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# Impact of Intelligent Manufacturing on Total-Factor Energy Efficiency: Mechanism and Improvement Path

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**Abstract:** Intelligent technology is the core driving force of the fourth industrial revolution, which has an important impact on high-quality economic development. In this paper, the panel data of 30 provinces from 2006 to 2019 were selected to construct a regression model to conduct an empirical analysis on the role and mechanism of intelligent manufacturing in improving total factor energy efficiency. The research results show that first, the productivity effect, scale effect and resource allocation effect of intelligent manufacturing can significantly improve the energy efficiency of the total factor, and the conclusion is still established after endogenous treatment and robustness testing. Second, the results of the action mechanism show that labor price distortion and carbon emission trading policy are important mechanisms for intelligent manufacturing to improve total-factor energy efficiency. Specifically, the corrected labor price can enhance the motivation of enterprise research and development and innovation and solve the dilemma of the low-end industrial structure, thus improving the efficiency of total-factor energy efficiency. The carbon emission trading policy strengthens the willingness of enterprises to improve the process, eliminate backward equipment and increase the research and development of green technology, and it has a positive regulatory role in the process of improving total-factor energy efficiency in intelligent manufacturing.

**Keywords:** intelligent manufacturing; total-factor energy efficiency; labor price distortion; energy carbon footprint; carbon emissions trading system; industrial robot



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## 1. Introduction

Energy is an important cornerstone of economic and social development. Since the reform and opening-up, the China government has unswervingly pushed forward the energy revolution, and the method of energy production and utilization has undergone significant changes, basically forming an energy supply system driven by coal, oil, gas, electricity, nuclear energy, new energy and renewable energy and making historic achievements in the energy industry. Since the 19th National Congress of the Communist Party of China, the CPC Central Committee has paid more attention to the energy revolution and proposed adhering to the new development concept, building a clean, low-carbon, safe and efficient energy system, and taking firm steps in building a beautiful China. High-quality development is leading China's economic development. When entering a new era, China's economy faces the problem of achieving better development. After years of rapid development, the constraints of resources, environment and population on economic development are becoming increasingly obvious. The extensive development model of "three highs and one low" in the past has been exhausted, which is not conducive to sustained and healthy economic development. At the same time, the energy structure of "rich in coal, poor in oil and less in gas" makes China fall into the dilemma of passively adapting to international energy trade and environmental governance rules [1]. Economic development faces the dual constraints of environmental pollution and energy shortage, and energy security is vulnerable to threats [2,3]. As the primary input factor of economic development, energy plays a vital role and has been regarded as an essential economic growth booster [4,5]. China is the world's largest energy consumer [6], and especially under the premise of the significant price advantage of coal, it will be difficult to reverse the consumption structure of coal for a long time in the future. In 2020, China imported 303.99 million tons, up 1.5% yearly; crude oil imports were 542.39 million tons (including 28.35 million tons of refined oil products), up 7.3% year on year, and overall energy imports have shown an upward trend in recent years. This means that it is still difficult to address the short- and medium-term energy constraints by increasing the proportion of renewable and clean energy consumption. In this regard, the report of the 19th CPC National Congress pointed out that "improving total factor productivity is an important and reliable path to achieve high-quality economic development." How to improve total-factor energy efficiency (TFEE), effectively control the total energy consumption and complete the "14th Five-year Plan" unit GDP energy consumption reduction target of 13.5% has become the urgent proposition of the present time.

Wright first put forward the concept of "intelligent manufacturing," pointing out that intelligent manufacturing is a process in which intelligent robots complete small batch production by themselves without human intervention by integrating knowledge engineering, manufacturing software systems, and robot vision [7]. With the acceleration of the new wave of the digital and intelligent technological revolution, IM has been endowed with new connotations in its development. With the joint development of its related advanced manufacturing concepts such as computer-integrated manufacturing, flexible manufacturing, and agile manufacturing in recent decades, the concept of "intelligent" in IM has been upgraded and broadened from the original narrow sense of "digital" to the current "digital, networked and intelligent" [8,9]. In addition to automatic and unmanned production, the more profound role of IM lies in helping enterprises to realize mass production to customized production through its "Prosumption" mechanism, which not only improves production efficiency but also optimizes resource allocation. IM can be understood as combining the new generation of information technology with advanced automation, sensing, control, digital, and management technology in a highly flexible and highly integrated way at all stages of the manufacturing industry. It also supports the real-time management and optimization within and between factories and enterprises, as well as the whole life cycle of products (product development and design, production and processing, operation management, maintenance service, and scrap disposal) [10,11]. As there is no unified definition of IM, this paper draws lessons from the Development Plan of Intelligent Manufacturing (2016–2020). It holds that IM is a new mode of production with the functions of self-perception, self-learning, self-decision-making, self-execution, and self-adaptation based on the deep integration of the new generation of information and communication technology and advanced manufacturing technology, which runs through all aspects of manufacturing activities such as design, production, management, and service.

In green and low-carbon development, the energy industry is the main battlefield [12,13]. Improving TFEE becomes the most feasible and realistic means of achieving green economy goals in the short term [14,15]. However, the current single-terminal governance model has struggled to meet the demand for improving TFEE. The integration of digital technology and natural economy development is becoming a realistic choice to reshape the competitiveness of high-quality development. The intelligent system relies on deep learning, independent decision-making, and dynamic monitoring, which can effectively and quickly provide countermeasures and help the upstream links such as raw material supply, intermediate goods transportation, and energy production to connect efficiently, which not only saves the time cost, transaction cost and transportation cost of enterprises, but also draws a more reasonable blueprint for energy supply on this basis, and improves the comprehensive utilization efficiency of energy in the whole city [16]. According to the data of "World Robots 2021 Industrial Robots" released by the International Federation of Robotics (IFR), in 2020, nearly 168,000 industrial robots will have been newly installed in

China, accounting for 43.8% of the world, and the level of automation and intelligence in the manufacturing industry is increasing day by day. The research report "Accelerating Energy Transformation by Using Artificial Intelligence," released by the World Economic Forum in 2021, pointed out that artificial intelligence technology has great productivity in the process of energy decentralization, digitization, and decarbonization, and it has strong application in renewable energy generation capacity and demand forecasting, power grid operation and optimization, energy demand, and distributed resource management. The report "Digital Energy 2030" released by Huawei also pointed out that digital technology can make the intelligent evolution of energy systems and promote the maximization of energy value, which is the core "pry point" to drive the transformation of the energy industry. From the perspective of intelligent manufacturing, exploring its impact on TFEE is of great reference value for ensuring national energy security, achieving the goal of "double carbon," and accelerating the construction of energy power.

## 2. Literature Review

To better promote the ecological environment's quality improvement, reduce greenhouse gas emissions and ensure national energy security, many scholars around the TFEE problem launched a lot of beneficial discussion and found fruitful results [17]. The existing literature on TFEE and IM can be divided into the following two categories.

