy implementation

As the digital economy continues to expand, China has prioritized the transformation and upgrading of its industries, with intelligent manufacturing emerging as a focal point. The country is pushing for a comprehensive integration of cutting-edge information technologies with its manufacturing sector to accelerate the transition towards artificial intelligence. In 2014, the Ministry of Industry and Information Technology of China initiated a nationwide pilot on the integration of industrialization and informatization. Enterprises conforming to the “Guidelines” were designated as pilot enterprises, using this integration as a strategic governmental tool to foster intelligent transformation and facilitate digital standardization across industries (MIIT, 2021). This initiative, spearheaded by the Ministry, served as a quasi-natural experiment to assess the economic impacts of AI-driven transformation within manufacturing enterprises. The Integration of Informatization and Industrialization Pilot (IIP) Policy specifically aims to enhance the green development of China’s manufacturing sector through the adoption and integration of artificial intelligence technologies, aligning with national goals for sustainable industrial growth and environmental efficiency.

Additionally, the advancement of internet infrastructure, the execution of the National Big Data Comprehensive Pilot Zone, and the Broadband China strategy have collectively amplified the quality of green innovation. These initiatives enhance the intelligent transformation’s impact on sustainability, particularly in the manufacturing sector, aligning with broader national objectives for sustainable growth and ecological improvement (Han & Mao, 2023).Together, these efforts underscore China’s commitment to integrating cutting-edge technological advancements with environmental stewardship, setting a blueprint for sustainable industrial development that harmonizes economic goals with ecological needs.

2.3 Green development of manufacturing

The “14th Five-Year Plan for Industrial Green Development” highlights the next five years as pivotal for China’s ambition to become a manufacturing powerhouse, emphasizing this period as essential for advancing green manufacturing (MIIT, 2021). Chinese manufacturing firms are thus urged to speed up their green transformation and boost their green innovation capacities to propel sustainable development (Han & Zhang, 2022). Yuan and Liu (2024) identifies notable temporal and spatial disparities in green development across the Yangtze River Economic Belt, observing a consistent upward trend with a complex regional hierarchy of “multiple peaks-multiple centres.” The study delineates a distinct inverted U-shaped relationship between manufacturing agglomeration and green development, with significant variances due to temporal, spatial, and urban heterogeneity. It also outlines three mechanisms through which manufacturing agglomeration influences green development: labour force upgrading, industrial structure enhancement, and technological innovation. These insights offer both theoretical and empirical frameworks for promoting sustainable growth in manufacturing sectors globally. From this analysis, the suggested policy directions include encouraging green business model innovation and applying differentiated support measures considering enterprise heterogeneity. These strategies can provide substantial theoretical backing and practical guidance for fostering green development in manufacturing sectors (Han & Zhang, 2022).

The interplay between manufacturing agglomeration, technological innovation, and sustainable growth underscores the critical role of targeted policy interventions in fostering green development. The identified mechanisms, such as labour force upgrading and industrial structure enhancement, serve as vital levers that can be activated through well-designed initiatives. In this context, the Integration of Informatization and Industrialization Pilot (IIP) policy emerges as a strategic approach to harmonise digital transformation with green industrial practices. Its potential to address the multifaceted challenges of green development provides the basis for the following hypothesis.

Hypothesis 1 The Integration of Informatization and Industrialization Pilot (IIP) policy significantly promotes green development within the manufacturing sector.

2.4 Intelligent transformation mechanism analysis

Efficiency-oriented business models in manufacturing, such as automation and intelligent manufacturing, are pivotal in advancing green innovation. By integrating digital technologies, manufacturing enterprises streamline their production processes, achieving autonomous control and dynamic operations that minimize resource use and emissions. Further analysis and intelligent application of production data enhance decision-making processes, leading to significant energy savings, emission reductions, and improved product quality. These innovations not only heighten resource utilization efficiency during production but also contribute significantly to reducing environmental pollution, thus promoting the green development of the manufacturing sector (Han & Zhang, 2022). Research also shows that intelligent transformation substantially enhances the quality of green innovation within corporations, driven by factors such as human capital, research and development spending, efficient information sharing, and optimized resource allocation (Han & Mao, 2023). A focused study on intelligent manufacturing enterprises revealed that environmental regulations and geographical proximity play crucial roles in fostering regional collaboration for green innovation, which positively affects both the economic and environmental performance of these enterprises. This highlights the significant impact that well-coordinated green innovation efforts can have on regional and organizational success in intelligent manufacturing (Ying et al., 2021).

Building on the above, it becomes evident that intelligent transformation represents a crucial pathway for achieving green innovation within the manufacturing sector. The integration of digital technologies and data-driven decision-making optimises production processes, enhances resource efficiency, and reduces environmental impact. Moreover, the role of factors such as human capital, R&D investment, and regional collaboration underscores the multifaceted benefits of intelligent manufacturing. These advancements highlight the potential for targeted policies to amplify the positive outcomes of intelligent transformation. Against this backdrop, the Integration of Informatization and Industrialization Pilot (IIP) policy provides a strategic mechanism to align digital transformation with green objectives, offering a promising avenue for fostering sustainable manufacturing practices. This sets the stage for the following hypothesis.

Hypothesis 2 The IIP policy fosters green development via the mechanism of intelligent transformation.

3 Methodology and model design

3.1 Data sources

This study leverages data spanning from 2007 to 2022, comprising 24,081 observations across 2880 listed manufacturing firms, as sourced from the Wind database, annual reports of enterprises, and the annual city yearbooks of the companies' locations, supplemented by meticulously collected firsthand data in policy data. The analysis focuses on a subset of 551 firms that began implementing the Integration of Informatization and Industrialization Pilot (IIP) policy at various points from 2014 onwards. This comprehensive dataset allows for a robust evaluation of the policy's impact on the green development indices of these enterprises, enhancing our understanding of the dynamic interactions between the Integration of Informatization and Industrialization Pilot policy and corporate green sustainable development and practices within the context of China's manufacturing sector.

3.2 Variables

See Table 1.

3.2.1 Independent variable: IIP policy dummy

In Table 1, the core independent variable is an interaction term designed to capture the effect of the Integration of Informatization and Industrialization Pilot (IIP) on manufacturing firms.

As the Eq. (1) shown, the interaction dummy variable $did_{i,t}$ takes a value of 1 if the firm is included in the IIP policy and 0 if it is not, incorporating a time dummy variable. This term, labeled as $did_{i,t}$ within a Difference-in-Differences (DID) framework, combines the policy group dummy variable and the time dummy variable to quantify the policy's impact. For companies located within cities where the IIP was piloted, the policy group dummy variable is set to 1, otherwise, it is 0. The time dummy variable is assigned a value of 1 for years 2014 and onward, reflecting the post-policy implementation period, and 0 for all years prior to 2014. This interaction term allows for a nuanced analysis of the temporal and policy-driven shifts in green development indices among the targeted manufacturing firms.

Table 1 Definition of variables

Variable type	Variable name	Variable symbol	Variable definition
Independent variable	IIP Policy effect	did	Dummy variable for IIP policy, if the listed company has been selected as the pilot demonstration enterprise, the value is 1, otherwise it is 0
Dependent variable	Green development index	GREEN	"Green Development" metrics in three main dimensions: Economic Performance, Social Value, and Environmental Benefits
Mediator variables	Intelligent Transformation Index	Score1	"Intelligent transformation index" metrics in three main dimensions: Intelligent Investments, Intelligent Applications and Intelligent Innovations
Control variables	Firms control variables	ListAge	The number of years a firm has been listed on the stock exchange
		SOE	State-Owned Enterprise: It is set to 1 if the firm is a state-owned enterprise, and 0 otherwise.
		ROA1	Return on Assets; Net profit divided by average total assets
		Top1	Number of shares held by the largest shareholder/total number of shares
		CMIR	Capital Maintenance and Appreciation Rate
		TobinQ	Tobin's Q value, a ratio comparing the market value of a firm to the replacement value of its assets

3.2.2 Dependent variable: GREEN

The paper focuses on evaluating the impact of the IIP policy on the green development indices of manufacturing firms listed on the stock market. Table 2 of indicators used to assess "Green Development" categorizes these metrics into three main dimensions: Economic Performance, Social Value, and Environmental Benefits. Economic indicators such as net profit margin, growth rate, and operational costs gauge the financial health and efficiency of these organizations. Social value indicators highlight the company's governance and contributions to its workforce, including management costs, earnings per share, and employee-related metrics. Environmental indicators, such as the environmental tax ratio and ISO9001 certification status, assess the firms' environmental impact and their commitment to sustainability. This comprehensive framework aids in understanding how the IIP policy may influence the overall green development trajectory of these manufacturing enterprises, highlighting the interconnectedness of informational and industrial advancements with sustainable practices.

