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*Original Research*

# Intelligent Manufacturing, Man-Machine Matching Degree and Urban Green Total Factor Productivity

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## Abstract

With the deep integration and development of artificial intelligence technology in the economy and society, intelligent manufacturing provides a new opportunity for "overtaking in corners" to improve green total factor productivity. In order to clarify the relationship between the application of intelligent manufacturing and local green development, based on the panel data of 262 cities at or above the prefecture level in China from 2008 to 2019, this paper analyzes the impact of intelligent manufacturing on the total factor productivity of urban green and investigates the role of man-machine matching in it by using the panel smooth transformation regression model. The research results show that the development of intelligent manufacturing can obviously promote the urban green total factor productivity, but this promotion effect will show an invisible slowdown with the continuous improvement of the application level of intelligent manufacturing. At the same time, intelligent manufacturing can significantly improve the green total factor productivity of China's non-resource cities, cities with a high level of digital economy development, and eastern regional cities. Further research found that when the man-machine matching degree crossed the threshold, intelligent manufacturing could fully release the promotion of green total factor productivity. The research conclusions and suggested measures are of great significance for China to grasp the technical characteristics and advantages of intelligent manufacturing and promote low-carbon economic transformation.

**Keywords:** intelligent manufacturing, green total factor productivity, panel smooth transformation regression model, man-machine matching degree, sustainable development

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## Introduction

Since the reform and opening up, China has made great achievements in economic construction. However, behind the rapid economic growth, is the depletion of resources and the deterioration of the ecological environment. Faced with the dual constraints of resource shortage and environmental carrying capacity, the contradiction between energy consumption and ecological environment governance has never been systematically resolved [1, 2]. The report of the 20th National Congress of the Party pointed out: "We should persistently promote green and low-carbon development, establish and improve a green and low-carbon circular development economic system, and promote green and low-carbon economic and social development". Indeed, industrial development has reached an important period of having to change the development model of "environment for growth", and it is urgent to improve green total factor productivity. In the context of the pursuit of building a strong country with quality, through the introduction of modern machinery and equipment, accelerating technological innovation, and increasing environmental regulation, it can promote the transformation and upgrading of traditional industries such as steel, non-ferrous metals, chemicals, and building materials, so as to greatly improve the degree of green production and resource utilization efficiency. This not only helps to promote the coordination and unity of economic, social, and ecological benefits, but also has great significance for achieving the goal of "carbon peak and carbon neutrality" [3].

With the in-depth development of the new round of scientific and technological revolution, the cross-border integration and deep application of digital technologies such as big data, cloud computing, and blockchain with various fields of economy and society have spawned a new economic form represented by intelligent manufacturing. With its powerful integration characteristics, intelligent manufacturing architecture is divided into five parts: resource layer, ubiquitous network layer, service platform layer, intelligent cloud service application layer, and safety management and specification layer, so that it can quickly penetrate into the whole product life cycle, promote the re-optimization and integration of industrial chain resources and information, reduce the consumption rate of energy resources in the supply chain, and accelerate the low-carbon economic transformation [4, 5]. At the same time, with the continuous development and innovation of intelligent manufacturing, the mobility barriers between regions have been greatly reduced, and the socio-economic effects have been effectively increased by stimulating innovation efficiency and optimizing industrial structure, thus enhancing the regional green total factor productivity. It can be seen that intelligent manufacturing, as the core driving force of the new round of industrial transformation, will reconstruct all links of economic activities, form new intelligent demands in various fields, and promote the overall leap of social productivity. However, the application of intelligent manufacturing in China is still in the initial stage of exploration. As far as the current trend of digital transformation is concerned, how to build sustainable competitiveness by changing the traditional technology model, accelerate the release of green development potential by intelligent technologies such as machine learning, knowledge mapping, and human-computer interaction, and enhance green total factor productivity has become a key breakthrough in grasping a new round of scientific and technological revolution and new opportunities for industrial transformation in the future.

In view of this, this paper uses panel data from China City from 2008 to 2019 and focuses on the influence mechanism of intelligent manufacturing on urban green total factor productivity. At the same time, the PSTR model is used to analyze whether the man-machine matching degree is helpful to tap the technological and structural dividends of intelligent manufacturing in green and low-carbon transformation. Finally, the realization path of promoting the green and high-quality development of the urban economy under the application conditions of the new generation of information technology is put forward in order to provide a useful reference for relevant theoretical research and policy practice.

The rest of the article is arranged as follows: The second chapter provides a literature review on the connotation and measurement of intelligent manufacturing, the influencing factors of energy utilization efficiency, and the mechanisms of intelligent manufacturing affecting energy utilization efficiency. The third chapter puts forward the research hypothesis of this paper, combs the influence path of intelligent manufacturing on energy utilization efficiency, and what role man-machine matching plays in this process. The fourth chapter describes the data and methods used in this paper. The fifth chapter uses a series of mathematical statistical models to verify the influence of intelligent manufacturing on energy efficiency and the threshold effect of man-machine matching. The sixth chapter summarizes the full text, provides corresponding policy suggestions, and expounds on the research limitations and future prospects. See Fig. 1 for an overview of the article.

## Literature Review

Intelligent manufacturing, as the adhesive of the organic integration of intelligence and industrialization, how to fully release the boosting power of intelligent manufacturing to urban green total factor productivity and empower the real economy to optimize factor allocation and improve output efficiency has become a hot issue of concern to the government and scholars in recent years. After sorting out the existing literature,

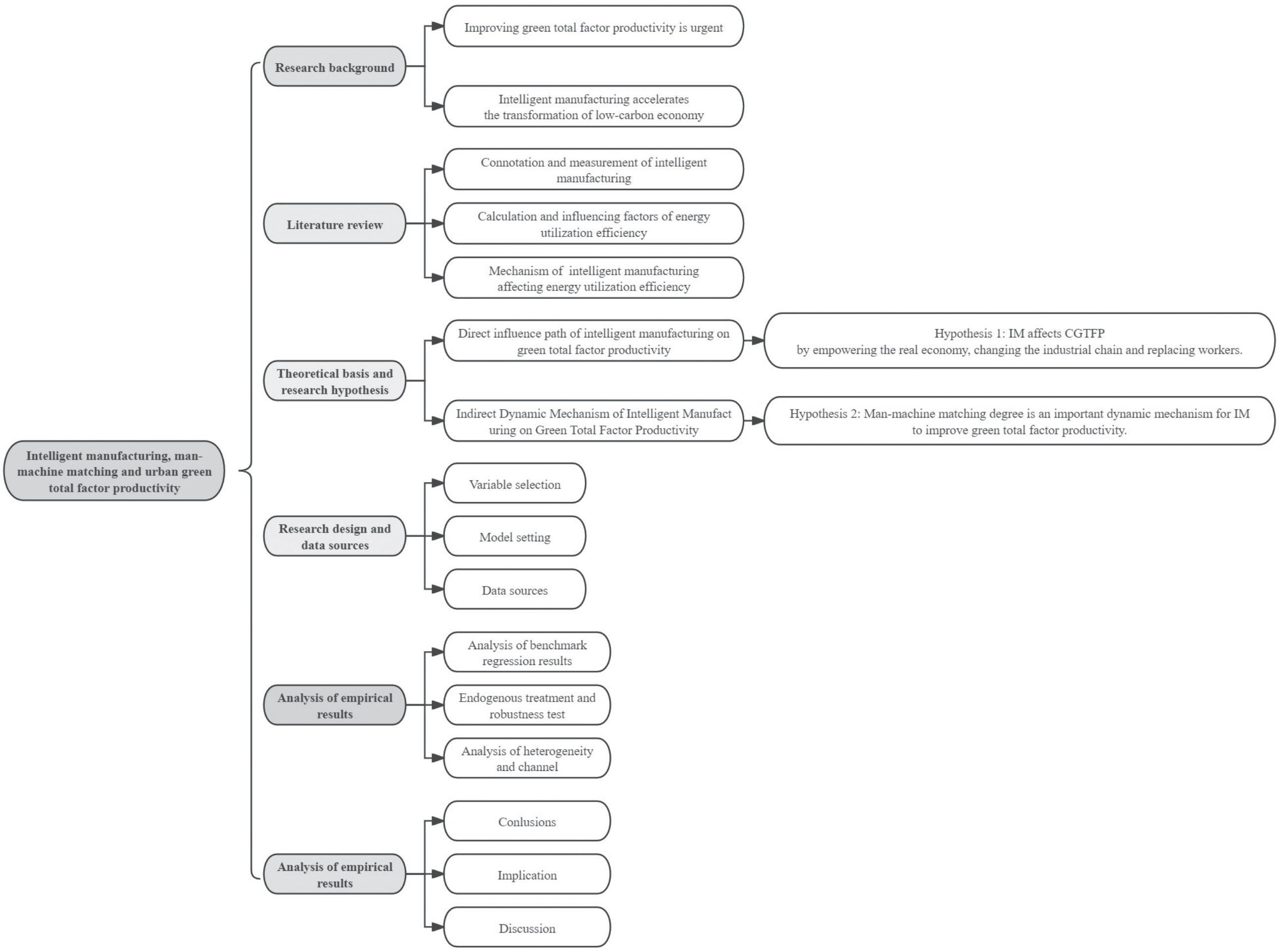


Fig. 1. A general picture of research.