### *2.1. Research on Measuring and Evaluating TFEE*

The evaluation index system constructed by the existing literature in the evaluation of TFEE is divided into single-factor energy efficiency (SFEE) and TFEE. However, with the deepening of research, there are some defects in the SFEE index; that is, only the energy input factor, capital, labor and other factors have not been included, while the TFEE index can greatly compensate for the impact of energy consumption, labor, capital and other factors on output. Li et al. [18] calculated the TFEE of each region in China by comparing the single-factor and the total-factor method, pointing out that the total-factor method has the advantage that the single-factor method cannot replace in evaluating the impact of the regional factor endowment structure on its TFEE. The measurement of TFEE is mainly based on the DEA method in the non-parametric estimation method. For example, Hu and Wang [19] measured the TFEE in various provinces in China based on the input DEA method. Such studies usually decompose the total factor measurement efficiency into pure technical efficiency and scale efficiency [20]. At the same time, there is a small part of the literature dedicated to establishing a single-sector production model containing energy elements according to the production function, which belongs to parameter estimation [21]. In the TFEE measurement method, the environmental pollution problem caused by the process of energy use is not included in the measurement scope, so it is possible to overestimate the TFEE. Therefore, to fill this gap, some research will have $SO_2$, wastewater, solid waste, or carbon emissions included in the DEA model to measure the TFEE that includes the undesired output [22,23]. In addition, some studies include unexpected output, such as energy exhaustion and ecological environment deterioration, into the efficiency measurement model, measure the TFEE at the provincial level, and find that there is a spatial difference of "high in the east and low in the west" [24]. In order to obtain more accurate data information of TFEE, relevant statistical models and evaluation systems are constantly updated and expanded [25].

### *2.2. Research on the Influence of Technological Innovation on TFEE*

Technological progress is the main source of economic development, which often leads to the improvement of resource allocation efficiency and production efficiency. Technological innovation can improve the TFEE is certain controversy: some scholars believe that technological progress is conducive to the improvement of TFEE [26–29]. In particular, Li and Du [30] believed that the role of the Internet in promoting the total factor productivity of energy in the digital economy era cannot be ignored. However, some scholars believe that there is a "rebound effect" between technological progress and TFEE; that is, the decrease in energy consumption caused by technological progress will be offset by the increase in energy consumption caused by the rebound effect, and there may also be a "threshold effect" [31–33]. As the main force of carbon emission reduction, the energy industry, actively carrying out digital transformation, is the key to developing green economy [34]. With the rapid popularization of modern information technologies such as blockchain and artificial intelligence, the impact of digital technology on TFEE has become the focus. The literature on how digital technology affects TFEE comes from the digital economy [35,36], digital electric power technology [37,38], energy Internet [39], digital finance [40], and digital encryption technology [41], and the economic effect of artificial intelligence technology on energy consumption mode, clean energy production behavior, and logistics chain transportation is explored, but digital technology will improve the TFEE and also lead to more energy consumption, especially the sharp increase in power demand. As a general technological progression, intelligent manufacturing can make decisions faster and more accurately through artificial intelligence, reduce transportation costs and transaction costs, formulate and design more reasonable energy utilization strategies and supervision systems, and thus improve TFEE [42]. Compared with the previous technological revolution, intelligent manufacturing technology can improve labor productivity and realize the "integration of production and consumption" in matching supply and demand to alleviate the contradiction between supply and demand and an overproduction to a certain extent [12]. Intelligentization is realizing the modernization of energy efficiency, benefiting all departments and end uses, and the scale of benefits is quite optimistic [43].

The social effect of technological innovation has a unique brand of timeliness and staged connotations. People's understanding of its potential social understanding and transmission mechanism is gradually deepening, and how digital technology affects the TFEE and its transmission mechanism is still unclear. Limited by the fact that the new generation of information technology is still in its infancy, the width and depth of digital technology in application scenarios need to be improved, and information technology has slowly evolved from automation to intelligence. There are still only few studies on how intelligent manufacturing affects TFEE, and even fewer articles explain its deep-seated mechanism from the perspective of the labor price mechanism and environmental regulation policy. Therefore, the potential marginal contribution of this paper is as follows: first, it analyzes its influence on TFEE from the perspective of intelligent manufacturing, deeply analyzes the internal mechanism of intelligent manufacturing to improve total TFEE, and deepens the research on the social effect of technological innovation. Secondly, this study combines intelligent technology with labor factors and constructs a theoretical framework for intelligent manufacturing to improve TFEE by alleviating the channel path of labor price distortion. Finally, the paper discusses how intelligent manufacturing affects TFEE under the regulatory role of market-based environmental regulations represented by carbon emission trading policies and verifies the mechanism and experience of synergistic promotion of green development policies and advanced digital technologies to improve the quality and efficiency of the energy industry.

## 3. Theoretical Framework and Research Hypothesis

### *3.1. The Mechanism Analysis of IM Affecting TFEE*

Productivity effect: TFEE reflects the input–output efficiency of electric energy, coal, oil and natural gas in production and life. Technological progress means expanding the forefront of production through technological improvement, human capital accumulation and organizational management efficiency improvement, so as to improve the maximum output capacity under the established factor combination input. A typical example of the "digital intelligence" of the real economy is the rapid popularization and large-scale application of intelligent robots in the industrial sector. By introducing big data in the process of traditional production and modern digital technology such as artificial intelligence, "intellectualization" can effectively improve the operation efficiency of different factors of production configuration combination to realize the traditional factors of production of marginal output, help traditional enterprises "old tree sprout", and fully promote the real economy sector to adapt to the new requirements of digital economy development [44]. As the IM of neutral technology progress, it naturally carries the penetration, synergy, and substitution characteristics of digital technology, which can penetrate all fields of social life [45]. On the one hand, the existence of Moore's Law makes the chip-based, digital and information-based products constantly updated, and the prices of related products will also drop rapidly with the change and popularization of technology, which will help related manufacturers to gradually phase out production equipment with high energy consumption and low efficiency, thus reducing energy consumption and improving marginal energy productivity. On the other hand, related industry standards and customer demand will be improved with the improvement of labor productivity, process technology, and production process. More stringent factory standards and high-level market demand will lead to the derivative demand of enterprises for high efficiency, cleanliness, and high quality. Therefore, enterprises can hedge the negative effects of increasing production costs and intensifying market competition by reducing total energy consumption, using intensity, and improving energy utilization efficiency.