Table 2 Green development index

	Dimension type	Indicator type	Specific calculation method
Green Development Index	Economic performance	Net profit margin on total assets (+)	The ratio of a company's total net profit to its average total assets
		Net profit growth rate (+)	The growth rate of the company's net profit for the current period compared with the net profit for the previous period
		Inventory to revenue ratio (+)	Inventory/operating income
		Net fixed assets (+)	The difference between the original value of fixed assets less accumulated depreciation and less impairment losses.
		Total factor productivity (+)	TFP measured by the fixed effects (FE) approach
		Enterprise size (+)	The logarithm of the total assets of the enterprise
		Operating cost (−)	(Main business costs) + (Other business costs)
		sales expense (−)	All sales expenses are added up
		Management costs (−)	Various expenses incurred by the enterprise administrative department to manage the organization's business activities, including company funds, labor union funds, employee education funds, labor insurance premiums, unemployment insurance premiums, board of directors fees, consulting fees, and audit fees
	Social value	Earnings per share (+)	Earnings per share = (Net profit for the period - Preferred stock dividends) / Annual weighted average total share capital
		Salaries paid to employees (+)	Total salary paid to employees
		Number of employees (+)	natural logarithm of number of employees
	Environmental benefits	Environmental tax (+)	The ratio of the logarithm of main business income to the natural logarithm of environmental taxes
		Whether it has passed ISO9001 certification (+)	If the enterprise has passed ISO9001 certification, the value is 1, otherwise it is 0

3.2.3 Mediator variable and entropy method

Intelligent transformation index

Intelligent transformation involves enterprises leveraging AI technology, like machine learning, to transition from traditional work structures to processes of self-learning (Yu et al., 2020), self-optimization, self-configuration, and self-diagnosis (Ilmudeen et al., 2019). This approach makes companies more adaptable and agile, enhancing competitiveness (Lasi et al., 2014) and boosting performance (Mohammad, 2019). Intelligent technology gives businesses the capability to transform and advance (Yu et al., 2021). In moving toward Industry 4.0—the next phase of industrial evolution—Zheng et al. (2018) proposed a framework illustrated as a matrix (data collection and analysis × industrial applications) based on scenarios such as user-focused personalized smart wearable devices, machine scheduling within intelligent factories, and 3D scanning for automated quality inspections. They also highlighted the potential for real-time data gathering and decision-making in smart manufacturing. Hamid et al. (2021) emphasized the necessity of focusing on essential factors like autonomous production lines, smart manufacturing practices, data challenges, process adaptability, and security, as well as aspects like humans, cyber systems, and physical components. Intelligent transformation is crucial in organizational processes. Yu et al. (2020) demonstrated that intelligent transformation affects the link between government support and financial outcomes.

This paper introduces innovative elements in its approach by using the entropy method to objectively determine the weights of various intelligent transformation indicators. This method allows for a data-driven evaluation of each dimension's importance based on information entropy and data variance. The formula used for calculating the entropy-based weights is presented in the Eqs. (1) and (2).

$$w_j = \frac{1-\left(-\frac{1}{\ln n}\sum_{i=1}^{n}\left(\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}\cdot\ln\left(\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}\right)\right)\right)}{\sum_{j=1}^{m}\left[1-\left(-\frac{1}{\ln n}\sum_{i=1}^{n}\left(\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}\cdot\ln\left(\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}\right)\right)\right)\right]} \tag{1}$$

Specifically, let x_{ij}, represent the observed value of the $j-th$intelligent transformationindicator for the $i-th$ firm-year observation, where i =1,2,…, n indexes all firm-yearcombinations in the panel data (i.e., each firm in each year), and j = 1,2,…, m denotes the set of second-level indicators (as listed in Table 3).

In Table 3, we outline a detailed framework for measuring Intelligent Transformation within manufacturing firms, employing indicators across three primary dimensions: Intelligent Investments, Intelligent Applications, and Intelligent Innovations. Each dimension is quantified through specific measures such as the proportion of AI-related intangible assets, industrial robot penetration, and AI-related patent counts. The entropy method was utilized to assign weights to these indicators, with 'SIA' (total AI-related intangible asset investments) and 'AIpat' (AI-related patents) receiving the highest weights of approximately 44.58% and 33.89%, respectively.

The resulting entropy-based weight for each indicator is denoted as w_j, which reflects the relative importance of indicator j based on its information variability across all firm-year samples. A higher value of w_j indicates that thecorresponding indicator carries greater informational contribution to overall firm-levelheterogeneity in intelligent transformation. The Intelligent Transformation indicator for each firm-year observation is then constructed as a weighted sum of the normalized indicators in the Eq. (2):

$$\text{Intelligent Transformation}_i = \sum_{j=1}^{m} w_j \cdot x_{ij} \tag{2}$$

This Intelligent Transformation indicator—denoted as Score1 in Table 3—captures the firm's overall degree of intelligent transformation by integrating diverse dimensions such as intelligent investment, application, and innovation. These weights indicate the substantial role these factors play in intelligent transformation, highlighting the financial and innovative impacts on firms. Such an approach not only provides a nuanced understanding of how different aspects of AI influence a firm's operations but also underscores the significance of investments in AI and technological innovation in driving sustainable practices within the manufacturing sector. This comprehensive and balanced measurement system is par-

Table 3 Intelligent transformation index

Measurement	First-level indicators	Second-level indicators	Definition and measurement	Entropy method proportion (%)
Intelligent Transformation (Score1)	Intelligent Investments	IntellInv	Proportion of total AI-related intangible asset investments to annual total assets of enterprises	10.74711
		SIA	Total amount of AI-related intangible asset investments by enterprises/1e7	44.5873
	Intelligent Applications	IntellTra2	Logarithm of AI-related term frequency plus one in corporate annual reports	6.26721
		Robot	The measurement of industrial robot penetration, calculated using industry-level and firm-level indicators, with U.S. industry data as an instrumental variable for China.	4.51206
	Intelligent Innovations	AIpat	The logarithm of 1 plus the number of patents filed by listed companies with titles containing the keywords “automation,” “intelligent,” or “artificial intelligence.”	33.88632

Table 4 Descriptive statistics

Descriptive statistics									
Variables	Obs.	Mean	Std. Dev.	Min.	Max.	p1	p99	Skew.	Kurt.
did	25,105	0.114	0.318	0	1	0	1	2.422	6.867
GREEN	24,081	0.038	0.047	0.005	0.251	0.007	0.118	0.929	1.903
ListAge	25,105	2.099	0.748	0.693	3.401	0.693	3.332	−0.325	2.087
SOE	25,105	0.32	0.466	0	1	0	1	0.774	1.599
ROA1	25,105	0.043	0.066	−0.373	0.257	−0.173	0.215	−0.808	7.788
Top1	25,105	33.482	14.118	8.02	75.843	9	71.315	0.535	2.797
CMIR	25,105	1.151	0.409	0.406	6.794	0.599	2.891	5.908	57.794
TobinQ	25,105	2.131	1.359	0.802	15.607	0.887	7.738	2.909	15.599

Table 5 Pearson correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	did	GREEN	ListAge	SOE	ROA1	Top1	CMIR	TobinQ
did	1.000							
GREEN	0.045^{***}	1.000						
ListAge	0.220^{***}	-0.056^{***}	1.000					
SOE	0.083^{***}	-0.041^{***}	0.442^{***}	1.000				
ROA1	−0.001	0.033^{***}	-0.174^{***}	-0.098^{***}	1.000			
Top1	0.011^{*}	−0.003	-0.120^{***}	0.143^{***}	0.136^{***}	1.000		
CMIR	-0.029^{***}	-0.020^{***}	−0.008	-0.016^{***}	0.304^{***}	0.019^{***}	1.000	
TobinQ	-0.083^{***}	-0.025^{***}	−0.004	-0.080^{***}	0.207^{***}	-0.070^{***}	0.035^{***}	1.000

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

ticularly effective in assessing the impact of the IIP policy on green development among Chinese manufacturing firms.