the research related to the theme of this paper can be roughly divided into the following aspects:

The first is about the connotational interpretation and measurement evaluation of intelligent manufacturing. As a deep integration of artificial intelligence and advanced manufacturing technology, intelligent manufacturing promotes the digitalization, networking, intelligent transformation, and upgrading of the industrial chain value chain through intelligent perception, human-computer interaction, decision-making, and execution technology [6, 7]. Wang et al. proposed that intelligent manufacturing, a new manufacturing method, would reconstruct all aspects of the manufacturing life cycle, such as products, production, and services, trigger complementary technological progress and innovation, and promote the overall leap of social productivity [8]. For the scientific measurement of the development level of intelligent manufacturing, some scholars use the methods of entropy weight and fuzzy comprehensive evaluation to measure it. For example, Yang et al. constructed a multi-dimensional analysis index system of intelligent manufacturing in China from three dimensions: input, output, and technology, and used a generalized Bonferroni curve to describe its temporal and spatial evolution and convergence [9]. According to the industry classification standards, attributes, and names, few scholars match the manufacturing industry classification published by the International Robotics Federation with the manufacturing sub-sectors in China and then calculate the number of industrial robots installed, so as to measure the regional intelligent manufacturing level [10-12].

The second is about the calculation and influencing factors of urban green total factor productivity. Most scholars use the stochastic frontier method, data envelopment analysis, the Solow residual method, and the algebraic index method to measure and analyze the green total factor productivity of different industries or regions, and it has become mainstream practice to modify the radial distance function and mixed distance function based on the data envelopment analysis method [13-15]. Tian et al. (2022) and Cheng et al. (2022) used the directional distance function and mixed distance function to calculate the green total factor productivity, respectively, and described its temporal and spatial evolution and convergence [16, 17]. Both showed that the green total factor productivity of various provinces in China was increasing year by year, and there were obvious regional differences. At the same time, the improvement of technical efficiency played a key role in promoting the green transformation of social and economic development modes. Sun et al., based on the three-stage DEA dynamic analysis model of spatial heterogeneity, found that the growth of green total factor productivity in China showed a geographical "blockchain" convergence trend, and there was an obvious radiation-driven effect [18]. In addition, the existing literature summarizes that technological innovation ability, industrial capital intensity, industrial structure, innovative human capital, environmental regulation, and other factors can effectively affect urban green total factor productivity, but the research conclusions revealed are not the same [19-22].

The third is the research on the mechanism and path of innovation in intelligent manufacturing affecting urban green total factor productivity. Because the concept of intelligent manufacturing has been put forward for a short period of time, there are few studies on the relationship between intelligent manufacturing and green total factor productivity, focusing on whether the application of artificial intelligence, big data, and other technologies can promote the improvement of urban green total factor productivity by optimizing the institutional environment, correcting the mismatch of factors, improving labor productivity, and exerting the effects of energy saving and carbon reduction [23-25]. Acemoglu et al. [26], and Li et al. [27] all show that with the continuous improvement of policies such as intelligent manufacturing, smart cities, and integration of the two industries, the algorithmic ability and digital intelligent decision-making ability of artificial intelligence technology can analyze, supervise, and limit the negative externalities of "three high" enterprises, improve the efficiency and green production of raw materials and products, and thus promote green. At the same time, in the context of man-machine division of labor and cooperation, when enterprises integrate technologies such as big data, cloud computing, and deep learning into their production activities, they should minimize the loss of production efficiency caused by man-machine mismatch and avoid weakening the promotion effect of intelligent manufacturing on green total factor productivity.

To sum up, the existing literature has done a lot of useful research on intelligent manufacturing and urban green total factor productivity, which provides ideas and experience enlightenment for this paper, but there are still some shortcomings in the following aspects: First, there are few studies on whether intelligent manufacturing has environmental dividends at home and abroad, the theoretical research foundation is weak, and the empirical research is still in its infancy. Moreover, few studies pay attention to the nonlinear relationship between intelligent manufacturing and green total factor productivity. Second, most of the existing research focuses on the provincial level, and few literatures discuss the effect of intelligent manufacturing applications based on city-level data. Thirdly, there are few studies to discuss whether blindly using intelligent manufacturing technology can improve urban green total factor productivity from the perspective of man-machine matching. Moreover, most of the previous studies used an ordinary threshold model to analyze the threshold effect of variables. Although the threshold can be obtained, it is still solved on the basis of a linear model; that is, the transformation of intelligent manufacturing near the threshold has abrupt characteristics that do not conform to the display law.

The research contributions of this paper are as follows: (1). Based on the data of China City, this paper quantitatively evaluates the impact of intelligent manufacturing on green total factor productivity and expands the research perspective and content of intelligent technology supporting the green development of industries represented by robots (2). Different from the simple geographical location division for heterogeneity analysis, this paper embeds factors such as urban location, resource endowment, and digital economy development level into the panoramic logical framework chain of intelligent manufacturing and green total factor productivity to identify the heterogeneous influence of intelligent manufacturing on green total factor productivity. These conclusions are more helpful for administrative departments and enterprise managers to take corresponding measures to make up for the shortcomings. (3). From the perspective of man-machine matching, this paper uses the PSTR model to identify the boundary conditions of intelligent manufacturing, promote green total factor productivity, and better describe the nonlinear relationship between economic variables. This provides valuable policy enlightenment for better realizing "man-machine coexistence".

## Influence Mechanism and Research Hypothesis

Different from computer integrated manufacturing, intelligent manufacturing has the characteristics of self-perceived learning, independent decision-making, and self-adaptive adjustment. It can realize the digitalization of production links, industrial chain transformation, and human-computer interconnection through key technologies such as the Internet of Things, cyber-physical systems, cloud computing, and large-scale data analysis, so as to enhance green total factor productivity with a lower energy consumption production mode and a stronger development paradigm. Based on the existing literature research and endogenous growth theory, combined with the properties of intelligent manufacturing, this paper studies the influence mechanism and effect of intelligent manufacturing on green total factor productivity, and the specific theoretical logical framework is shown in Fig. 2.