Scale effect: The most striking feature of emerging technologies is to replace low-skilled labor and supplement high-skilled labor. This will relieve the dependence of enterprises on labor factors through digitalization, informatization, and intelligence, quickly complete the repetitive tasks of packaging, sorting, and transit that human labor cannot complete in a short time, and use the same energy consumption and labor to obtain greater economic output, to improve the total factor productivity of enterprises [46]. IM, in the process of intelligent activities, involves the collaborative interaction and cooperation of people and intelligent machines and uses the concept of automation for flexible, intelligent and highly integrated working, so as to realize traditional factory to digital factory transformation, which makes manufacturing enterprises, through digital development, improve product quality and management efficiency. A mature, intelligent manufacturing factory or enterprise often does not simply transform its production equipment intelligently but integrates market demands and consumer demands into production processes and product design. All aspects of product production are connected in series with the help of intelligent products, intelligent design, intelligent production, and intelligent management. Enterprise managers use technologies such as the Internet and the Internet of Things to realize horizontal integration and vertical expansion of intelligent production, and then use mobile communication technology and intelligent equipment to realize digital transformation of the whole intelligent production value chain, thus forming and smoothing the whole intelligent management system [47]. Enterprises also introduce industrial robots and high-tech talents, expand production scale, promote the continuous improvement and extension of related industrial chains and supply chains through economies of scale, and improve resource utilization efficiency.

Resource allocation effect: IIM can reduce energy consumption per unit output and improve comprehensive TFEE. A typical example is that the traditional energy industry only pays attention to watt flow, and the nodes of power generation, transmission, distribution, storage, and use are isolated, making it cooperate, resulting in low operating efficiency of the energy system. Moreover, there are many "dumb devices" in the full link, and the operation and maintenance efficiency are low with manual maintenance. IM digitally processes energy by introducing digital technologies such as 5G, AI, and big data, innovatively integrates power electronics technology with digital technology, adds bit streams based on watt flow, and manages watts with bits to realize complete link interconnection, digitization, and intelligent collaboration and to maximize power production efficiency, equipment operation and maintenance efficiency and TFEE. In addition, at the present stage, the world's energy system is undergoing structural restructuring and map reconstruction: centralized and decentralized variable renewable energy is incorporated into the power grid, the electrification trend of energy consumption is becoming increasingly prominent, and consumers involved in production activities are emerging. Energy demand flexibility features increasingly emphasize the timeliness and efficiency of the energy supply. Energy digitization enables intelligent buildings, transport, vehicles, and industrial facilities to provide new flexible load sources for energy systems, helping suppliers cut energy supplies and supporting communities to better consume the energy they produce. By improving the use efficiency of end users and system efficiency, the entire energy system will benefit from avoiding repeated investments in energy facilities, reducing ineffective losses in production and distribution, optimizing the combination of renewable resources, and enhancing energy security. As a general progression in technology, IM itself represents typical non-competitive public goods. When it performs innovation activities in a certain area, it will often produce "energy technology diffusion" and "energy technology spillover", that is, the unconscious outflow of technological innovation and the unconscious acceptance of relevant subjects [48]. The spillover effect of IM is specifically manifested in the embedding of the automation technology of machinery and equipment into the application department, realizing the interaction between factor input and science and technology in the production link, and then promoting the production, transportation, storage and consumption to form a new enterprise production mode and the new energy technology and equipment, energy conservation and environmental protection awareness. At the same time, the artificial intelligence platform contributes to the sharing of data elements. With the help of factor circulation and knowledge technology spillover, it builds an intelligent management system of energy interconnection and global energy allocation network and integrates traditional chimney independent system architecture and remote island management into a unified architecture, unified management, and comprehensive application to realize overall planning, coordination, and optimization of the whole link, thereby promoting low-carbon development of the whole society and improving energy utilization efficiency. The combination of artificial intelligence technology and traditional factors of production can effectively improve the allocation quality and combination efficiency of the original factors of production by expanding the application scenarios of digital energy and upgrading digital management, thus enhancing the coordination of organization and management of production enterprises and the overall efficiency of factors. For example, Datang Group Co., Ltd. (Beijing, China), China realizes a 3D virtual power plant through advanced communication technology and software architecture and realizes the aggregation, coordination, and optimization of spatial and geographical dispersion. Its intelligent control system controls the power production process in real-time and completes energy storage and rational allocation.

Accordingly, for theis study, Hypothesis 1 is proposed:

**Hypothesis 1 (H1)**. *The productivity effect, scale effect and resource allocation effect of IM carrying can improve the TFEE.*

### *3.2. The Intermediary Path of Labor Price Distortion*

In the neoclassical economic growth theory, the primary source of total factor productivity improvement lies in technological progress and resource allocation efficiency [49]. The price mechanism is the essential reflection of the allocation of resources in the market economy. However, the distorted factor price cannot truly reflect the scarcity degree and the relationship between the supply and demand of resources in the factor market. Factors of production are the starting point of the economic cycle, and the distortion of factor price will affect the macroeconomic variables such as consumption, investment, total output and total factor productivity by affecting the efficiency of resource allocation [50]. The loss of production efficiency caused by ineffective factor allocation or overcrowding is considered an essential factor in reducing the efficiency of resource allocation and even the welfare of residents in a country. Moreover, existing studies find that the contribution of the improvement of factor allocation efficiency to the improvement of total factor productivity is improved [51,52]. The labor factor has strong initiative and adsorption and is an important link to other factors of production, knowledge, technology, management, and data elements attached to the labor itself and through the labor bridge to achieve activation and operation. However, the distorted labor market not only may make the resource allocation imbalanced between enterprises but will also stop the efficient enterprises entering the market, therefore producing greater efficiency loss [53–55].

Currently, China's labor price is mainly manifested as low price distortion, the remuneration of labor suppliers is lower than the marginal contribution, and the price distortion in less developed areas is severe [56,57]. Underestimated labor remuneration will enable enterprises with low production efficiency to use many tangible low-cost factors to obtain more profits. The arbitrage space formed by it will lead to a large number of laborers flowing to extensive production projects with quick results and low uncertainty, which will make economic growth stand out as factor-driven epitaxial growth, aggravate the low-end lock-in of industrial structure, and is not conducive to the improvement of TFEE in the production process [58]. As far as labor price distortion is concerned, negative price distortion causes enterprises to have the illusion that labor elements are vibrant, and then they will hire cheaper labor. This price advantage of low-cost labor reduces the demand of enterprises for capital factors and technological innovation attached to capital goods, which makes managers stay in low-end production links for a long time, resulting in a low contribution of technological progress to TFEE. In addition, the distortion degree of labor factors is different in different regions, and there is regional heterogeneity in the distortion degree of factor prices. This difference will cause the price of labor factors in some areas to be seriously underestimated, which will enable those enterprises that should have been eliminated by the market to continue their production and business by moving and transferring to lower-cost areas. This aggravates the dilemma of low-end locking of industrial structure in those areas where labor-intensive industries are the leading industries, and it is difficult to develop the rationalization and upgrading of industrial structure, which is not conducive to technological progress and the improvement of TFEE.