3.2.4 Other control variables

To control for the influence of other listed company characteristics on green development growth, this study employs Double Debiased ML, adept at managing high-dimensional control variables through regularization algorithms. Control variables such as the number of years a firm has been listed, ownership structure, return on assets, ownership concentration, capital appreciation, and market valuation are included. The model also incorporates quadratic terms for these variables to refine accuracy and includes city and time fixed effects to account for unobserved heterogeneity across different locations and periods. This comprehensive approach ensures a robust evaluation of the factors impacting green development among China's listed manufacturing firms (Wen et al., 2024).

3.3 Descriptive statistics and correlation

See Tables 4 and 5.

3.4 Model design

3.4.1 Traditional methods of policy evaluation: DID

The DID method is widely used for identifying policy effects due to its effectiveness in establishing causal relationships. This study leverages the DID approach to examine the impact of the Integration of Informatization and Industrialization Pilot (IIP) on the green development of Chinese manufacturing listed companies. By utilizing a quasi-natural experiment with panel data from Chinese manufacturing firms, this study formulates the DID model as shown in Eq. (3) to quantitatively assess the potential effects of the IIP policy on the green development index:

$$GREEN_{i,t} = \alpha_{\,i} + \beta \; did_{i,t} + \sum_{k=1}^{k} Control_{i,t} + \lambda_{\,t} + \zeta_{\,i} + \epsilon_{i,t} \tag{3}$$

In the Eq. (2), $GREEN_{i,t}$ represents the dependent variable indicating a firm's green development index. The interaction dummy variable $did_{i,t}$ takes a value of 1 if the firm is included in the IIP policy and 0 if it is not, incorporating a time dummy variable. The primary independent variable of interest is the interaction variable $did_{i,t}$, where the subscripts i and t refer to the firm and year, respectively. The coefficient β estimates the intervention effect based on the DID model regression, and it is significantly positive when the policy is effective. $Control_{i,t}$ denotes a set of control variables. To account for digital transformation trends and unobserved heterogeneity that may influence green development, we incorporate fixed effects in the research design by including both time- and region-fixed effects. The study employs a two-way fixed effects panel model, with $\epsilon_{i,t}$ representing the error term, where $\zeta_{\,i}$ and $\lambda_{\,t}$ capture firm- and year-fixed effects, respectively.

3.4.2 Double debiased machine learning

While the DID method is effective for identifying the effects of policy interventions, it has certain limitations in its application and other aspects. Even when data samples satisfy the parallel trend assumption, estimation bias can still occur in extreme cases. Popular matching methods, such as propensity score matching (PSM), involve a high degree of subjectivity in variable selection. To address the shortcomings of traditional sample matching methods, this study employs the double debiased machine learning method for enhanced causal inference, drawing on the work of Chernozhukov et al. (2018) and Farbmacher et al. (2022).

A key methodological innovation of this paper is the adoption of the Double Debiased Machine Learning (DDML) framework (Chernozhukov et al., 2018), which significantly enhances causal inference when evaluating the impact of intelligent transformation on green economic development. Unlike traditional regression-based approaches that often suffer from the curse of dimensionality and multicollinearity due to the inclusion of numerous covariates—such as firm fundamentals, corporate governance characteristics, and macroeconomic conditions—DDML is specifically designed to handle high-dimensional settings by combining machine learning with econometric techniques. It automatically selects relevant covariates from a large set using flexible algorithms, such as Lasso or Random Forest, and corrects for biases introduced by overfitting and model misspecification through orthogonalization and cross-fitting. This results in more accurate and consistent estimation of the causal parameter of interest, even in the presence of complex nonlinear relationships.

Furthermore, DDML offers a robust solution to a common challenge in IIP policy evaluation: the validity of counterfactual prediction. In this study, a control group is used to construct a data-driven prediction function based on pre-treatment characteristics, which allows the model to estimate what each firm's green development outcome would have been in the absence of intelligent transformation. This improves the credibility of the estimated treatment effect by reducing reliance on strong parametric assumptions. The integration of machine learning enhances the model's ability to capture subtle patterns in the data, thereby improving the robustness, precision, and interpretability of the results. Taken together, the application of the DDML method represents a significant methodological advance in this context, offering a powerful and reliable tool for isolating the causal impact of intelligent transformation on green economic outcomes (Chernozhukov et al., 2018).

When assessing the effects of IIP policy, the relationship between variables may be inherently nonlinear, making traditional parametric regression models prone to misspecification due to their reliance on predefined functional forms (Wei et al., 2024). In contrast, the Double Debiased Machine Learning (DDML) framework adopts a non-parametric approach, which does not require prior assumptions about the functional form of relationships among variables. This flexibility enables DDML to better accommodate complex, nonlinear interactions, thereby reducing bias arising from incorrect model specification (Yuan & Liu, 2024). Moreover, DDML addresses the regularization bias commonly associated with machine learning methods by implementing a two-stage procedure: it first uses flexible algorithms to predict nuisance parameters and then applies residual-on-residual regression with cross-fitting. This structure helps to deliver more reliable and asymptotically unbiased treatment effect estimates, even in small sample settings.

In light of these advantages, this research applies the Double Debiased Machine Learning model to evaluate the effects of the IIP policy. A partially linear double debiased machine learning model is constructed as outlined in the following Eqs. (4) to (7):

$$Y_{i,t} = \gamma_0 IIP_{i,t} + p_0\left(X_{i,t}\right) + U_{i,t} \tag{4}$$

$$E\left(U_{i.t}|IIP_{i,t}, X_{i,t}\right) = 0 \tag{5}$$

$$IIP_{i,\,t} = k_0\left(X_{i,t}\right) + V_{i,t} \tag{6}$$

$$E\left(V_{i,t}|X_{i,t}\right) = 0 \tag{7}$$

In Eq. (3), $p_0\left(X_{i,t}\right)$ represents a non-parametric function of high-dimensional covariates estimated via machine learning, capturing the systematic effect of control variables on the outcome. $U_{i,t}$ denotes the orthogonalized residual term, accounting for unobserved firm-level heterogeneity and ensuring consistent estimation of the treatment effect γ_0.