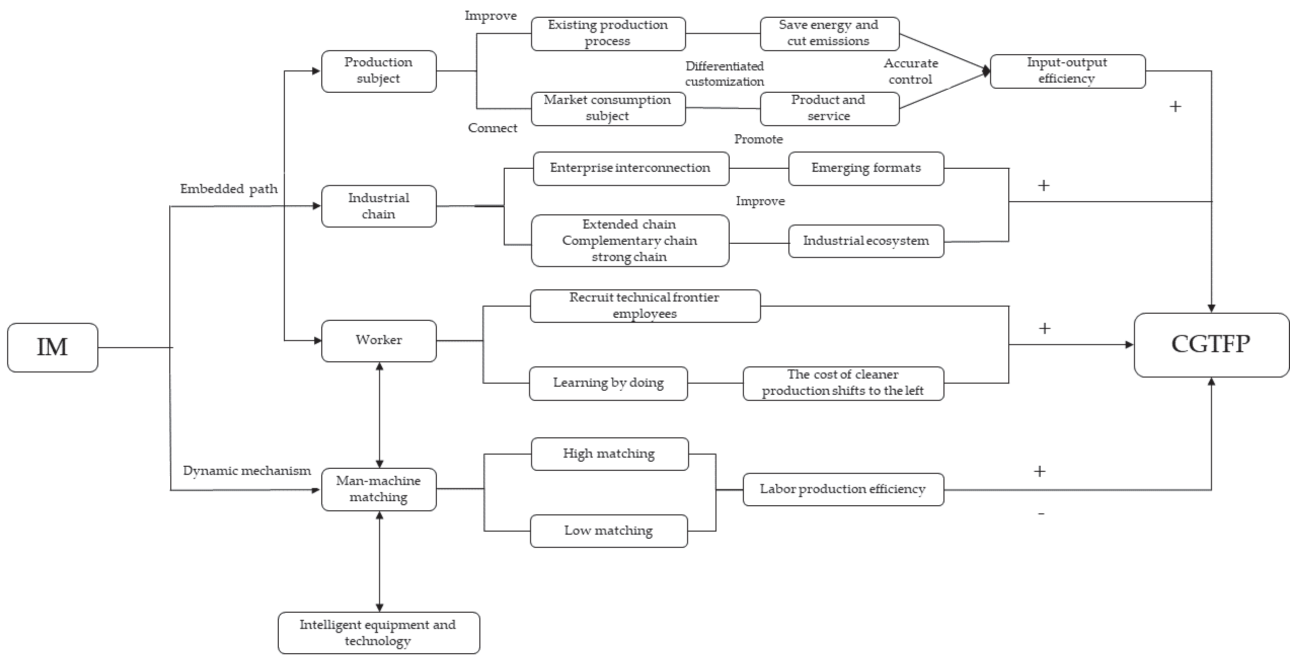


Fig. 2. Theoretical analysis diagram.

## Direct Influence Path of Intelligent Manufacturing on Green Total Factor Productivity

Promoting green total factor productivity can be regarded as an overall and systematic long-term process. External shocks such as environmental regulation and market competition will induce the "extensive extension" industry development mode to turn to "intensive connotation", which will drive green total factor productivity in a limited, short-term, and discontinuous way. However, the fundamental way to effectively improve green total factor productivity is through continuous technological progress [28, 29]. As a major technological innovation in the era of Industry 4.0, intelligent manufacturing takes the digitalization, networking, and intelligent integration of the product life cycle value chain as the main line and realizes efficient, high-quality, low-consumption, green, and safe manufacturing and service with the support of vertical management and control integration within enterprises and networked collaborative consumers.

First of all, from the perspective of the production subject (enterprise), intelligent manufacturing empowers the real economy, and the process of digitalization, networking, and intelligence in the manufacturing industry is accelerated, which helps to promote the ubiquitous connection and optimal allocation of resource elements. Based on the comprehensive consideration of production technology, operation management, and other data, enterprises can improve existing production processes, such as product R&D and design, manufacturing, logistics, and warehousing, order acquisition, and service tracking, with the help of blockchain and BDA technology, to achieve more accurate supply chain management and financial management, reduce material waste, reduce warehousing pressure, and reduce operating costs. At the same time, by introducing highly flexible production equipment, mainly CNC machine tools and robots, enterprises can comprehensively collect and deeply analyze the data of "people, machines, materials, methods, environment, and measurement", effectively cope with the complexity of production activities, explore the deep-seated reasons leading to production bottlenecks and product defects, and continuously improve production efficiency and product quality, thus preventing overcapacity and environmental pollution and boosting green total factor productivity. In addition, on the basis of the deep integration of mobile internet, artificial intelligence, and the manufacturing industry, with the help of intelligent connection carriers such as search engines, social media, e-commerce platforms, and application stores, multi-party market transaction subjects are brought together to break through the blocking points of key links in the economic cycle process such as production, exchange, and sales, and accurately capture, analyze and meet the needs of consumers in real time, so as to promote dynamic feedback and two-way interaction between consumers and production subjects, thus achieving more flexible and efficient production methods and improving the market [30-32].

Secondly, from the perspective of industrial chain reform, based on the economic characteristics of strong permeability, wide coverage, and high innovation, intelligent manufacturing can break the spatial stability of the industrial chain, promote the interconnection and integrated sharing of factor resources, and accelerate enterprises to get rid of obstacles such as geographical location and factor endowment, thus comprehensively accelerating the pace of industrial chain extension, supply chain filling, value chain jumping, and innovation chain upgrading in the economic system, forming a multi-node and strongly related product network, technology network, and market network, and finally expanding enterprises' own products and markets [33, 34]. This not only provides a new opportunity for improving green total factor productivity, but also creates a new dynamic foundation for developing the cooperation mechanism of industrial clusters and optimizing the ecosystem. In addition, industrial chain integration under the empowerment of "wisdom" will blur the boundaries of production and business activities among different types of enterprises, improve the convenience and utilization efficiency of resource acquisition, reduce unnecessary waste, and thus provide beneficial conditions for improving the environmental performance of enterprises.

Finally, from the perspective of workers, with the popularization of unmanned factories and intelligent production systems, it will replace most workers engaged in simple production tasks, such as assembly workers and data loggers on production lines, so that they can be liberated from heavy physical labor and repetitive labor. The spare time can be adapted to technological changes and new work requirements by constantly learning and upgrading their own skills, thus accelerating the release of the promotion effect of intelligent manufacturing on green total factor productivity in a wider coverage and more diverse subject levels [35, 36]. At the same time, although intelligent manufacturing can replace material production labor and all kinds of repetitive work, the operation, maintenance, and research and development of intelligent machines still need a large number of high-quality talents to participate. This means that enterprises need to recruit more technical frontier employees and employees with rich management experience, accelerate the penetration of artificial intelligence and green technology, and optimize management processes, thus providing more human capital for the improvement of green total factor productivity [37, 38]. In addition, with the increase of highly skilled workers and the construction of the industrial internet, relying on the information interaction mode of intelligence, customization, and dynamic feedback, the "learning by doing" effect among workers can be realized, which will drive the cleaner production cost curve of enterprises to move to the left, thus reducing the average production cost. To sum up, this paper puts forward research hypothesis 1:

Hypothesis 1: Intelligent manufacturing affects green total factor productivity by empowering the real economy, changing the industrial chain, and replacing workers.

## Indirect Dynamic Mechanism of Intelligent Manufacturing on Green Total Factor Productivity

Intelligent manufacturing, as a new manufacturing mode, uses the new generation of information and communication technology (ICT) and artificial intelligence technology to break down the barriers between design, manufacturing, and service, realize cross-domain global information integration and deep interaction between information and manufacturing space, effectively improve traditional industrial production lines, and then improve production efficiency and quality. With the continuous transformation of social productive forces and production relations by intelligent manufacturing, production tasks are becoming more and more complicated and specialized, and "machine substitution" is gradually changing into "man-machine matching", which has spawned new decision-making paradigms and organizational paradigms. The so-called man-machine matching refers to the cooperative work and interaction between human beings and robots, computers, or other intelligent systems, aiming at combining the intelligence of machines with human creativity and decision-making ability to achieve more efficient, accurate, and innovative work. Therefore, under the background of intelligence, the social demand for human capital is changing from quantity to quality, which improves the complementary requirements of human capital and material capital. In the initial stage of the development of intelligent manufacturing, the technical complexity of the production environment is low, and machinery and equipment are usually used to perform repetitive, high-intensity, and routine tasks, such as assembly, inspection, packaging, and other routine manual tasks on the production line, without the direct participation of workers, so that they have more time and energy to engage in creative and high value-added work [39, 40]. Enterprises can also produce the same or even more products with lower labor costs. However, with the wide application of machines and automation equipment, low-skilled workers cannot dynamically match the complex environment of artificial intelligence development, and it is difficult to alleviate the negative effects of technological changes on human capital. According to the theory of employee organization matching, the application of intelligent technology cannot be separated from the matching of high-quality employees, and the combination of information technology and highly-skilled human capital can create higher production efficiency. In difficult-to-code and unconventional tasks such as R&D design, production deployment, and post-operation maintenance, workers with low education levels can't quickly adapt to and assist intelligent devices to extract valuable information and knowledge from massive data, thus failing to provide more accurate and comprehensive data support for the completion of production tasks, causing labor productivity loss and ultimately reducing green total factor productivity [41, 42]. At the same time, the mismatch between man and machine is likely to cause the parameters of intelligent equipment, such as accuracy, speed, or pressure, to be inconsistent with the product requirements, which will lead to a decline in the accuracy and quality stability of products produced by enterprises, invisibly slow down the market competitiveness of enterprises themselves, and restrict the optimization of intelligent technology on the efficiency of resource allocation. Therefore, it is worth knowing that even if intelligent manufacturing technology is rapidly updated and iterated in the face of complex tasks, only by improving the cooperative matching ability between workers and machinery and equipment can intelligent manufacturing promote green total factor productivity to the greatest extent. Moreover, the improvement of man-machine matching is helpful to realize more refined energy management. By optimizing the operating parameters of the machine and the work arrangement of human employees, human resources can be allocated reasonably, and energy consumption and waste discharge in enterprises can be reduced, thus achieving a more efficient, safer, and more stable production process and green production [43, 44].