Guiding the labor force with higher human capital to flow to the regions, departments, and industries with advanced productive forces will help to improve the total factor productivity. IM has substantial advantages in correcting the distortion of the labor factor market, unimpeded factor channel, and strengthening the efficiency of resource allocation. First, the rapid development of intelligent technology with the underlying logic of IM helps to reduce the cost of information search and simplify the collection path. With the help of Internet technology, workers can collect, sort out, compare and analyze information such as job salary, skill demand, and labor demand to form accurate information about the rationality of labor remuneration and help reduce market information asymmetry. At the same time, they can simplify the market transaction business process and improve the information transparency of the transaction process to form a nationwide network transaction system, to a certain extent, to reduce the market segmentation formed by local protectionism and administrative barriers and to reduce price distortion [51,59]. Second, the Internet technology-derived network platform has weakened the physical barriers of distance and time, information can be spread more quickly across regions and across time, cross-sectoral transmission and sharing can occur, element demanders and labor suppliers can combine their expectations in broader market-accurate matching, saving transaction cost time, thus opening free flow channels for labor elements, and the level of factor–market integration can be improved. New online working methods, such as telecommuting, online meetings, and remote services, enable workers to participate in the division of labor in the whole of society without changing their residence and workspace, forming invisible mobile labor, and following the trajectory of a low rate of return to a high rate of return, therefore reducing price distortion. Third, the market impact of IM on employment is mainly produced through productivity efficiency, compensation effects, and destructive effects. IM technology uses technological advantages and capital advantages to replace conventional, programmable rules of labor, and human labor has the comparative advantage of new tasks, economic activities, and work forms being constantly created;

different skills of workers in the digital technology leads to the higher efficiency of the digital industry and needs to be implemented in emerging jobs to achieve efficient matching and obtain more reasonable labor remuneration. Accordingly, Hypothesis 2 is proposed for this research:

**Hypothesis 2 (H2)**. *IM can improve TFEE by mitigating labor price distortions.*

*3.3. The Moderating Effect of the Carbon Emission Trading Policy*

Coase Property Rights Theory shows that under the premise that property rights can be clearly defined, spontaneous market transactions can realize the Pareto optimal resource allocation. The profound logic of carbon emission trading policy is the commercialization, asset, and data of carbon emission rights. By limiting control of enterprise greenhouse gas emissions and emission quotas, with the help of market mechanisms to transform environment negative external cost into enterprise internal production costs, this reverses transmission control to complete the performance conditions, promotes the carbon market to reach the Pareto optimal situation, and finally realizes the quality and efficiency of energy utilization, energy conservation and emission reduction of the whole economy and society [60,61]. An appropriate and reasonably designed environmental regulation policy will promote the constrained individuals to stimulate the consciousness of technological innovation under limited conditions, dynamically integrate the factor input combination, and improve the green total factor productivity [62]. The carbon emission trading policy releases the guiding signal of environmental regulation, and the diffusion of its policy influence can not only promote energy reform, consumption revolution, and the green industrial system through the "pilot diffusion" under superior administrative instruction and promote the improvement of the green low-carbon cycle development economic system, but it can also guide and encourage scientific research and development and technological innovation, expand the application scenarios of advanced green technology, and promote the "active diffusion" self-organization after learning and imitation in non-pilot areas [63]. As a means of market-oriented environmental regulation, carbon emission trading policy impacts TFEE in three ways: cost pressure, policy guidance, and interest incentive. Specifically, according to the requirements of carbon emission intensity regulation, the government issues a certain free emission quota to each market participant with the carrier of the "carbon emission permit" system. Regulators who exceed the quota need to buy carbon emission quotas in the trading market, and enterprises with carbon reduction advantages can sell carbon emission rights or transfer green technologies as profits. Based on the consideration of controlling emission costs and removing fossil energy consumption dependence, the original energy-intensive enterprises will independently carry out energy conservation and emission reduction, increase green technology research and development, continuously optimize the production process, improve production technology, and replace and eliminate backward equipment, thus bringing higher TFEE [64,65]. At the same time, policy instructions' long-term, mandatory, and supportive characteristics will optimize the distribution mode and correlation of production factors among industries. Carbon trading policy released green market signals to guide capital, technology, talent, energy, and other elements to the low-carbon industry. The original energy-intensive, high-carbon-emission old industry, due to pressure from environmental constraint pressure, has been forced to change into a green, high-efficiency, low-carbon new industry. The direct impact is that a region will eventually undergo advanced industrial structure change, while reducing carbon emissions and improving TFEE. As an essential booster of low-carbon transformation, with deep integration among the digital network, "Metcalfe Law", advanced intellectualization technology and traditional power, energy, and transportation industries, can effectively assign enterprises green IM and energy management, lead the green industry and process reengineering, promote the critical carbon industry's whole lifecycle of energy consumption, and realize TFEE and the production efficiency of double promotion. Moreover, digital technology helps administrative departments to find out the "carbon background", carry out "carbon investigation" and "carbon planning" under the background of carbon emission regulation, and significantly enhance the government departments to monitor urban carbon emissions and low-carbon governance capacity [66]. Therefore, in improving TFEE by IM, carbon emission trading policy mainly forces industrial upgrading and low-carbon transformation by imposing environmental pressure on "three high" enterprises to further weaken enterprises' dependence on energy consumption and ultimately improve TFEE. Based on this, research Hypothesis 3 is proposed:

**Hypothesis 3 (H3)**. *The carbon emission trading policy will strengthen the positive effect of IM on improving TFEE.*

## 4. Study Design and Data Sources

### *4.1. Definitions of Variables*

#### 4.1.1. Explained Variable

Total-factor energy efficiency (TFEE): In order to avoid statistical errors caused by traditional measurement methods as much as possible and to obtain as much expected output as possible with as little resource consumption and environmental pollution under certain factor input combination conditions, this paper uses the SBM direction distance function and GML index method to measure TFEE. The evaluation system of TFEE continues the idea of Cobb–Douglas (C-D) production function, selecting labor, capital, land, and energy consumption (10,000 standard tons of coal) as the input vectors. The expected output selects each province based on the actual GDP in 2000 as the proxy variable. The undesired output uses the energy carbon footprint as the proxy variable. Carbon footprint is a concept based on ecological footprint, which measures the effect of nature's response to carbon emissions from human activities [67]. The calculation method mainly uses the conversion coefficient method. This study is based on carbon emission calculations provided in the IPCC Guidelines for National Greenhouse Gas Inventories [68]. The calculation process is:

$$CO_2 = \sum_{j=1}^{9} C_j \times D_j \times E/F_j = \sum_{j=1}^{9} C_j \times D_j \times 29.27/F_j \quad (1)$$

In Equation (1), $CO_2$ is the total carbon emission of energy consumption, $C_j$ is the amount of energy consumption of category $j$, $D_j$ is the standard coal conversion coefficient, $E$ is the calorific value conversion coefficient, and $F_j$ is the $j$ footprint conversion coefficient of energy. Energy types and their coal conversion coefficient are shown in Table 1.