In this model, $Y_{i,t}$ denotes the green development index. $IIP_{i,t}$ represents the treatment indicator for the IIP policy. We aim to obtain the estimator $\widehat{\gamma_0}$ using a double debiased machine learning approach, as detailed in the Eq. (8):

$$\widehat{\gamma}_0 = \frac{Cov\left(IIP_{i,t}\,, Y_{i,t} - \widehat{p_0}(X_{i,t})\right)}{Var\left(IIP_{i,t}\right)} = \frac{\frac{1}{n}\sum_{i\in I,\, t\in T} IIP_{i,t}\left(Y_{i,t} - \widehat{p_0}(X_{i,t})\right)}{\frac{1}{n}\sum_{i\in I,\, t\in T} IIP^2_{i,t}} \tag{8}$$

In this context, n denotes the sample size. Utilizing the aforementioned estimation formula allows for a detailed examination and subsequent isolation of any estimation biases in the Eq. (9):

$$\begin{aligned}\sqrt{n}\left(\widehat{\gamma}_0 - \gamma_0\right) = &\left(\frac{1}{n}\sum_{i\in I,\, t\in T} IIP^2_{i,t}\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,\, t\in T} IIP_{i,t}U_{i,\,t} \\ &+ \left(\frac{1}{n}\sum_{i\in I,\, t\in T} IIP^2_{i,t}\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,\, t\in T} IIP_{i,t}\left[p_0\left(X_{i,t}\right) - \widehat{p_0}\left(X_{i,t}\right)\right]\end{aligned} \tag{9}$$

To accelerate convergence and ensure the unbiasedness of the treatment effect estimators in small samples, an auxiliary regression is constructed as follows Eqs. (10) and (11):

$$IIP_{i,\,t} = q_0\left(X_{i,t}\right) + V_{i,t} \tag{10}$$

$$E\left(V_{i,t} \mid X_{i,t}\right) = 0 \tag{11}$$

Initially, the auxiliary regression $\widehat{q_0}\left(X_{i,t}\right)$, is estimated using machine learning algorithms, and the residuals $\widehat{V}_{i,t}$ are obtained. Subsequently, the same machine learning algorithms are employed to estimate $\widehat{p_0}\left(X_{i,t}\right)$. Finally, $\widehat{V}_{i,t}$ is used as an instrumental variable for IIP in the regression to obtain an unbiased estimator of the coefficient $\widehat{k_0}\left(X_{i,t}\right)$, as outlined of the Eq. (12):

$$\widehat{\gamma}_0 = \frac{\frac{1}{n}\sum_{i\in I,\, t\in T} V_{i,t}\left(Y_{i,t} - \widehat{p_0}(X_{i,t})\right)}{\frac{1}{n}\sum_{i\in I,\, t\in T} V_{i,t}\, IIP_{i,t}} \tag{12}$$

Consequently, the above equation, which presents challenges in achieving unbiasedness, can be reformulated into the format of Eq. (13):

$$\begin{aligned}\sqrt{n}\left(\widehat{\gamma}_0 - \gamma_0\right) = &\frac{\frac{1}{\sqrt{n}}\sum_{i\in I,\, t\in T} V_{i,t}U_{i,\,t}}{E\left(V^2_{i,t}\right)} \\ &+ \frac{\frac{1}{\sqrt{n}}\sum_{i\in I,\, t\in T}\left[q_0 s\left(X_{i,t}\right) - \widehat{q_0}\left(X_{i,t}\right)\right]\left[p_0\left(X_{i,t}\right) - \widehat{p_0}\left(X_{i,t}\right)\right]}{E\left(V^2_{i,t}\right)}\end{aligned} \tag{13}$$

In summary, while prior research has delved into the effects of socioeconomic policies on green development (Yuan & Liu, 2024), few studies have specifically examined the relationship between the Integration of Informatization and Industrialization Pilot (IIP) policy and the green development of publicly listed manufacturing firms in China. This research targets these firms, employing the double debiased machine learning (DDML) model to evaluate the impact of the IIP policy, which began rolling out in pilot cities in 2014. To clarify the empirical design and the relationships among DID, PSM–DID, and DDML in this study, the methodological roadmap is illustrated in Fig. 2. The study focuses on the IIP policy treatment and the dependent variable "green development of manufacturing firms". Moreover, it incorporates artificial intelligence-driven transformation as a mediating variable to assess how technological transformation mediates the effect of the IIP policy on firms' green development. The schematic visualization depicts the methodological distinctions between the different approaches, while the proposed framework offers a clear method for evaluating industrial policy effects on green development.

4 Empirical result

4.1 Parallel trend test result for DID regression

The parallel trends test is a critical precursor to interpreting DID results because it establishes the foundational assumption necessary for the validity of the method. As such, Fig. 3 illustrates the results from a parallel trends test in the DID analysis, aimed at assessing the impact of the Integration of Informatization and Industrialization Pilot (IIP) on the green development index of manufacturing firms listed from 2014 onwards. Prior to the policy's implementation, the trends in the treatment and control groups display no significant divergence from zero, suggesting adherence to the parallel trends assumption, which is crucial for the validity of DID estimations. The post-implementation effects of the policy, as indicated by the estimates, generally hover near zero but show a positive trend during the later periods (years 1 through 6). This trend suggests a potential beneficial impact of the IIP on corporate green development. However, the increasing variability in confidence intervals during the post-implementation phase introduces rising uncertainty in these estimates.

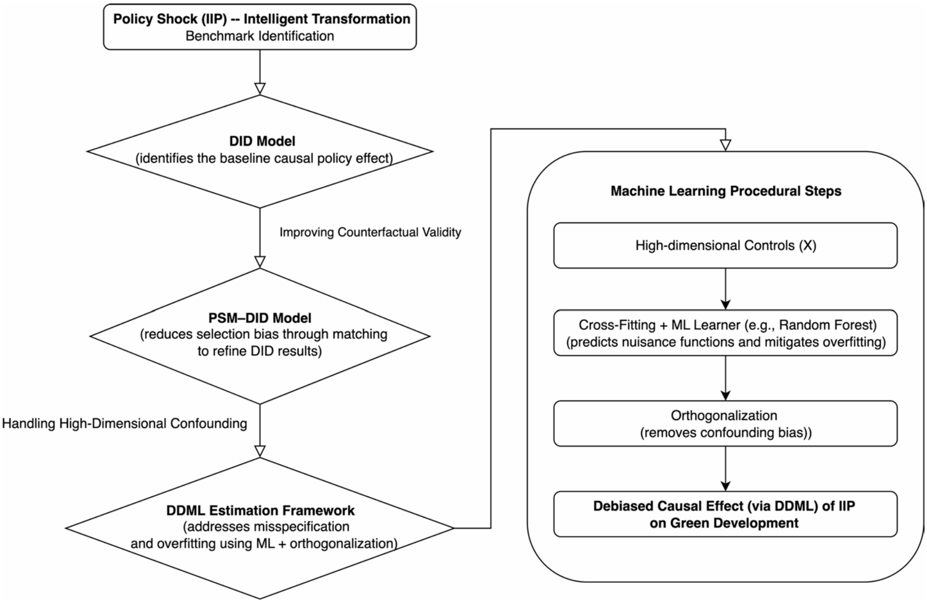

Fig. 2 Schematic Diagram of the relationships and distinctions among DID, PSM–DID, and DDML

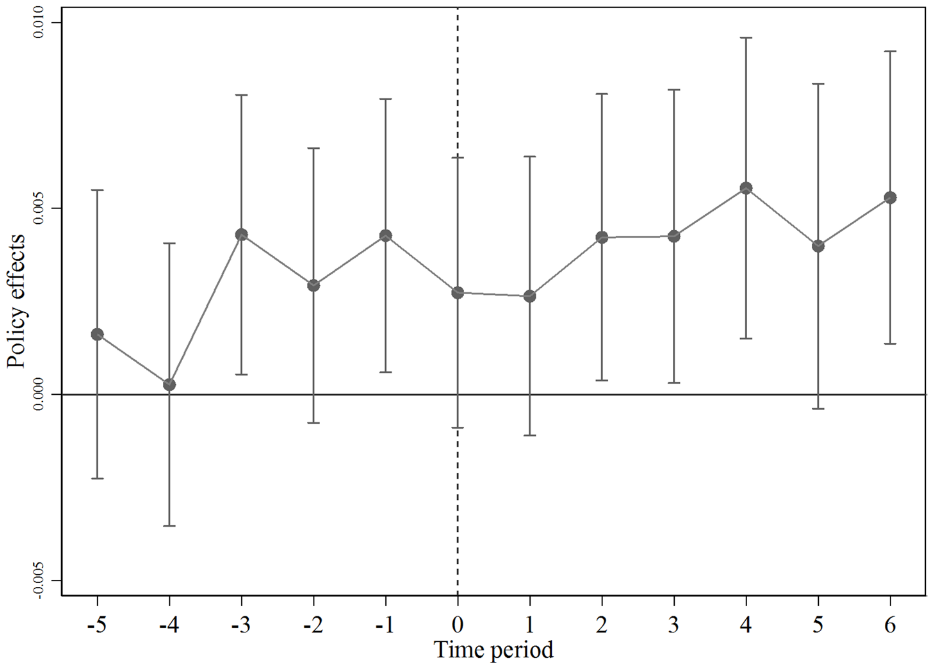

Fig. 3 Parallel trend test

While the preliminary findings support hypothesis 1, further robust analysis is needed to confirm these conclusions.