To sum up, this paper puts forward research hypothesis 2:

Hypothesis 2: Man-machine matching degree is an important dynamic mechanism for intelligent manufacturing to improve green total factor productivity.

## Methods and Data Source

### Variable

#### *Explained Variable*

Green total factor productivity in cities (CGTFP). CGTFP integrates environmental resources into the analysis framework of economic growth and becomes an important indicator to measure the coordination between resources, the environment, and economic development. Referring to the research ideas of published literature [45-47], this paper constructs an evaluation index system for urban green total factor productivity and uses the non-radial and non-angular relaxation directional distance function (SBM) under the hypothesis of variable scale returns (VRS) to measure it, combined with the global ML index. Specific indicators are selected as follows:

1. Factor input. Based on the theory of production factors, labor, capital, and energy consumption are selected as the input indicators of factors. Among them, labor input is represented by the sum of the number of employees in units and the number of private and individual employees at the end of each city. Capital investment refers to the practice of published literature, using the perpetual inventory method to calculate the actual capital stock of the city as a proxy variable [48]. The calculation formula is: $K_{it} = (1 - d)\ K_{i,t-1} + I_{it}$. Where $K_{it}$ and $I_{it}$ respectively represent the capital stock of city i in the t year and the newly-increased social fixed asset investment. The capital stock in the base period is $K_0 = I_0/(g_i + d)$, $g$ is the geometric growth rate of fixed assets investment in each city, and $d$ is the depreciation rate of fixed assets, which is set at 10.96%. Considering the serious lack of energy consumption data such as coal and oil at the city level, this paper refers to the practice of Guan et al. [49] and selects the electricity consumption of the whole society in each city as the proxy variable of energy consumption.

2. Expected output variables. The GDP of each city in China is measured, and the year 2008 is used as the base period to reduce it, so as to eliminate the influence of price factors.

3. Unexpected output variables. Referring to the practices of Peng et al. [50], the three industrial wastes (industrial $SO_2$ emissions, industrial wastewater emissions, and industrial soot emissions) in cities are selected as proxy variables of unexpected output.

#### *Core Explanatory Variable*

At present, there are no unified measures for intelligent manufacturing in domestic and foreign literature, and there are two mainstream practices: one is to select the proportion of information transmission, computer services, and software industry's total fixed assets in GNP to represent intelligent manufacturing [51, 52]. The other is to measure it by using the installation density or penetration of industrial robots [53, 54]. With the continuous development of robot technology, the intelligent manufacturing mode with green, digital, and intelligent as the core is becoming the main direction of industrial development, which is of great significance to improve the added value of products, improve the working environment, and reduce labor intensity. In view of this, this paper refers to the research ideas of published literature [55-57], and the Batik tool variable method was used to calculate the penetration of industrial robots in China to measure intelligent manufacturing. Specifically, according to the China industry categories published by IFR and the National Economic Industry Classification (GB/T4754-2002), this paper obtains the number of industrial robots installed in various industries in China, selects 2005 as the reference year to calculate the weight of robot installation density in sub-industries in China, and then calculates the penetration of industrial robots at the city level. The calculation formula is as follows:

$$IM_{jt} = \sum_{i=1}^{I} \frac{labor_{i,j,t=2005}}{labor_{j,t=2005}} * \frac{robot_{it}}{labor_{i,t=2005}} \tag{1}$$

In Eq. (1), i, j and t respectively represent industry, city, and year; $robot_{it}$ represents the number of industrial robots installed in industry i in the t year; $labor_{i,t=2005}$ and

$labor_{j,t=2005}$ represents the labor force scale of industry i and city j in 2005, respectively.

### *Threshold Variable*

Man-machine matching (Match). Man-machine matching can fully reflect the workers' proficiency in the operation of intelligent mechanical equipment and judge whether to accelerate the work process and improve production efficiency through the powerful computing power and data processing ability of the machine. In view of this, this paper refers to the practices of published literature [58, 59], and uses the coordination degree between the intelligent manufacturing level and human capital to measure the man-machine matching degree. The specific calculation formula is as follows:

$$Match = \sqrt{U * V} \quad (2)$$

$$U = 2\sqrt{IM * HC}/(IM + HC) \quad (3)$$

$$V = 0.5 * IM + 0.5 * HC \quad (4)$$

### *Control Variable*

In order to minimize the error caused by the omission of important variables in the causal inference of the model, this paper selects the following control variables according to the research perspective of existing literature (1). Urbanization level (Urban). The continuous improvement of urbanization levels will accelerate the flow of production factors and industrial agglomeration, which will directly affect the original economic development system and environmental quality of the city. Therefore, referring to the practice of Xiao et al. [60], the proportion of the urban resident population to the total population is selected to measure it (2). The degree of opening up (Open). Because the introduction of foreign advanced factor resources can accelerate domestic technological change and institutional mechanism innovation, resulting in a "pollution halo" effect, thus improving economic production efficiency, at the same time, the introduction of high-pollution and high-emission enterprises has aggravated the pressure on the local ecological environment. Therefore, referring to the practice of Dong et al. [61], the proportion of actually used foreign investment in GDP is selected to measure it (3). The size of the city (Cis). With the deepening of urbanization, the "urban diseases" such as personnel congestion and waste of resources have increased sharply, which has hindered the development of an urban green economy. Therefore, referring to Yang et al. [62], the urban population density at the end of the year is selected to measure it (4). Industrial structure (Ins). Considering that the environmental effect and green economy effect played by the tertiary industry in the process of social and economic development account for a large proportion, it is measured by the proportion of the added value of the tertiary industry and the added value of the secondary industry with reference to the practice of Xu et al. [63]. (5). Degree of financial development (Fin). Schumpeter's growth model shows that financial development can reduce the information asymmetry between capital demanders, improve the efficiency of rational allocation of financial resources, and provide a financial guarantee for industrial green technology innovation. Therefore, according to Chiu et al. [64], the loan balance of urban financial institutions is selected as the proportion of GDP (6). Industrial energy consumption intensity (Energy). With the increase in energy consumption intensity, regional environmental quality deteriorates, which further restricts the sustainability of urban economic growth and further affects green total factor productivity. Therefore, referring to the practice of Lyu et al. [65], the proportion of urban industrial electricity consumption in industrial added value is selected to measure it.