**Table 1.** Energy Ecological Footprint Calculation System.

| Energy Type | Energy Projects | Coal Conversion Coefficient | Energy Footprint Conversion Coefficient |
|---|---|---|---|
| Coal | coal | 0.714 | 56 |
| | coke | 0.971 | |
| Petroleum | crude oil | 1.429 | 73 |
| | kerosene | 1.471 | |
| | gasoline | 1.471 | |
| | diesel oil | 1.457 | |
| | fuel oil | 1.429 | |
| Power | power | 0.123 | 1000 |
| Natural gas | natural gas | 0.133 | 96 |

#### 4.1.2. Explained Variable

Intelligent Manufacturing (IM): At the present stage, technological progress is no longer only used to improve the effects of human labor, but more to replace the human labor force. Robots are the apple of the manufacturing industry's eye. Accordingly, this paper adopts the industrial robot installation density to characterize the IM. Since IFR published national industry-level data, it cannot be directly used for the data analysis of this paper. To further mitigate the concerns of confounding factors that may be correlated with both the industry-level spread of robots in China and labor market outcomes, we construct an instrument variable by exploiting the industry-level spread of robots in other economies [69]. In this regard, according to the research ideas of published research [70–72], the mobile share method is used to construct the "Bartik instrumental variable" to calculate the installation density of industrial robots in each province. (Since this method needs to use the proportion of employed people in each province in the total number of employed people as the weight, the two-way causal and endogenous relationship between robots and the number of employed people should be considered.) The specific calculation formula is follows:

$$Rob_{it} = \sum_{j=1}^{14} \frac{L_{jit}}{L_{it}} \times \frac{Rob_{jt}}{L_{jt}} \times \frac{MRob_t}{L_{2005}} \tag{2}$$

In Equation (2), $Rob$ represents the installation density of industrial robots, $L_{jit}$ represents the number of employees in $j$ of $i$ province in t year, $L_{it}$ represents the total number $j$ of employees of i province in t year, $Rob_{jt}$ indicates the number of industrial robots installed in $j$ in $t$, and $L_{jt}$ represents the total number of employees in $j$ in $t$. $MRob_t/L_{2005}$ is the instrumental variable selected in this paper, where $MRob_t$ represents the number of industrial robots installed in the United States year $t$, and $L_{2005}$ represents the number of manufacturing employees in the United States in 2005.

#### 4.1.3. Mediating Variable

Labor price distortion (LPD): Considering that factor price will affect resource allocation [73–76], the idea of factor price distortion continues. Assuming that labor mismatch exists in the form of price tax $\tau_{Li}$, the calculation process of LPD as follows:

$$\tau_{Li} = 1/\gamma_{Li} \tag{3}$$

In Equation (3), $\gamma_{Li}$ represents the absolute labor force distortion factor. Since it cannot be directly observed or measured in the real world, it is generally replaced by the relative distortion coefficient $\hat{\gamma}_{Li}$, whose expression is as follows:

$$\hat{\gamma}_{Li} = \left(\frac{L_{it}}{L_t}\right) / \left(\frac{w_{it}\beta_{Li}}{\beta_L}\right) \tag{4}$$

In Equation (4), $w_{it} = p_{it}y_{it}$ represents the proportion of region $i$ output in year t in the total output of the entire economic system, $L_{it}/L_t$ represents the proportion of labor force and the total number of labor force in the economic system and represents the labor force contribution calculated using output weighting, and $\beta_L = \sum_{i=1}^{N} w_{it}\beta_i$ represents the theoretical proportion of labor input in region $i$ in the year t of effective labor allocation. $\gamma_{Li}$ indicates the degree to which the labor price deviates from the optimal allocation, namely the degree of the relative price distortion of the labor factors. When $\gamma_{Li=1}$, it indicates that there is no distortion, at which point labor allocation is most effective. The specific calculation process of labor output elasticity is as follows: Firstly, the C-D production function with the constant return to scale is established. Then, the two ends of the production function are treated logarithmically, and finally, the fixed effect of individual time is included on the right side of the equation. We can thus obtain

$$\ln(Y_{it}/L_{it}) = \ln A + \beta_{Ki} \ln(K_{it}/L_{it}) + \lambda_i + \nu_t + \varepsilon_{it} \tag{5}$$

In Equation (5), $Y_{it}$ represents the GDP of region $i$ in year $t$, $A$ represents total factor productivity, $K_{it}$ represents capital input, and $L_{it}$ represents labor input. Among them, $Y_{it}$ uses the actual GDP based on the price level in 2000; labor input and capital input are consistent with labor and capital in the TFEE evaluation index system.

#### 4.1.4. Moderating Variable

Carbon emission trading policy (CETP): The National Development and Reform Commission in November 2011 issued a notice on pilot carbon emission trading, established in Beijing, Tianjin, Chongqing, Shenzhen, Shanghai, Hubei, and Guangdong, commissioning the carbon emission trading policy. Subsequently, the pilot carbon emission trading policies of the two provinces and five cities were formally implemented in 2013. Considering rational expectations, the article uses 2011 as the starting year of the emissions trading policy. The years before 2011 were a non-pilot period assigned 0; the years after 2011 (including 2011) were a pilot period assigned 1. The two provinces and five cities are designated as the experimental group with a value of 1; the remaining areas are the control group with a value of 0. The time virtual and regional virtual interaction items finally form the proxy variable of carbon emission trading policy.

#### 4.1.5. Control Variables

Because there are many factors affecting TFEE, to avoid endogenous problems caused by missing important variables, the study was also designed to obtain more accurate estimates, referring to the published literature [77,78]; thus, seven variables were selected as control variables, specifically speaking: foreign direct investment (FDI), choosing the actual use of foreign direct investment in each province as the agent variable; industrialization (IZ), choosing the proportion of the secondary industry in the GDP as the proxy variable; Macro control (MC), selecting the proportion of local financial general budget expenditure in GDP as the proxy variable; green technology innovation (GTI), selecting the number of green patent applications in each province as the agent variable; population density (PD), using the population number per square kilometer of the built-up area as the proxy variable; green credit (GC), using the proportion of interest of six energy-consuming industries in industrial credit interest as the proxy variable; and energy structure (ES), using the proportion of coal consumption in the total energy consumption as the proxy variable.

### *4.2. Econometrics Model*

In order to identify the average effect of IM on TFEE and verify whether IM can improve TFEE based on the perspective of historical data, the following mathematical statistical model is constructed according to the selection and setting of the variables above:

$$TFEE_{it} = a_0 + a_1 IM_{it} + a_2 \sum_{m=1}^{8} Control_{itm} + \lambda_i + \nu_t + \varepsilon_{it} \quad (6)$$

In Equation (6), the subscripts $i$ and $t$ represent the province and year, respectively. a represents the parameters to be estimated, $\alpha_0$ is the constant term, $\nu_t$ is the time-fixed effect, $\lambda_i$ is the individual-fixed effect, $\varepsilon_{it}$ is the random disturbance term, and control means a series of control variables. In order to alleviate the influence of heteroscedasticity, all variables were logarithmized in the actual fitting calculation process.