4.2 Baseline regression: DID regression

The DID regression analysis consistently demonstrates a positive effect of the Integration of Informatization and Industrialization Pilot (IIP) on the green development of manufacturing firms, as evidenced by the difference-in-differences estimator across multiple model specifications. Despite variations in the magnitude of impact—ranging from 0.0027 to 0.0103 and notable across all models in Table 6—the results are statistically significant, affirming the robustness of IIP's influence, which validates Hypothesis 1. The effectiveness of the IIP in advancing green practices within the manufacturing sector highlights its utility as a policy instrument. This perspective is further supported by Jin and Chen (2024), who underscore the significance of the Intelligent Manufacturing Demonstration Project (IMDP) in facilitating intelligent transformation, mitigating information asymmetry, and fostering collaborative innovation. Collectively, these initiatives underscore the profound influence of policy interventions in promoting sustainable development and technological innovation within the industry.

4.3 Placebo test

The placebo test in Fig. 4 results depicted in the graph demonstrate robustness in the original difference-in-differences analysis assessing a policy's impact on the green development

Table 6 Baseline DID regression

	(1) GREEN	(2) GREEN	(3) GREEN	(4) GREEN
did	0.0103^{***}	0.0031^{***}	0.0027^{**}	0.0028^{**}
	(10.0337)	(2.7692)	(2.4270)	(2.5536)
ListAge		0.0101^{***}	0.0103^{***}	0.0101^{***}
		(15.7336)	(15.8067)	(15.6478)
SOE		0.0030^{*}	0.0036^{**}	0.0029^{*}
		(1.7217)	(2.0609)	(1.6585)
ROA1		0.0122^{**}	0.0118^{**}	0.0112^{**}
		(2.2362)	(2.1616)	(2.0429)
Top1		0.0000	0.0000	0.0000
		(0.0393)	(0.2782)	(0.0626)
CMIR		-0.0017^{**}	-0.0016^{**}	-0.0016^{**}
		(−2.4445)	(−2.3349)	(−2.2796)
TobinQ		-0.0009^{***}	-0.0008^{***}	-0.0008^{***}
		(−3.5576)	(−3.1949)	(−3.2859)
_cons	0.0372^{***}	0.0193^{***}	0.0134	0.0154
	(142.3943)	(7.5181)	(1.0463)	(1.4078)
ID FE	No	No	No	Yes
Province FE	No	No	Yes	Yes
Industry FE	No	No	Yes	No
N	24,081	23,270	23,270	23,270
R^2	0.005	0.020	0.026	0.022

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

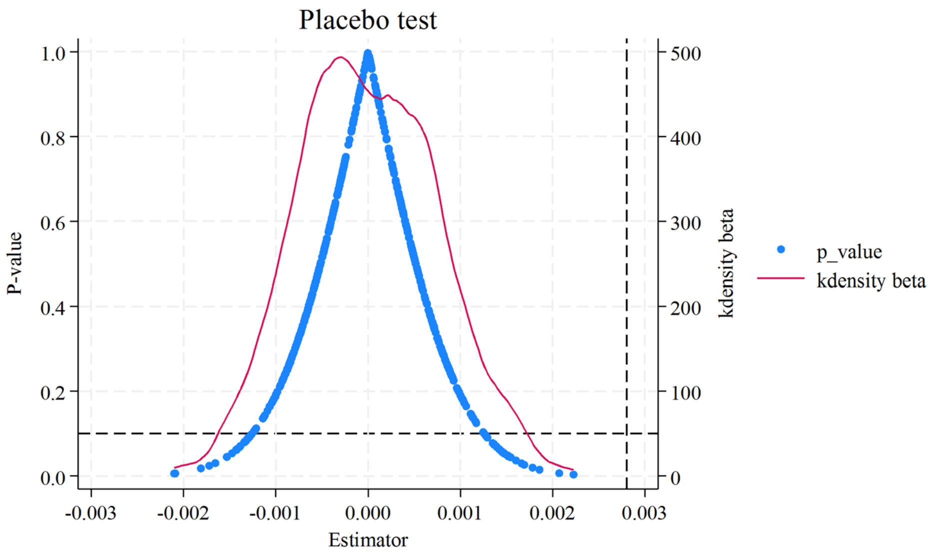

Fig. 4 Placebo test

of firms. All p-values from the placebo tests significantly exceed the 0.05 threshold, and the distribution of placebo effect sizes is tightly centered around zero. These findings indicate that the significant effects observed in the actual DID analysis are not due to random variation or unobserved confounders but are likely genuine effects of the policy, thus validating the credibility of the analysis and confirming the IIP policy's impact on enhancing green development within firms.

4.4 PSM-DID

4.4.1 PSM-DID matching

Figures 5 and 6 provided kernel density plots demonstrate the application of propensity score matching (PSM) in a PSM-DID analysis to enhance the robustness of evaluating a policy's impact. Initially, the distribution of propensity scores for the treated and control groups was significantly different, indicating potential imbalances. After implementing nearest-neighbour 1:1 matching with control variables (ListAge, SOE, ROA1, Top1, CMIR, TobinQ), the distributions align closely, suggesting successful mitigation of selection bias and confounding variables. This alignment substantiates the credibility of the causal inferences drawn from the DID analysis, affirming that observed effects are more likely due to the policy rather than baseline differences or selection bias.

4.4.2 PSM-DID regressions

In Table 7 the PSM-DID regression results consistently demonstrate a positive impact of the policy on firms' green development. By employing nearest neighbour matching on a 1:1 basis, the study ensures that the control variables are effectively matched, thus enhancing the robustness of the analysis. The significant coefficients of the DID variable across