## Research and Data Methodology

### *SBM-GML Model*

By sorting out the existing research, the measurement methods of urban green total factor productivity mainly focus on data envelopment analysis (DEA) and stochastic frontier methods (SFA). Among them, the DEA method can avoid the resulting bias caused by the preset production function form and the distribution characteristics of error terms, so it has obvious advantages in measuring the production efficiency of multi-input and multi-output independent decision-making units. Therefore, this paper uses data envelopment analysis to measure urban green total factor productivity. At the same time, considering that the traditional DEA method often leads to biased results due to different radial and angular choices in the production efficiency calculation process, in order to eliminate this bias, this paper imitates the ideas of published literature [66, 67] and constructs a super-efficient slacks-based measure (SBM) model with unexpected output, which solves the problem that the traditional DEA model does not consider the input or output variables to some extent. The model is constructed as follows:

$$\rho^* = min\frac{1 - \frac{1}{M}\sum_{i=1}^{M}\frac{S_m^x}{x_{m_0}}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\frac{S_r^g}{y_{r_0}^g} + \sum_{k=1}^{S_2}\frac{S_k^b}{b_{k_0}^b}\right)} \quad (5)$$

$$s.t.\begin{cases}\sum_{j=1}^{J}\lambda_j^t Y_{rj}^t - S_r^g = y_{rj}^t, r=1,\dots,S_1\\ \sum_{j=1}^{J}\lambda_j^t b_{kj}^t + S_k^b = b_{bj}^t, k=1,\dots,S_2\\ \sum_{j=1}^{J}\lambda_j^t X_{mj}^t + S_m^x = x_{mj}^t, m=1,\dots,M\\ \sum_{j=1}^{J}\lambda_j^t = 1, \lambda_j^t \ge 0, j=1,\dots,J\\ S_k^b \ge 0, S_r^g \ge 0, S_m^x \ge 0, J=1,..,Z\end{cases} \quad (6)$$

In Eqs. (5) and (6), M, $S_1$, and $S_2$ respectively represent the input-output variables in the effective production decision-making unit in the system; $S^x$, $S^g$ and $S^b$ are slack variables; $\lambda$ is the weight matrix; ρ represents the target efficiency value, ρ∈[0,1]. As far as a specific production decision-making unit is concerned, when ρ = 1, it shows that the decision-making unit is completely effective, the factor input ratio is optimal, and there is no efficiency loss caused by unexpected output redundancy and insufficient expected output. When 0≤ρ<1, it shows that the production decision-making unit has the problem of efficiency loss, which can be improved by optimizing the configuration of elements. It should be noted that a larger ρ value means the lower inefficiency value calculated by the distance function in the SBM direction, so the 1 – ρ conversion is carried out in the process of actually calculating the efficiency value.

Considering that the directional distance function is a production possibility set constructed by using the current production technology, it is impossible to make cross-period comparisons or even draw the conclusion of "technological retrogression". In view of this, referring to the idea of global reference modeling proposed by Zhan et al. [68], this paper constructs a global production technology set including all sample points, that is, $P_G(x) = P_1(x_1)\cup P_2(x_2)\cup\dots\cup P_t(x_t)$, so as to determine the optimal frontier. At the same time, this paper combines the global production technology set with Malmquist-Luenberger (ML) to construct the global ML (GML) index, so as to solve the non-transitivity defect of the traditional ML index and avoid the problem of linear programming without a solution. The specific expression is as follows:

$$CGTFP_t^{t+1} = (x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t)$$
$$= [\frac{\overrightarrow{S^t}(x^{t+1}, y^{t+1}, b^{t+1})}{\overrightarrow{S^t}(x^t, y^t, b^t)} * \frac{\overrightarrow{S^t}(x^{t+1}, y^{t+1}, b^{t+1})}{\overrightarrow{S^t}(x^t, y^t, b^t)}]^{1/2} \quad (7)$$

In Eq. (7), $CGTFP_t^{t+1}$ represents the change rate of urban green total factor productivity in the period from t to t+1 of each production decision-making unit and can be further divided into technical progress index (GTC) and technical efficiency index (GEF), namely $CGTFP_t^{t+1} = GTC_t^{t+1} + GEF_t^{t+1}$.

### *Econometric Model*

1. Benchmark regression analysis model. In order to verify the direct impact of intelligent manufacturing on urban green total factor productivity, combined with research hypothesis 1, this paper constructs the following panel econometric model:

$$CGTFP_{it} = \alpha_0 + \alpha_1 IM_{it} + \alpha_2 Control_{it} + \nu_t + \lambda_i + \varepsilon_{it} \quad (8)$$

Where $\alpha_0$ represents a constant term; $\alpha_1$ and $\alpha_2$ represent regression coefficients to be fitted and calculated; Subscripts i and t represent individuals and time, respectively. *Control* represents all control variables except the core explanatory variables; $\lambda_i$ stands for individual fixation effect and $\nu_t$ stands for time fixation effect; $\varepsilon_{it}$ represents the random disturbance term that obeys the white noise process. Considering that there may be a nonlinear relationship between intelligent manufacturing and urban green total factor productivity, this paper puts the square term ($IM_{it}^2$) of intelligent manufacturing into the model framework for investigation, and in order to avoid collinearity, *IM* is decentralized and then multiplied by square, thus establishing the following econometric model:

$$CGTFP_{it} = \alpha_0 + \alpha_1 IM_{it} + \alpha_2 IM_{it}^2 + \alpha_3 Control_{it} + \nu_t + \lambda_i + \varepsilon_{it} \quad (9)$$

2. Panel smooth conversion regression model. In order to verify the channel effect of man-machine fit in the process of intelligent manufacturing affecting urban green total factor productivity, this paper constructs a panel smooth conversion model with man-machine fit as the conversion variable. By replacing the discrete characteristic function in the panel threshold regression model, this model realizes the smooth transition of model parameters between different regression "zones" and then better identifies the heterogeneity of section units. In view of this, the article refers to the practices of Wu et al. [69] and makes the following provisions on the model form:

$$CGTFP_{it} = \beta_0 + \beta_1 IM_{it} + (\beta_2 IM_{it} + \delta_{itk}\sum_{k=1}^{7}\overrightarrow{Control_{itk}}) * g(Sub_{it}; \gamma_j; c_j) + \varepsilon_{it} \quad (10)$$

In Eq. (10), $\beta_1$ and $\beta_2$ represent the estimation coefficients of linear and nonlinear parts of intelligent manufacturing, respectively; $g(Sub_{it}; \gamma_j; c_j)$ is a bounded continuous transformation function with man-machine matching degree as the transformation variable, and the function value range is [0,1], which is specifically expressed as the following logical function form:

$$g(Sub_{it};\gamma_j;c_j) = [1 + exp(-\gamma \prod_{j=1}^{m} Sub_{it} - c_j)]^{-1} \tag{11}$$

In Eq. (11), $\gamma_j$ represents the smooth conversion coefficient of the conversion function, and the values are all greater than 0. The conversion speed between different conversion mechanisms is determined by the smooth conversion coefficient. $c_j$ represents the position parameter, which is the inflection point of conversion between different mechanisms, that is, the threshold value. $m$ represents the position parameter of the conversion function, that is, where $m$ conversion occurs. It should be noted that: (1). When $m = 1$, $\gamma = 1$, $g(Sub_{it}; \gamma_j; c_j)$ is smoothly converted between 0 and 1, and the smooth conversion coefficient is divided into low-range system and high-range system (2). When $m = 1$, $\gamma \to \infty$, the model is transformed into a two-system PTR model (3). When $m = 2$, the transfer function gets the minimum value at $(c_1 + c_2)/2$ (4). When $\gamma \to 0$, regardless of the value of $m$, the model degenerates into the traditional linear fixed effect model.

Before estimating the PSTR model, it is necessary to test the existence of a nonlinear relationship. The original hypothesis of the linear test is $H_0$:$\gamma = 0$, which shows that the model has only one operating mechanism and is suitable for estimation by using a linear framework. The alternative hypothesis is $H_1$:$\gamma \neq 0$, which shows that it is reasonable to use the PSTR model to explore the relationship between intelligent manufacturing and urban green total factor productivity. In the specific test process, the first-order Taylor expansion of the transfer function $g(Sub_{it}; \gamma_j; c_j)$ is often used to construct the auxiliary regression model, and the specific expression is as follows:

$$\begin{aligned} CGTFP_{it} = \delta_0 + \delta_1 IM_{it} + \delta_2 IM_{it}Sub_{it} + \ldots + \delta_m IM_{it}Sub_{it}^m \\ + \varepsilon_{it} + R_m(Sub_{it};\gamma_j;c_j) \end{aligned} \tag{12}$$

In Eq. (12), $R_m$ is the remainder of the Taylor expansion; $\delta_1$, $\delta_2$, ..., $\delta_m$ is the multiplier of $\gamma$, that is, the existence test parameter of system transformation. In the auxiliary function, the Lagrange multiplier method ($LM$), the Lagrange multiplier method ($LMF$), and the likelihood logarithm method ($LRT$), which are gradually equivalent to the $\chi^2$ distribution, are constructed to test the parameters. The specific expressions are as follows:

$$LM = \frac{TN(SSR_0 - SSR_1)}{SSR_0} \sim \chi^2(mk) \tag{13}$$

$$LMF = \frac{(SSR_0 - SSR_1)/mk}{SSR_0/(TN - N - mk)} \tag{14}$$

$$LRT = -2log\frac{SSR_1}{SSR_0} \sim \chi^2(mk) \tag{15}$$

In Eqs. (13) to (15), $k$ represents the number of explanatory variables; $SSR_0$ and $SSR_1$ respectively represent the sum of squares of residuals under linear and nonlinear conditions.