### *4.3. Data Sources and Description*

Following the principle of data availability, panel data from 30 provinces in China (excluding Tibet, Hong Kong, Macao and Taiwan) from 2006 to 2019 were selected as the investigation samples. The raw data of related variables involved in the measurement model are mainly obtained from the China Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, China Agricultural Statistical Yearbook, State Intellectual Property Office (SIPO), National Bureau of Statistics, and EPS databases. Very few missing values were found by the linear interpolation method. It should be noted that since the TFEE value measured by the SBM-GML index method is 1 in the first year of the investigation period, in order to avoid the problem of finding a value of 1 in all provinces in the first year and the remaining cut-off of sample data in the first year, the sample period of the TFEE measured in this paper is 2005–2019. A descriptive statistical analysis of each variable is shown in Table 2.

**Table 2.** Descriptive Statistics of the Variables.

| Variables | Code | Mean | Standard Error | Min | Max |
|---|---|---|---|---|---|
| Total-factor energy efficiency | TFEE | 0.431 | 0.619 | −2.587 | 3.290 |
| Intelligent manufacturing | IM | 2.986 | 1.918 | −0.976 | 6.809 |
| Foreign direct investment | FDI | 10.877 | 1.432 | 7.601 | 14.485 |
| Industrialize | IZ | 3.795 | 0.224 | 2.785 | 4.119 |
| Population density | PD | 3.980 | 0.244 | 3.313 | 4.495 |
| Green credit policy | GC | −0.651 | 0.284 | −1.652 | −0.099 |
| Macro control | MC | 3.044 | 0.397 | 2.125 | 4.141 |
| Green technology innovation | GTI | 3.391 | 0.792 | −1.403 | 6.226 |
| Level of economic development | LED | 10.527 | 0.611 | 8.663 | 12.009 |
| Energy structure | ES | −0.156 | 0.507 | −3.695 | 0.901 |
| Labor price distortion | LPD | −1.275 | 0.993 | −6.632 | 1.085 |
| Carbon emissions trading policy | CETP | 0.133 | 0.340 | 0 | 1 |

## 5. Empirical Results

### *5.1. Baseline Regression*

According to the results of the Houseman test and F test, the fixed effect (FE) model is most suitable for the sample data in this paper, so the two-way fixed effect (TWFE) model is used as the benchmark regression. For model robustness, this paper still reports the estimation results of Pooled OLS (POLS). The fitting results of Equation (6) are shown in Table 3.

As seen from Table 3, in the POLS model with an uncontrolled time effect and individual effect, the estimated coefficient of IM on TFEE is 0.209, passing the 1% significance test, indicating that IM can improve TFEE. From the results of the TWFE, the estimated coefficient without any control variables is 0.560, the estimated coefficient with the addition of three control variables is 0.651, and the estimated coefficient with the addition of all control variables is 0.658, all of which pass the 1% significance test. In other words, based on more rigorous statistical extrapolation results, intelligent manufacturing can improve TFEE, and the H1 is verified. The results of this study are consistent with the conclusions of existing studies [79]. By comparing the fitting coefficients of the three models in column (2), column (4), and column (5), it can be found that the TWFE model with all the control variables has the maximum estimated coefficient, the TWFE model with the control of the three variables has a smaller estimated coefficient, and the fitting coefficient of the POLS is at the minimum level. This result indicates that the transmission process of IM to improve TFEE is also affected by other macro variables, which indirectly proves the necessity of adding control variables.

**Table 3.** Descriptive Statistics of the Variables.

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| IM | 0.090 *** (6.12) | 0.209 *** (9.50) | 0.560 *** (3.03) | 0.651 *** (6.22) | 0.658 *** (6.02) |
| LED | | −0.317 *** (−4.42) | | 1.557 *** (9.32) | 1.145 *** (4.83) |
| ES | | −0.703 *** (−6.56) | | −0.461 *** (−4.65) | −0.479 *** (−4.89) |
| GC | | 0.597 *** (3.81) | | 0.538 *** (3.63) | 0.481 *** (3.31) |
| GTI | | 0.077 *** (3.05) | | 0.101 * (1.89) | 0.110 ** (2.02) |
| IZ | | 1.472 *** (10.69) | | | 0.774 *** (2.31) |
| PD | | −0.225 *** (−3.67) | | | −0.375 *** (−3.61) |
| FDI | | 0.024 (1.04) | | | −0.191*** (−2.60) |
| MC | | −0.127 (−1.21) | | | −0.294 (−1.10) |
| Constant term | 0.161 *** (5.30) | 0.242 (0.30) | 0.338 *** (2.80) | −14.798 *** (−9.24) | −8.175 *** (−3.28) |
| Observed value | 420 | 420 | 420 | 420 | 420 |
| Individual effect | No | No | Yes | Yes | Yes |
| Time effect | No | No | Yes | Yes | Yes |
| Hausman test | | | | 57.62 *** | 30.77 *** |
| F test | | | | 18.78 *** | 13.77 *** |

Note: *, **, *** are significant at 10%, 5% and 1% significance levels, respectively, in the following tables. The t-statistics are reported in parentheses.

### 5.2. Endogeneity

Although more control variables are added to the model to alleviate the endogenous problem of missing variables, the endogenous problem caused by measurement error and reverse causality is still an unavoidable obstacle in causal inference in this paper. In order to eliminate the endogenous problem, this paper uses the two-stage least squares method (2SLS). According to the existing literature practices, the urban land area is selected as the tool variable [80–82]. From the theoretical and logical point of view, the smaller the administrative area, the more limited the land area available for the development of the manufacturing industry is. The smaller the land supply, the higher the land price and the restriction of industrial expansion. Due to cost pressure, some market players will take the initiative to move out or transform production lines to improve work efficiency. When the number of industrial robots introduced and installed in the region is fixed, if the factory moves to the central and western parts of China where the labor price and land price are lower, the mechanization rate and intelligence rate of the new place will be improved accordingly. Given a limited land supply, those that can thrive and still have a good position in the market are often capital- or technology-intensive. This type of enterprise has less demand for tangible factors of production, such as factory buildings, production lines, and raw materials, than labor-intensive enterprises, so it is reasonable to think that land area is related to IM. Furthermore, each region's area and administrative units have historical continuity and time stability. The land area and boundary range of administrative regions have been gradually formed through a long period of evolution throughout history. The existing land area of each region was established before this paper investigated the research. Therefore, this paper argues that land area can affect the layout and expansion of the manufacturing industry during the study period, but it cannot directly affect TFEE in order to meet the exogeneity requirements.

The validity test results of tool variables show that LM statistics reject the unrecognizable original hypothesis of tool variables at the 1% significance level. The F statistic is 21.37, which is greater than the 16.38 of the critical value of 10%, indicating that the working variable meets the exogenous condition. These two results show that the tool variables selected in this paper are influential, and there are no weak tool variables or unrecognizable problems. As can be seen from Table 4, the estimation coefficient of TFEE by IM is 1.452 and has passed the 1% significance test, indicating that the result that IM can improve TFEE after eliminating endogenous problems is still valid.