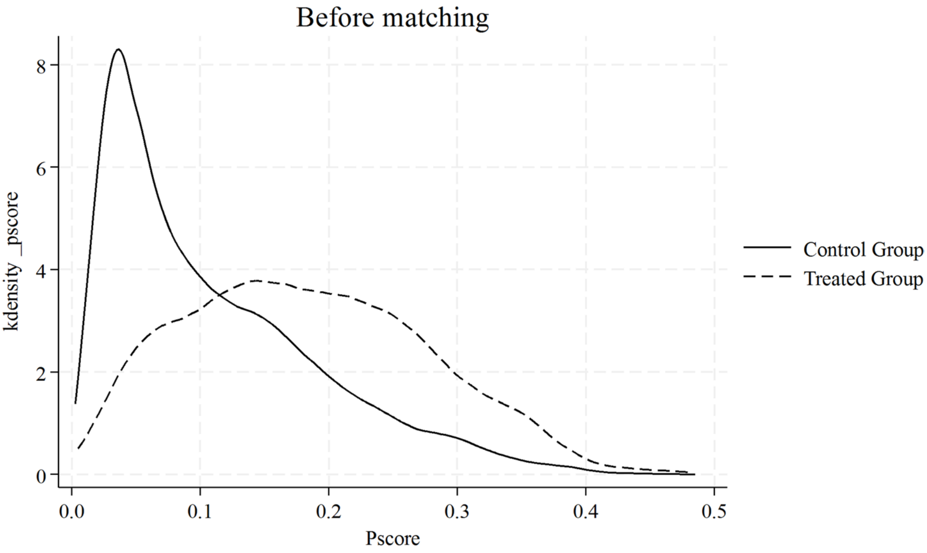

Fig. 5 Before matching

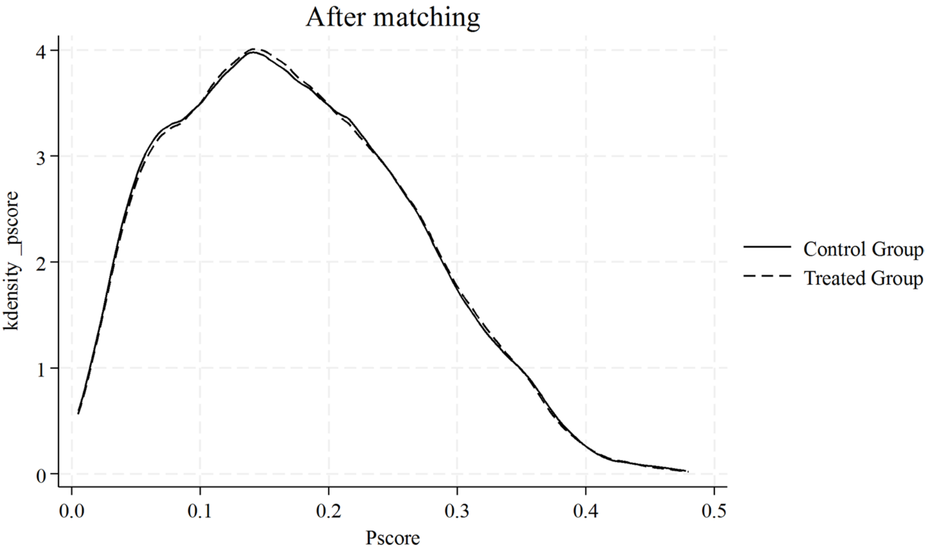

Fig. 6 After matching

all models, even after accounting for various firm-specific characteristics through control variables and different fixed effect, indicate the policy's effectiveness.

4.5 Other robustness check

4.5.1 Replacement variable dependent variable

In a robustness check where the dependent variable was shifted from the green development of firms to green total factor productivity (GTFP), the analysis consistently revealed a significant positive impact of the policy across the model (3) and model (4) in the Table 7. The coefficients predominantly ranged between 0.0638 and 0.0644 in these models. This consistency across different specifications solidifies the conclusion that the policy not only promotes specific green initiatives but also broadly enhances the environmental efficiency and productivity of firms, affirming its effectiveness in advancing sustainable practices. Yang et al. (2020) similarly supported the perspective that smart manufacturing can lead to higher levels of innovation. Additionally, companies can improve the transparency of production workflows, minimize energy wastage during production activities, and support the advancement of green innovation.

5 Double debiased machine learning regression results

5.1 Double debiased machine learning baseline regression

Using traditional causal identification and sample matching methods, previous studies have shown that the IIP policy has a positive impact on the green development of manufacturing

Table 7 Robustness tests: PSM-DID and replacement of dependent variable

	(1)	(2)	(3)	(4)
	PSM-DID		Replacement variable dependent variable	
	GREEN	GREEN	GTFP	GTFP
did	0.0027**	0.0028**	0.0644***	0.0638***
	(2.4270)	(2.5536)	(41.2222)	(40.6463)
ListAge	0.0103***	0.0101***	0.1865***	0.1877***
	(15.8067)	(15.6478)	(206.4904)	(208.3850)
SOE	0.0036**	0.0029*	−0.0329***	−0.0342***
	(2.0609)	(1.6585)	(−13.8590)	(−14.3836)
ROA1	0.0118**	0.0112**	0.0985***	0.1029***
	(2.1616)	(2.0429)	(13.2757)	(13.8011)
Top1	0.0000	0.0000	0.0000	0.0000
	(0.2782)	(0.0626)	(0.8199)	(0.3682)
CMIR	−0.0016**	−0.0016**	−0.0113***	−0.0115***
	(−2.3349)	(−2.2796)	(−12.1949)	(−12.2985)
TobinQ	−0.0008***	−0.0008***	−0.0056***	−0.0057***
	(−3.1949)	(−3.2859)	(−15.9684)	(−16.2979)
_cons	0.0134	0.0154	0.6076***	0.6330***
	(1.0463)	(1.4078)	(36.7056)	(45.5303)
ID FE	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
N	23,270	23,270	24,258	24,258
R^2	0.026	0.022	0.772	0.769

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

firms in China. To further reduce estimation bias and enhance causal inference in high-dimensional settings, this study adopts the Double Debiased Machine Learning (DDML) framework to identify the causal effect of the IIP pilot policy, following Chernozhukov et al., 2018). DDML combines machine learning with orthogonalized estimation to address model misspecification and overfitting. In the first stage, we apply the Random Forest algorithm to estimate nuisance components, including treatment probability and outcome prediction. This method captures non-linear interactions and performs well with moderate sample sizes, making it suitable for our firm-level panel data. Following Chernozhukov et al. (2018), the dataset is split in a 1:5 ratio for cross-fitting: five-sixths of the data (the auxiliary sample) are used to train the machine learning models, while one-sixth (the main sample) is used for second-stage estimation. This ratio achieves a balance between reducing model misspecification bias and controlling overfitting, as a smaller main sample mitigates overlap-induced bias while maintaining acceptable variance. The Random Forest algorithm itself is a non-parametric ensemble learning method that constructs multiple decision trees and aggregates their outputs to enhance predictive accuracy and reduce variance, making it particularly suitable for estimating flexible functional forms in high-dimensional settings.

Although deep learning—specifically artificial neural networks—has shown strong predictive capacity in a variety of domains and is considered a promising candidate for the first-stage learner in DDML, its theoretical properties (e.g., consistency and asymptotic normality) are not yet fully established for very deep and wide architectures under the DDML framework (Farrell et al., 2021; Schaffer & University, 2024). Nonetheless, DDML remains flexible and allows for neural networks or other advanced learners to be used as long as they meet certain regularity and convergence conditions. Future work could consider extending this framework by incorporating neural networks to enhance predictive accuracy, particularly in large-scale or highly non-linear settings. In this study, we prioritize model interpretability and robustness, and thus adopt Random Forest as a suitable and theoretically supported learner for DDML implementation.

The DDML analysis not only reveals the positive impact of the Integration of Informatization and Industrialization Pilot (IIP) on green development in Chinese manufacturing firms but also accounts for the influence of control variables in both linear and quadratic forms across different model specifications. Specifically, the "did" coefficients, which range from 0.0043 to 0.0065, consistently indicate a robust positive effect of the policy. The inclusion of linear and quadratic terms of control variables allows the model to capture potential non-linear effects and interactions. Additionally, the application of Province and Industry Fixed Effects in some models controls for unobserved heterogeneity, enhancing the accuracy and reliability of the results, using a sample size of 23,270 (Table 8). The DDML analysis underscores the efficacy of IIP in enhancing green practices among firms, with the nuanced modelling approach providing a comprehensive understanding of the policy's dynamics.

5.2 Robustness test using an alternative DDML specification

5.2.1 Replacement variable dependent variable

The DDML regression analysis using Green Total Factor Productivity (GTFP) as the dependent variable as a replaced dependent variable consistently demonstrates the positive impact of the policy (did), with statistically significant coefficients across all model configurations. Coefficients range from 0.0521 to 0.0613, underscoring the robustness of the policy's beneficial effects on environmental productivity (Table 9). The inclusion of both linear and

Table 8 DDML regression -Based treatment effect estimates of the IIP policy

	(1)	(2)	(3)	(4)	(5)
	GREEN	GREEN	GREEN	GREEN	GREEN
did	0.0065***	0.0065***	0.0054***	0.0054***	0.0043***
	(5.5134)	(5.5298)	(3.3294)	(3.3828)	(2.6783)
_cons	−0.0011***	−0.0011***	0.0058***	0.0058***	0.0042***
	(−3.8806)	(−3.9719)	(22.6480)	(22.5439)	(16.5140)
Control_variable_linear_term	Yes	Yes	Yes	Yes	Yes
Control_variable_quadratic_term	No	Yes	No	Yes	Yes
ID_FE	No	No	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	No	No	Yes
N	23,270	23,270	23,270	23,270	23,270

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

quadratic control terms, alongside Province and Industry Fixed Effects (with occasional ID Fixed Effects), addresses potential confounders effectively, highlighting the policy's efficacy in enhancing sustainable practices within the manufacturing sector across varying regional and industry contexts.