### Data Source

Following the principle of data availability and consistency of statistical caliber, this paper selects the panel data of 262 cities at the prefecture level and above in China from 2008 to 2019 as the research sample after excluding the urban samples with the above variables missing for four years or more. The original data for all variables mainly comes from the China Statistical Yearbook, the China Environmental Statistical Yearbook, the China Energy Statistical Yearbook, the China City Statistical Yearbook, the International Robot Union database, the CNRDS database, the EPS database, and the statistical bulletins of cities.

## Results and Discussion

### Analysis of Benchmark Regression Results

Considering that the F statistic of the likelihood ratio test is 21.58 and the Hausman test is 52.06, both of them reject the original hypothesis at the level of 1%. So, this paper chooses the two-way fixed effect model for fitting calculations according to the econometric model set in Equation (8). At the same time, in order to prevent heteroscedasticity, sequence correlation, and cross-section correlation from causing biased and inconsistent estimation results, this paper adopts clustering robust standard errors to deal with them and uses a feasible generalized least squares method (FGLS) for auxiliary verification. The specific estimation results are shown in Table 1.

Considering the robustness of the model, this paper still reports the estimation results of the POLS and RE models. As can be seen from Table 1, the results without adding the lag term show that the average estimation coefficient of intelligent manufacturing is 0.014 and it is significant at the significance level of 1%, which indicates that intelligent manufacturing has a significant promotion effect on urban green total factor productivity. The possible reason behind this is that with the powerful cloud computing capability of artificial intelligence, production links such as material supply, product R&D design, intelligent scheduling, product quality traceability, and management are connected in series, and all production indicators are monitored in real time, thus reducing the incidence of human errors and the waste of resources caused by the inefficient connection of various production links, promoting the improvement of production efficiency and production scale, and

Table 1. Benchmark regression result.

| Variable | POLS | RE | FE | FGLS | FE | FGLS |
|---|---|---|---|---|---|---|
| *IM* | 0.009** | 0.006** | 0.014*** | 0.007* | 0.024** | 0.021** |
| | (2.15) | (1.98) | (2.61) | (1.73) | (2.41) | (2.15) |
| $IM^2$ | | | | | -0.05* | -0.004* |
| | | | | | (-1.72) | (-1.82) |
| *Urban* | 0.119*** | 0.175 | 0.147*** | 0.167* | 0.118*** | 0.118*** |
| | (5.70) | (0.89) | (4.74) | (1.73) | (5.63) | (5.43) |
| *Open* | -0.051 | -0.066 | -0.070* | -0.054* | -0.081 | -0.049 |
| | (-1.56) | ( -1.46) | (-1.69) | (-1.86) | (-1.41) | (-1.54) |
| *Cis* | 0.122** | 0.137 | 0.146* | 0.138* | 0.121 | 0.123** |
| | (2.38) | (1.55) | (1.69) | (1.88) | (0.93) | (2.49) |
| *Fin* | -0.026 | -0.039 | -0.012** | -0.066* | -0.047* | -0.170 |
| | (-0.78) | (-0.34) | (-2.41) | (-1.94) | (-1.71) | (-0.82) |
| *Energy* | -0.018* | -0.063 | -0.028* | -0.037** | -0.065* | -0.087* |
| | (-1.74) | (-0.25) | (-1.79) | (-2.07) | (-1.92) | (-1.94) |
| *Ins* | 0.014*** | 0.010*** | 0.013*** | 0.025*** | 0.024*** | 0.014*** |
| | (6.57) | (5.95) | (3.36) | (5.36) | (5.05) | (6.64) |
| *Constatn* | 0.732*** | 0.697*** | 0.765*** | 0.626*** | 0.773** | 0.743*** |
| | (8.42) | (8.13) | (6.08) | (9.35) | (8.53) | (6.56) |
| $R^2$ | 0.6942 | 0.7594 | 0.7632 | 0.7125 | 0.8703 | 0.7721 |

Note: * * *, * *, and * mean significant at 1%, 5%, and 10% significance levels, respectively. The following table is the same.

ultimately improving the green total factor productivity of the whole industry [70, 71]. At the same time, with the application of intelligent manufacturing in energy operation control and comprehensive energy services for end users, the use of traditional energy sources such as coal and oil by enterprises has been reduced, and the popularization of renewable energy and equipment has been accelerated, thus promoting the transition of energy development modes from consumption to sustainable, renewable, and more environmentally friendly development tracks and realizing the transition from "end pollution control" to "source control". From the square term of intelligent manufacturing, its fitting coefficient is -0.05, and it has passed the significance test of 10%, which shows that the blind promotion of intelligent manufacturing does not promote urban green total factor productivity. At the same time, after considering heteroscedasticity, autocorrelation, and cross-section correlation, FGLS estimation results still support this conclusion. Intelligent manufacturing does not mean the blunt embedding of digital technology, but promotes the multi-directional integration of production business, enterprise organizational structure, and business model in a data-driven way, which is bound to have a threshold requirement for material capital and high-knowledge compound talent endowment, thus affecting the realization of multi-party collaboration in the industrial value chain, leading to a hidden slowdown in the promotion effect of intelligent manufacturing on green total factor productivity.

## Endogenous Treatment

Although more control variables were selected to alleviate the endogenous problems caused by missing important variables and measurement errors when analyzing the relationship between intelligent manufacturing and urban green total factor productivity, the model setting still faces the simultaneous endogenous problems of mutual causality. In view of this, considering the rigor of the conclusion, this paper refers to the ideas of published literature [72]. We selected the product of the average penetration of industrial robots and the first-order difference of the penetration of industrial robots in other cities in the same province except this city to construct the tool variable and adopted the two-stage least square method (2SLS) to deal with it. At the same time, considering the heteroscedasticity and serial autocorrelation of macroeconomic variables, this paper further uses the two-step optimal generalized moment method (GMM) to test it, so as to obtain more accurate parameter estimation results.

Table 2. Endogenous treatment and robustness test results.

| Variable | Endogenous treatment | | Robustness test | | |
|---|---|---|---|---|---|
| | IV2SLS | GMM | Tail shrinking treatment | Change the sample size | Replace explanatory variables |
| *IM* | 0.051*** | 0.121*** | 0.053*** | 0.014** | 0.019** |
| | (3.58) | (2.60) | (3.89) | (2.16) | (2.13) |
| Control variable | Control | Control | Control | Control | Control |
| Weak instrumental variable test | 191.079 | | | | |
| Unidentifiable test | 339.642*** | | | | |
| Over-identification test | 0.386 | 1.12 | 0.887 | | |
| $R^2$ | 0.8158 | 0.7932 | 0.7054 | 0.7187 | 0.7866 |

As can be seen from Table 2, the models have all passed the unidentifiable test, weak instrumental variable test, and over-identification test, and it shows that after eliminating the possible endogenous problems, the influence utility of intelligent manufacturing in promoting urban green total factor productivity still supports the conclusions in the benchmark regression analysis, and even the estimation coefficient has increased slightly.

## Endogenous Treatment

In order to ensure the reliability of the benchmark regression results, this paper uses the following three methods to demonstrate:

1. Tail-shrinking treatment. If industrial development is hindered by force majeure or major natural disasters, all kinds of enterprises will face huge competitive risks, prolonged financing projects, oversaturation of the market, and difficulties in realizing products, which will lead to outliers in the sample data and thus bias the regression results. Therefore, in this paper, all continuous variables are truncated by 1% up and down and then re-estimated by the fixed effect model.