**Table 4.** Endogeneity test and robustness tests.

| Variables | 2SLS | | Robustness Test | | |
|---|---|---|---|---|---|
| | First Stage | Second Stage | GS2SLS | Substitution Variable | Robust Regression |
| IM | | 1.452 *** (3.00) | 0.188 *** (4.91) | 0.755 *** (7.00) | 0.135 *** (4.03) |
| Instrumental variable | 0.212 *** (4.62) | | | | |
| Control variable | Yes | Yes | Yes | Yes | Yes |
| Individual effect | Yes | Yes | Yes | Yes | Yes |
| Time effect | Yes | Yes | Yes | Yes | Yes |
| Unidentifiable test | | 21.40 *** | | | |
| Weak instrumental variable test | | 21.37 | | | |

Note: *** is significant at 1% significance level. The second phase of the 2SLS model reports the z statistics in the parentheses, and the t statistics are in the remaining results.

### *5.3. Robustness Test*

In order to verify the robustness of the results in the benchmark regression model, this paper uses three methods to test this. According to the new economic geography, there are spatial spillover effects of various economic factors at the spatial level. Especially for economic variables that may have spatial correlation attributes, such as advanced technology progress, energy consumption, and TFEE, the original assumption of individual interdependence among samples is becoming increasingly unreliable. As a result, the results of fitting analysis of spatial sample data by classical statistical methods are often biased or not optimal. Therefore, the generalized spatial two-stage least squares (GS2SLS) method is used to incorporate the spatial information of economic variables into the econometric model to investigate the spatial spillover effect of economic factors at the spatial level. The second method is to use the first time lag of IM as an explanatory variable to investigate the time lag effect. It takes some time to install and build industrial robots, from introduction, installation, and production to large-scale application, and the optimization of industrial technology and the production process also needs practical exploration. Under traditional statistical methods, a small number of outliers in the data may have a damaging impact on the analysis results, or even lead to completely wrong statistical conclusions, which makes some classical statistical analysis methods worthless. For example, economic shocks in some years or significant technological breakthroughs in a certain region may make the influence of IM on TFEE biased, and the existence of extreme values still poses a certain threat to regression results. The S estimation method in robust regression can overcome the defect of least square regression being distorted by outliers and obtain an estimate closer to the actual value [83]. As can be seen from Table 4, the three test methods all show that IM can improve TFEE, and the significance and sign direction do not change, which is consistent with the benchmark regression results. This result shows that the conclusion that IM can improve TFEE is stable and reliable.

## 6. Mechanism Analysis

### *6.1. Mediating Effect*

Considering that the traditional three-stage model of the mediating effect has been increasingly questioned, one of the critical questions is that this method leaves the analysis of mediating mechanism to "accidental events," and statistical inference is not strictly causal inference, so the endogeneity problem is severe. Based on the methods of published studies [83–85], this paper used grouping regression to examine the mediating mechanism of LPD. Specifically, the study divided the sample into high and low groups based on the mean of LPD, and then performed group regression calculations using TWFE.

As can be seen from Table 5, in the low and high samples, the regression coefficients of IM on TFEE are 0.576 and 0.528, respectively, and both are significant at the 1% level. By comparing the coefficient sizes of the two, it can be found that the regression coefficient of IM is more prominent in the samples with a lower degree of LPD. This conclusion suggests that IM can improve TFEE in the samples with lower LPD. Hypothesis 2 is thus verified. From the perspective of economic reality, industrial robots have a pronounced driving effect on labor productivity in the manufacturing industry. The application of robots in China is mainly concentrated in the manufacturing sector, which will further promote the development of producer and high-end services related to manufacturing through the "scale–productivity effect". This phenomenon is a concrete reflection of the effect of automation technology on job creation. Part of the low-skilled labor force being replaced by robots gradually shifts to producer services and other industries, contributing to the redistribution of labor force factors in various fields. Workers' deeper participation in the detailed division of labor in a more reasonable way will help ease the mismatch between labor and pay. In addition, the intelligent manufacturing and Internet platforms under the background of digitalization share the factor information in the cloud in real-time and fully tap the "information potential energy" for relevant demanders to inquire anytime and anywhere. That is to say, the fairness, real-time performance, and interaction of digital technology enable demanders (suppliers) to break through the limitations of information acquisition in time and space and realize real-time interaction between supply and demand. This effectively reduces job search costs and information asymmetry, promotes labor flow across regions or "invisible flow", and alleviates price distortion.

**Table 5.** Results of the mechanism test.

| Variables | Full Sample | Lower LPD | Higher LPD | TFEE |
|---|---|---|---|---|
| IM | 0.658 ***<br>(6.02) | 0.576 ***<br>(2.62) | 0.528 ***<br>(4.00) | 0.601 **<br>(2.76) |
| Interaction term | | | | 0.036 **<br>(2.72) |
| Control variables | Yes | Yes | Yes | Yes |
| Individual effect | Yes | Yes | Yes | Yes |
| Time effect | Yes | Yes | Yes | Yes |

Note: *** and ** are significant at the 1% and 5% significance levels, respectively, in the following tables. The t-statistics are reported in parentheses.

### 6.2. Moderating Effect

The carbon emission trading policy gives enterprises more independent decisions, and the production mode and factor output efficiency may form a new virtuous cycle driven by the policy and finally improve the energy production efficiency. However, the carbon emission trading market construction in China is still in the initial stage, and the quota allocation and price formation mechanism are not perfect, without giving full play to the expected positive effect of market mechanism on TFEE, and even market failure under certain conditions [86]. In order to verify the effectiveness of policy regulation, this paper takes the CETP as the moderate variable and adds the interaction item of IM and carbon emission trading policy, which can obtain:

$$TFEE_{it} = c_0 + c_1 IM_{it} + c_2 CETP_{it} + c_3 IM_{it} \times CETP_{it} + c_4 \sum_{m=1}^{8} Control_{itm} + \lambda_i + \nu_t + \varepsilon_{it} \quad (7)$$

In Equation (7), $C_3 IM_{it} \times CETP_{it}$ represents the interaction term of intelligent manufacturing and carbon emission trading policy, and the significance and symbol direction of its fitting coefficient $C_3$ is the focus of this paper. The significance and symbol direction of the fitting coefficient are the focus of this paper, and the other variables and the meaning of compliance are the same as Equation (6).

The tests obtained by modeling the regulatory effects are shown in Table 5. The fitting coefficient of the interaction item between IM and carbon emission trading policy is 0.036 and passed the 5% significance test, indicating that the carbon emission trading policy plays a positive regulatory role in the process of IM to improve TFEE, which verified H3. According to the Coase property rights theory, the carbon emission trading policy measures, commercialized and asset carbon dioxide emissions, endows carbon emission commodity attributes in the way of right emission quota, transforms the external problems of environmental pollution to the internal cost, and then stimulates the emission reduction power of the emission subject. Under the premise of qualified carbon emission quotas in the market, while the surplus quota of the enterprise's main body can sell carbon emissions to increase profits, investigate whether its essence is reward-advanced, punish backward market ideas from the perspective of cost-incentive backward production technology, and encourage non-environmental-protection enterprises to carry out green production, reverse-transmission traditional enterprises to improve energy input structure and green technology innovation to promote TFEE.