5.2.2 Replacement of the sample folds ratio

The analysis varied the k-folds in cross-validation to test the model's robustness against sample selection (Bach et al., 2024). Models (1) and (2) with 3 folds, and Models (5) and (6) with 5 folds, all exhibit significant positive coefficients for the "did" variable, indicating that the policy consistently enhances green development across these different validation setups (Table 10). The coefficients range from 0.0058 to 0.0069, underscoring a modest remains robust across these variations.

5.2.3 Replacement of machine learning methods

Machine learning algorithms were varied to evaluate how different modelling techniques might influence the results. Models (3) and (4), utilizing Gradient Boosting (gradboost), and Models (5) and (6), employing Neural Networks (nnet), both demonstrate significant positive impacts from the IIP policy, with coefficients between 0.0081 and 0.0069 (Table 10). This variation in machine learning methods helps confirm the reliability of the policy's positive effects, illustrating that the findings are not artifacts of a specific analytical approach (Chang, 2020).

Table 9 Robustness check using an alternative dependent variable (GTFP)

	(1)	(2)	(3)	(4)	(5)
	GTFP	GTFP	GTFP	GTFP	GTFP
did	0.0521***	0.0523***	0.0613***	0.0611***	0.0580***
	(26.8900)	(27.4605)	(22.0562)	(22.3750)	(21.7516)
_cons	0.0001	0.0002	−0.0074***	−0.0074***	−0.0064***
	(0.1869)	(0.3157)	(-13.1310)	(-12.9707)	(-11.5623)
Control_variable_linear_term	Yes	Yes	Yes	Yes	Yes
Control_variable_quadratic_term	No	Yes	No	Yes	Yes
ID_FE	No	No	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	No	No	Yes
N	24,258	24,258	24,258	24,258	24,258

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Table 10 DDML results under an alternative machine learning setup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Replacement of the sample folds ratio		Replacement of machine learning methods				IV method	
	GREEN	GREEN	GREEN	GREEN	GREEN	GREEN	GREEN	GREEN
did	0.0058^{***}	0.0048^{***}	0.0081^{***}	0.0082^{***}	0.0200^{***}	0.0069^{***}	0.2700^{***}	0.2486^{***}
	(3.8076)	(3.1661)	(7.8349)	(7.9861)	(15.9405)	(4.2518)	(6.5645)	(5.6724)
_cons	0.0064^{***}	0.0047^{***}	0.0001	0.0001	0.0077^{***}	0.0156^{***}	0.0022^{***}	0.0015^{***}
	(24.4734)	(18.0742)	(0.3069)	(0.3006)	(25.3142)	(43.4206)	(3.6516)	(2.6906)
Control_variable_linear_term	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control_variable_quadratic_term	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ID_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	No	Yes	No	Yes	No	Yes	No	Yes
Winsor treatment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	rf	rf	gradboost	gradboost	nnet	nnet	rf	rf
Sample split ratio	kfolds (3)	kfolds (3)	kfolds (5)	kfolds (5)	kfolds (3)	kfolds (3)	kfolds (5)	kfolds (5)
N	23,270	23,270	23,270	23,270	23,270	23,270	20,441	20,441

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

5.2.4 Instrumental variable method

In this study, the instrumental variable (IV) is employed to address potential endogeneity concerns in the double-debiased machine learning (DDML) framework (Huang & Tong, 2024). The IV is constructed based on the Terrain Ruggedness Index (TRI) of the city where a firm is located, interacted with the year, specifically calculated as TRI multiplied by (year-2006) (Zhang & Li, 2023). The Terrain Ruggedness Index (TRI) refers to the difference in elevation between the highest and lowest points within a specific area. It is a macro-level indicator used to describe the topographical characteristics of a region. By utilizing GIS to extract data from Digital Elevation Models (DEM), the terrain ruggedness for various levels can be calculated (Liu et al., 2015). Given the dataset covering Chinese manufacturing firms from 2007 to 2022, this approach helps to address endogeneity. The instrument's relevance lies in its correlation with the informatization and industrialization integration of firms (endogeneity) and its exogeneity, as it is unrelated to green development outcomes. The IV method in the DDML model, used in Models (7) and (8), aims to correct for any potential endogeneity issues, providing a more causally interpretable estimate. The "did" coefficients in these models are notably larger (0.2700 and 0.2486), significantly enhancing our understanding of the policy's impact (Table 10), which have robustly supported Hypothesis 1. These results suggest that when potential endogeneity is properly addressed, the effect of the IIP policy on green development might be substantially greater than estimated by standard models. By integrating cyber-physical systems, there is a deep integration between cyberspace and the physical world (Tao et al., 2018), leading to the exploration of new manufacturing models such as process manufacturing, discrete manufacturing, networked collaborative manufacturing, mass customization, and remote operation services (Zhou et al., 2018). Consequently, this has also accelerated the AI-driven transformation of enterprises.

The consistent and significant positive results across various robust and sophisticated models indicate that the IIP policy effectively promotes green development within China's manufacturing sector. The application of DDML models incorporating advanced machine learning methods and instrumental variables ensures a comprehensive and bias-minimized analysis, revealing the true efficacy of the policy (Schaffer & University, 2024). This approach not only highlights the policy's success but also its crucial role in pushing China's manufacturing industry towards more sustainable practices.

5.3 Mechanism analysis results using the DDML

The study explores the impact of the IIP policy on firms' green development, using artificial intelligence-driven transformation as a mediating variable. The mediating variable, firms' intelligent transformation, is quantified using an Intelligent Transformation index confirmed through the entropy method. This index is derived from three dimensions: Intelligent Investments, Intelligent Applications, and Intelligent Innovations, calculated using five sub-variables. The mechanism analysis in DDML model suggests that intelligent transformation plays a significant role in mediating the policy's effect on green development, highlighting how AI integration can enhance the environmental sustainability of firms.

The DDML analysis using "Score1", a composite index of intelligent transformation, as a mediating variable, reveals that the Integration of Informatization and Industrialization Pilot (IIP) significantly enhances green development in manufacturing firms, with "did" coefficients ranging from 0.0188 to 0.0276 across various models, all statistically significant at the 0.01 level (Table 11). This mediation indicates that intelligent transformation—encompassing Intelligent Investments, Applications, and Innovations—is crucial for amplifying the IIP's impact on sustainable practices. Model (2) shows the highest impact (0.0276***), suggesting that when intelligent transformation is accounted for with both linear and quadratic control variables alongside province and industry fixed effects, the policy's influence on green development is most pronounced. These results not only validate the IIP's effectiveness but also highlight the importance of fostering intelligent capabilities within firms to achieve enhanced environmental outcomes, which have robustly confirmed Hypothesis 2 by using double debiased machine learning model. Yang et al. (2020) arrived at a comparable conclusion, demonstrating that the implementation of intelligent manufacturing significantly contributes to the improvement of financial performance and the enhancement of innovation capabilities within manufacturing enterprises.