2. Change the sample size. Because Chinese municipalities (Beijing, Tianjin, Shanghai, and Chongqing) have taken the lead in issuing relevant plans, standards, and supporting policies for intelligent manufacturing and there is heterogeneity between them and other cities in terms of digital infrastructure construction, innovation ability, resource endowment, and personnel training, this paper excludes them and re-estimates them by using a fixed effect model.

3. Change the explanatory variables. Referring to the practice of Sheng et al. [73], the penetration of industrial robots at the city level is re-calculated by replacing the installed number of industrial robots with the stock of industrial robots, and the fixed effect model is used for re-estimation.

According to the results of the robustness test (Table 2), intelligent manufacturing has a positive effect on urban green total factor productivity at least at the level of 5% significance, and the only difference is that the estimation coefficient changes slightly, which fully shows that the benchmark regression results are reliable and robust.

## Analysis of Path Mechanisms

### *Heterogeneity Analysis*

1. Resource endowment. According to the National Sustainable Development Plan for Resource-Based Cities (2013-2020) issued by the State Council, the sample is divided into resource-based cities and non-resource-based cities for regression estimation. At the same time, according to the differences in resource development degree and sustainable development ability of cities, resource-based cities are further classified into four types: growth type, mature type, recession type, and regeneration type, so as to more clearly define the future development direction and key tasks of various cities. From the regression results, it is not difficult to see that intelligent manufacturing plays a more significant role in promoting the green total factor productivity of non-resource-based cities, while the influence of resource-based cities is not significant. This shows that the unbalanced and uncoordinated contradiction between resource development, economic and social development, and ecological environment protection in resource-based cities is still outstanding at this stage, and the pressure of maintaining stability is great, which makes it difficult for intelligent manufacturing to break the industrial "path dependence" development pattern of resource-based cities relying on traditional mining and smelting resources and cannot effectively drive the improvement of green total factor productivity [74]. For non-resource-based cities, the lack of resource endowment makes them more dependent on technological innovation to improve the efficiency of resource utilization, thus promoting economic development. Intelligent manufacturing adopts advanced technologies such as

big data, cloud computing, and the Internet of Things, which effectively promote the transformation of an enterprise's production organization mode to large-scale personalized customization, so that product designers and producers can accurately distinguish users' explicit needs from real needs, so as to carry out customized R&D and flexible production and improve the green performance of products. At the same time, under the blessing of industrial intelligence, enterprises in non-resource-based cities will design product recycling and reuse processes based on user preferences, effectively reducing resource and energy consumption.

2. Digital economy. The rapid development of the digital economy has created a good development condition and technical environment for the artificial intelligence industry, and intelligent manufacturing to improve the efficiency and accuracy of the manufacturing process by using advanced manufacturing technologies such as artificial intelligence, big data analysis, and industrial robots and make more intelligent decisions for enterprises in product design, production planning, and supply chain management. In view of this, this paper refers to the practice of Zhao et al., which takes the development of the internet as the measurement core, uses the principal component analysis method to measure the development level of the digital economy in each city, and estimates the sample division with the median value [75]. According to the regression results, intelligent manufacturing can significantly promote green total factor productivity only in cities with a high level of digital economy development. This means that the digital economy is profoundly changing the traditional manufacturing industry and reshaping the traditional manufacturing model. By introducing new technologies, new processes, and new equipment that are environmentally friendly, the efficiency of enterprise resource use and total factor productivity are improved, and the coordinated progress of economic, social, and ecological benefits is realized.

3. Urban location. As the sample involves 262 cities at or above the prefecture level in China, the regional span is large, and there are differences in policy planning, location advantages, industrial bases, and resource endowments among cities, resulting in certain heterogeneity in their respective levels of intelligent manufacturing development and industrial ecological environment. At the same time, with the continuous acceleration of urbanization, there is a spatial dependence on carbon emissions and energy consumption between neighboring cities [76]. In view of this, referring to China's Physical Geography, this paper divides the urban geographical area of China into the east, the middle, and the west and further investigates the difference in the influence of intelligent manufacturing on the urban green total factor productivity. From Table 3, it is known that intelligent manufacturing has a significant role in promoting the green total factor productivity of cities in eastern China, but the central and western regions have not passed the significance test. This is closely related to the development trend that the regional distribution of intelligent manufacturing in China is "strong in the east and weak in the west". The eastern coastal cities represented by Jiangsu, Zhejiang, and Guangdong have strong economic strength, abundant scientific and technological resources, and the development speed of intelligent manufacturing is relatively fast. Many large manufacturing enterprises have basically realized the transformation from mechanization to automation, creating sufficient space for improving green total factor productivity.

### *Channel Analysis*

In order to further investigate the realization conditions of intelligent manufacturing promoting urban green total factor productivity, this paper constructs a panel smooth conversion model with man-machine matching degree as the threshold variable for estimation. Before model parameter estimation, it is necessary to calculate the cross-section heterogeneity test and non-reserved heterogeneity test of the PSTR model by LM, LMF, and LRT estimators in different position parameter dimensions. The specific results are shown in Table 4.

Table 3. Heterogeneity analysis results.

| Variable | Resource endowment | | Digital economy | | Urban location | | |
|---|---|---|---|---|---|---|---|
| | Resource-based cities | Non-resource cities | High digital economy | Low digital economy | Eastern region | Middle region | Western region |
| *IM* | 0.018 | $0.015^{**}$ | $0.039^{**}$ | 0.008 | $0.105^{***}$ | 0.030 | 0.009 |
| | (1.03) | (1.99) | (2.22) | (1.08) | (3.04) | (1.34) | (1.55) |
| Control variable | Control | Control | Control | Control | Control | Control | Control |
| Regional effect | Control | Control | Control | Control | Control | Control | Control |
| Time effect | Control | Control | Control | Control | Control | Control | Control |
| $R^2$ | 0.8792 | 0.7712 | 0.8687 | 0.6808 | 0.6387 | 0.7959 | 0.8681 |

Table 4. Results of the cross-section heterogeneity test and the non-reserved heterogeneity test.

| Statistic | m = 1 | | | m = 2 | | |
|---|---|---|---|---|---|---|
| | LM | LMF | LRT | LM | LMF | LRT |
| Cross-section heterogeneity test ($H_0$:$r$ = 0; $H_1$:$r$ = 1) | 28.262 | 1.625 | 28.389 | 33.436 | 3.840 | 33.611 |
| | (0.029) | (0.055) | (0.028) | (0.000) | (0.000) | (0.000) |
| Non-reserved heterogeneity test ($H_0$:$r$ = 1; $H_1$:$r$ = 2) | 5.725 | 0.871 | 5.730 | 12.112 | 0.689 | 12.135 |
| | (0.455) | (0.515) | (0.454) | 0.736 | (0.808) | (0.735) |
| AIC | -6.425 | | | -6.421 | | |
| BIC | -6.390 | | | -6.385 | | |

Note: The P value is in brackets, and m represents the dimension of the position parameter.

As can be seen from Table 4, when the position parameters take values of $m$ = 1 and $m$ = 2 respectively, the test results all indicate that the original hypothesis is rejected at the level of 1% significance, which means that the influence of intelligent manufacturing on urban green total factor productivity will change with the change of man-machine matching degree, and the model setting is reasonable. Furthermore, when $m$ = 1, the values of AIC and BIC are smaller than those when $m$ = 2, so the number of optimal transfer functions and the number of optimal position parameters of the model are established as 1. Based on the above test results, this paper further estimates the model parameters and obtains the regression coefficients of explanatory variables under different mechanisms. The results are shown in Table 5.