5.4 Heterogeneity analysis results using the DDML

The heterogeneity analysis in Table 12, utilizing the Double Debiased Machine Learning (DDML) method, reveals nuanced variations in the impact of the Integration of Informatization and Industrialization Pilot (IIP) on green development across different segments of the manufacturing sector. In the regional analysis, firms within the Yangtze River Economic

Table 11 Mechanism analysis results using the DDML

	(1)	(2)	(3)	(4)	(5)
	Score1	Score1	Score1	Score1	Score1
did	0.0273^{***}	0.0276^{***}	0.0193^{***}	0.0195^{***}	0.0188^{***}
	(20.6809)	(21.1621)	(10.7959)	(10.9977)	(11.0707)
_cons	-0.0008^{***}	-0.0009^{***}	0.0042^{***}	0.0041^{***}	0.0018^{***}
	(−2.9411)	(−3.1949)	(17.7802)	(17.2255)	(8.0458)
Control_variable_linear_term	Yes	Yes	Yes	Yes	Yes
Control_variable_quadratic_term	No	Yes	No	Yes	Yes
ID_FE	No	No	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	No	No	Yes
N	24258.000	24258.000	24258.000	24258.000	24258.000

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Belt exhibit a positive response to IIP with a did coefficient of 0.0060, significant at the 0.05 level, whereas those outside the belt show a slightly weaker but still positive effect with a coefficient of 0.0048, significant at the 0.1 level. Industry-specific results indicate a stronger impact on polluting industries with a did coefficient of 0.0075, significant at the 0.05 level, compared to non-polluting sectors which also benefit, albeit with a lower coefficient of 0.0043, also significant at the 0.05 level. Regarding firm size, larger firms demonstrate a more substantial benefit from IIP, with a coefficient of 0.0068, significant at the 0.01 level, while smaller firms show a beneficial effect with a coefficient of 0.0051, significant at the 0.05 level.

The heterogeneity analysis also reveals that the IIP's impact on green development varies across different contexts. Firms within the Yangtze River Economic Belt, polluting industries, and larger firms experience stronger benefits from the policy. This suggests that regional economic priorities, industry characteristics, and firm capabilities in managing and implementing green technologies play significant roles in how effectively the IIP influences green development. Production and services will increasingly become faster, more cost-effective, efficient, flexible, personalized, and of higher quality, thereby boosting added value and competitive advantage (Porter & Heppelmann, 2014; Xu & Duan, 2019; Zhong et al., 2017). These findings underscore the necessity for intelligent manufacturing policy measures that are specifically tailored to regional and sectoral characteristics, optimizing the effectiveness of initiatives aimed at promoting sustainable practices. In the context of

Table 12 Heterogeneity analysis results using DDML

	(1)	(2)	(3)	(4)	(5)	(6)
	Yangtze River Economic Belt = 1	Yangtze River Economic Belt = 0	Pollute = 1	Pollute = 0	Large size = 1	Large size = 0
	GREEN	GREEN	GREEN	GREEN	GREEN	GREEN
did	0.0060^{**}	0.0048^{*}	0.0075^{**}	0.0043^{**}	0.0068^{***}	0.0051^{**}
	(2.2987)	(1.9491)	(2.0854)	(2.3481)	(3.0902)	(2.0447)
_cons	0.0041^{***}	0.0026^{***}	0.0027^{***}	0.0041^{***}	0.0026^{***}	0.0047^{***}
	(10.5045)	(6.9810)	(5.6674)	(13.9414)	(5.1334)	(16.0195)
Control_variable_linear_term	Yes	Yes	Yes	Yes	Yes	Yes
Control_variable_quadratic_term	Yes	Yes	Yes	Yes	Yes	Yes
ID_FE	Yes	Yes	Yes	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes
Winsor treatment	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	rf	rf	rf	rf	rf	rf
Sample split ratio	kfolds (5)	kfolds (5)	kfolds (5)	kfolds (5)	kfolds (5)	kfolds (5)
N	9765	10,676	6933	16,337	5886	17,384

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

the ongoing technological revolution, enterprises that proactively respond to these policies are better positioned to secure additional resources and support, thereby enhancing their capacity to innovate and compete in a dynamic market landscape (Ying et al., 2021). Moreover, the analysis highlights the utility of using Difference-in-Differences Machine Learning (DDML) to dissect the nuanced impacts of these policies across heterogeneous groups, offering valuable insights for policymakers seeking to improve the efficacy of green development programs.

6 Conclusions

This study's main findings robustly demonstrate the Integration of Informatization and Industrialization Pilot (IIP) significantly enhances the green development of manufacturing firms in China. The parallel trend tests confirm compliance with pre-implementation conditions, and subsequent analyses post-implementation indicate a modest but positive effect on green development. The DID regression and PSM-DID regression employing nearest neighbor matching consistently show significant improvements in the environmental efficiency and productivity of firms resulting from the IIP. Furthermore, robustness checks using Green Total Factor Productivity as the dependent variable, along with comprehensive DDML analyses, confirm the policy's substantial impact across various models and settings, adjusting for potential biases, including endogeneity issues addressed using the Terrain Ruggedness Index as an instrumental variable. The mechanism analysis utilizing the DDML model underscores that intelligent transformation acts as a critical mediator, significantly boosting the policy's effectiveness. Additionally, heterogeneity analysis reveals that the IIP policy particularly benefits firms in the Yangtze River Economic Belt, heavily polluting industries, and larger firms, suggesting that customized policies could further optimize environmental outcomes. Overall, this article provides readers with theoretical and practical guidance on understanding the impact of the IIP policy on green development within manufacturing firms and the role of intelligent transformation in this process.

Methodology contribution

In particular, the application of the Double Debiased Machine Learning (DDML) framework represents a key methodological contribution of this study. Compared to traditional causal inference techniques such as DID and PSM-DID, DDML enhances the credibility of the estimated treatment effects by addressing model misspecification, high-dimensional confounding, and potential overfitting. Through orthogonalized estimation and cross-fitting, DDML allows for more accurate and unbiased identification of the causal impact of the IIP policy, even in the presence of nonlinear interactions and complex covariate structures. This methodological advancement not only strengthens the empirical validity of the findings but also demonstrates the value of integrating modern machine learning techniques into policy evaluation research. As such, the study contributes both substantively and methodologically to the growing literature on green industrial transformation and intelligent policy assessment.

Policy implication

The findings indicate that China's Integration of Informatization and Industrialization Pilot (IIP) initiatives effectively promote intelligent manufacturing and green development by driving digital–industrial integration and supporting the emergence of new industries such as industrial software and information services. These policies help cultivate a resilient industrial ecosystem, attract technology-oriented enterprises and talent, and enhance urban development efficiency, thereby contributing to sustainable economic growth. Importantly, the implications extend beyond China: international evidence based on data from European economies (e.g., Slovenia) and emerging regions such as MERCOSUR shows that the digital economy's network structure and ICT development can enhance resource coordination, institutional quality, and environmental sustainability (Manfreda & Indihar Štemberger, 2019; Qayyum et al., 2024). This suggests that the China's policy experience in digital–industrial integration provides a valuable reference for other developing countries seeking to promote intelligent transformation and green development, provided that policies are adapted to local institutional and technological conditions.

Limitation and future directions

While this study offers valuable insights into the impact of the IIP policy on green development, it has certain limitations that suggest directions for future research. In particular, a potential limitation of the dataset lies in the fact that it focuses primarily on listed manufacturing firms, which may not fully capture the heterogeneity of China's broader manufacturing sector. These unlisted firms may exhibit different patterns of digital transformation and green development due to variations in resource availability, policy exposure, and governance structures. Moreover, the dataset is limited to the Chinese context, and future studies could incorporate data from developed countries to enable cross-country comparisons and improve the external validity of the findings. Further studies could also examine the specific policy instruments—such as subsidies, tax incentives, and technical support—that facilitate intelligent transformation, to better understand how different mechanisms influence firms' adoption of green practices. Methodologically, although the use of the DDML framework enhances causal inference in high-dimensional settings, future work could improve the model by incorporating advanced learners like deep neural networks or by exploring time-varying treatment effects to better capture policy dynamics. These extensions would contribute to a more comprehensive and generalizable evaluation of intelligent policy interventions promoting sustainable industrial transformation.

Data availability Data is available upon request from the corresponding author.

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2026-12-31

Chen S, Alexiou C. (2026) Intelligent transformation and green development: a double debiased machine learning evaluation of china’s IIP initiatives. Annals of Operations Research, Available online 22 January 2026

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