The results show that the estimated value of the position parameter is 0.1079, which means that when the man-machine matching degree is lower than 0.1079, the conversion function $g(Sub_{it}; \gamma_j; c_j)\rightarrow 0$. The estimated coefficient of intelligent manufacturing in the linear part is -0.0511, and it has passed the test at the 1% significance level. When the man-machine matching degree is exactly 0.1079, the conversion function $g(Sub_{it}; \gamma_j; c_j)$ = 0.5, and the influence coefficient of intelligent manufacturing on urban green total factor productivity is -0.012 (-0.0511+0.5 * 0.0782). When the man-machine matching degree is higher than 0.1079, the transfer function $g(Sub_{it}; \gamma_j; c_j)\rightarrow 1$, and the positive promotion effect of intelligent manufacturing on urban green total factor productivity gradually appear, with an influence coefficient of 0.0271 (-0.0511+0.0782). In addition, in order to more clearly depict the nonlinear influence of intelligent manufacturing on urban green total factor productivity, combined with the parameter estimation results in Table 5, this paper draws the transfer function diagram of the two, as shown in Fig. 3. When the transfer function $g(Sub_{it}; \gamma_j; c_j)$ fluctuates in the range of (0,1), the model realizes a smooth transition between different zones; that is, with the man-machine matching degree from weak to strong, the influence of intelligent manufacturing on urban green total factor productivity also changes from a negative inhibition effect to a positive promotion effect.

From this point of view, although intelligent manufacturing empowers the industrial chain with technologies such as cloud computing, blockchain, and automation, it can automatically adapt to and handle a variety of complex production tasks and can integrate, transform, and upgrade traditional production factors. However, intelligence is not a production subject that exists independently of human beings. When workers

Table 5. Parameter estimation results of the PSTR model.

| Variable | Linear part | | Nonlinear part | |
|---|---|---|---|---|
| | Parameter | Estimated value | Parameter | Estimated value |
| *IM* | $\beta_{11}$ | -0.0511*** | $\beta_{21}$ | 0.0782*** |
| *Urban* | $\beta_{12}$ | -0.0141*** | $\beta_{22}$ | 0.0396** |
| *Cis* | $\beta_{13}$ | 0.0069** | $\beta_{23}$ | -0.0079* |
| *Open* | $\beta_{14}$ | -0.0006* | $\beta_{24}$ | 0.0008** |
| *Fin* | $\beta_{15}$ | -0.0007** | $\beta_{25}$ | 0.0064* |
| *Energy* | $\beta_{16}$ | 0.0037* | $\beta_{26}$ | -0.0078* |
| *Ins* | $\beta_{17}$ | 0.0014* | $\beta_{27}$ | 0.0043** |
| | $\gamma$ | 51.0297 | $m$ | 0.1079 |

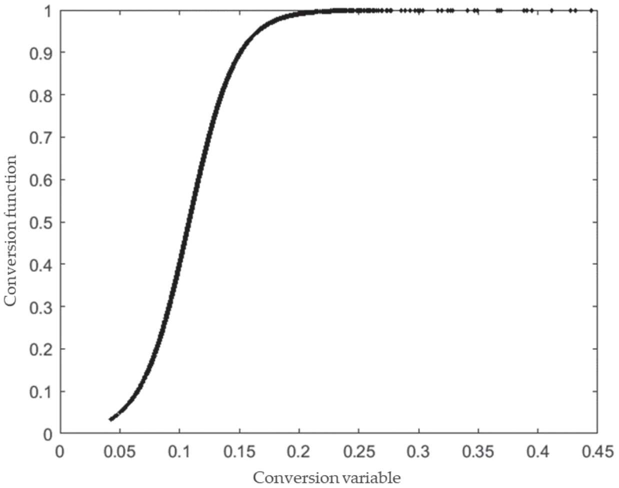


Fig. 3. Transfer function diagram.

and machines cannot fully cooperate, there will be a "Solo Paradox", which will restrict the realization of a benign interaction between intelligent manufacturing and green total factor productivity [77-79].

## Conclusions and Implications

### Conclusions and Discussion

The development of intelligent manufacturing with data elements as the core has gradually become an important driving force to transform the economic development mode and realize sustainable green development. Based on the panel data of 262 cities in China from 2008 to 2019, this paper verifies the direct impact of intelligent manufacturing on green total factor productivity and uses the PSTR model to deeply explore the indirect impact mechanism of man-machine matching. The results show that: firstly, intelligent manufacturing can significantly improve urban green total factor productivity, and this conclusion still holds after a series of robustness tests and endogenous treatment. Secondly, from the results of heterogeneity analysis, intelligent manufacturing has significantly promoted the green total factor productivity of non-resource cities, cities with high levels of digital economy development, and cities in the eastern region of China. Thirdly, from the results of channel analysis, it is found that with the continuous improvement of man-machine matching, the promotion of intelligent manufacturing to urban green total factor productivity has been further strengthened.

Different from previous studies, this paper not only innovatively constructs a unified logical framework of "IM – Match – CGTFP", but also investigates the mechanism of IM on CGTFP by using city-level panel data. The conclusion of this paper is similar to that of published literature [80, 81], that is, the development of intelligent technologies such as the Internet, the digital economy, and robots can provide lasting kinetic energy for the improvement of CGTFP. However, different from the existing research, this paper considers that the complexity of economic phenomena often leads to a large number of nonlinear relationships among economic variables, and it will be difficult to effectively explain economic reality by ignoring this nonlinear relationship. Therefore, on the basis of analyzing the nonlinear characteristics of IM affecting CGTFP, this paper uses the PSTR model to test the role of man-machine matching and provides a basis for better grasping the development law of intelligent technology.

### Implications

The above conclusions provide important policy implications for China to deepen the application of intelligent manufacturing, promote the transformation and upgrading of traditional industries, and further improve the utilization rate of resources, energy, and environmental benefits. In view of this, this paper puts forward the following policy suggestions: First, improve the construction of digital facilities and extend the coverage, enrich the application scenarios of intelligent manufacturing in industrial production, energy saving, and consumption reduction, such as industrial quality inspection, intelligent warehousing, operation optimization, flexible production, etc., actively cultivate emerging business models and lead the green transformation of production methods. Second, fully consider the heterogeneity of urban location, resource endowment, industrial structure, and talent reserve, implement an intelligent manufacturing development strategy according to local conditions, and strive to make up for shortcomings, and forge long boards, thus effectively promoting the growth of green total factor productivity. For example, digital technology has the characteristics of high creativity, strong permeability, and wide coverage, so as to reduce the dependence of resource-based cities on traditional resources and strengthen the circular economy and green development. For cities in the central and western regions, we should strengthen the implementation of energy-saving and environmental protection measures, further eliminate backward industries with high energy consumption, encourage enterprises to strengthen the research and development and application of green intelligent technologies, and give some support in terms of funds, talents, and technology, so as to fully release environmental dividends. Third, enterprises should strengthen the introduction and training of talents with mathematical intelligence to improve the ability of man-machine matching. Through the integration of science and education, production and education, we will cultivate all kinds of talents with environmental awareness, engineering ability, and intelligent technical literacy, provide intellectual support for enterprises to realize intelligent and green transformation, give full play to the advantages of man-machine cooperation, and release the driving advantage of intelligent manufacturing on green total factor productivity.

## Research Limitations and Prospects

Although this paper provides some enlightenment for the government's decision-making and research in the field of intelligent manufacturing and promoting green economic development, there are still some limitations. First, based on the availability of data, this paper uses city-level data to discuss the impact of China's intelligent manufacturing development level on green total factor productivity from 2008 to 2019. Future studies can explore how intelligent manufacturing restructures enterprise production processes by adjusting research methods and perspectives, thus affecting green total factor productivity. Secondly, from the perspective of the research area, as the vanguard of actively promoting the integration of intelligent manufacturing and the real economy, the artificial intelligence innovation and development pilot zone has played an important role in promoting new breakthroughs in a new generation of intelligent core technologies and promoting the effective transformation of ecological resources. Therefore, in the future, the artificial intelligence innovation development pilot area can be incorporated into the research framework, so as to draw more profound conclusions. Finally, this study is an empirical study at the level of statistics and econometrics, and the conclusion of the study does not provide a detailed operation plan. In future research, it will be beneficial to analyze the specific measures and experiences of intelligent manufacturing to improve the green total factor productivity in specific cases by using the method of case analysis.

## Conflict of Interest

The authors declare no conflict of interest.

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## Data Availability Statement

The datasets used during the current study are available from the corresponding author on reasonable request.

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