## 7. Conclusions and Policy Implications

### *7.1. Conclusions*

With the accelerated innovation of digital technologies such as big data, cloud computing, blockchain, and automation, the free flow of various production factors and the deep integration of various market entities have been promoted in recent years. The application of industrial robots is a concrete reflection of the integration of artificial intelligence technology and industry. Its extensive promotion and popularization in the manufacturing field not only bring about a change in production mode but also significantly impact the method of resource combination and energy utilization efficiency. This study innovatively introduces the CETP and LDP pathway mechanism and verifies the impact of intelligent manufacturing on total-factor energy efficiency from the installation and introduction of industrial robots by enterprises. More precisely, first, this paper sorts out the influence mechanism of IM on TFEE from the theoretical level and then tests it in combination with the panel data of 30 provinces from 2006 to 2019. As mentioned by Singh et al. [87], intelligent technology has a great capacity to achieve energy sustainability goals. The development of digital technologies, including the Internet of Things (LoT), has transformed traditional energy grids into smart grids, enabling more reliable energy management. The research results show that:

(1) The productivity effect, scale effect and resource allocation effect produced by IM technology can significantly improve the TFEE, and the conclusion is still valid after the robustness test and dealing with endogenous problems.

(2) LPD and CEPT are important mechanisms for IM to improve TFEE. On the one hand, IM helps to eliminate workers' information search costs and search process, promote labor factors in a broader market configuration, more efficiently match labor supply and job demanders, and ease labor price distortion, and corrected LPD can strengthen the enterprise research and development and innovation and crack regional industrial structure low-end locking, ultimately improving the TFEE. On the other hand, CEPT, by imposing cost pressure on enterprises and supplemented by policy guidance and interest incentive, can strengthen enterprises' willingness to develop green technology research and development, optimize the process, and replace backward equipment, so as to positively regulate IM and improve TFEE.

### *7.2. Policy Enlightenment*

In order to give full play to the driving role of intelligent manufacturing in improving TFEE as much as possible, combined with the research perspective and conclusion of this paper, the following policy suggestions are put forward:

(1) Government departments should deepen the reform of IM systems and continuously improve the business environment of the digital economy. First, we will give full play to the role of the government in the top-level design and deepen the reform of the government management system. Starting from the perspective of industrial integration systems, we will expand the coverage space of intelligent manufacturing policy support, plan intelligent manufacturing production, equipment, technology, management, and other fields, and improve the policy system of intelligent manufacturing. At the same time, the government's policy preference for intelligent manufacturing should be based on the principle of "market leading, government guidance", give full play to the decisive role of the market in the allocation of intelligent manufacturing resources, and promote the rapid development of intelligent manufacturing industry. Second, we should increase the financial support for the development of intelligent manufacturing and deepen the reform of the financial system. We should implement the particular policy of preferential tax treatment for intelligent manufacturing enterprises, including the R&D expenditure of intelligent manufacturing technology in the list of VAT deductions to encourage intelligent manufacturing enterprises to strengthen independent innovation and carry out deep cooperation with the government in capital and technology, so that enterprises can reasonably enjoy the policy dividend. Third, we will optimize the talent supply and training structure, deepen the reform of the talent system, and alleviate the mismatch between labor industries and regions. On the basis of improving the supporting policies for talent introduction, the government builds a training platform for intelligent manufacturing talents and attracts foreign high-tech talents to reflux by improving economic treatment, politics, treatment, family treatment, and other forms. At the same time, we will support institutions of higher learning and vocational colleges to set up intelligent-manufacturing-related majors or practical courses, promote the construction of this discipline at different levels, and reserve sufficient professional talents for intelligent manufacturing enterprises and scientific research institutes. Fourth, we will promote the construction of a digital government to release the information dividend. With the implementation of e-government and the construction of a smart city as the starting point, we must integrate digital government into the digital transformation of the whole city, jointly promote the construction of a digital government and an innovative city, digital community, and digital countryside, and build the construction of a coordinated linkage represented by "three integration and five spans." Using digital intelligence to drive the system remodeling, we must actively explore data governance and government function reform, restore the "business flow" with departmental "data flow," promote the integration of government service links and process optimization of government services, realizing the "one network" of government services and leading the digital development with the construction of digital government. Fifth, we should accelerate the establishment of a multi-functional and integrated national carbon trading market data-sharing platform. We will continue to pilot carbon trading in parallel with the national carbon market and give full play to the positive regulatory role of carbon emission trading policies. It is necessary to make full use of intelligent manufacturing, artificial intelligence, and blockchain advanced information technology, and optimize and integrate Guangdong carbon trading, China carbon city, Shenyang Carbon trading, and other local carbon trading user terminal information platforms, building a national-integrated, multi-functional carbon trading user terminal and data analysis platform and striving to eliminate information barriers.

(2) Governments must make breakthroughs in the core technologies of intelligent manufacturing and strengthen the strategic layout. First, they must strengthen basic

industrial research to seize the advantages of intelligent manufacturing technology. With the industrial and supply chains as the main lines, we will make significant breakthroughs in the "five new types of infrastructure" engineering, industrial production, and application in essential fields such as intelligent equipment and new materials and constantly improve the essential capacity of intelligent manufacturing. We must strengthen the construction of industrial Internet infrastructure in public places and intelligent manufacturing industrial agglomeration parks, strengthen information security control, and promote the integration and interaction of manufacturing technology and information technology in all links of industrial manufacturing. Second, we will strengthen our strategic layout and give full play to its exemplary and leading role. Administrative departments can build regions and industrial parks with a good foundation of intelligent manufacturing into intelligent manufacturing demonstration bases and adopt the "reveal the list and take the lead" approach to concentrate high-end national resources, taking the lead in breaking through the key core technologies that restrict the development of intelligent manufacturing, to give full play to the positive leading role of pilot demonstration projects. At the same time, the leading enterprises of intelligent manufacturing should accelerate the cooperation of domestic and foreign universities and scientific research institutions, build an industrial innovation platform, and drive the upstream and downstream linkage and cooperation of the industrial chain and innovation chain. Third, we must learn lessons from advanced foreign experience to develop intelligent manufacturing essential software. For the weak link of the intelligent manufacturing essential software industry in China, a software development-related support policy encourages industrial enterprises and software development park building technology demand communication platform, real-time tracking enterprise demand to jointly develop intelligent manufacturing basic software and operating system, solve the problem of software system development lags behind the intellectual level of China.

(3) Enterprise must build "intelligent" employees in the digital era and build a community of interests. First, we must reshape the corporate culture of the digital age through thinking. Intelligent manufacturing enterprises should give up the traditional top-down, inside-out planning and control mechanism, break the status quo of hierarchical decision-making, and change the enterprise development from "controlling employees" to "trusting employees." At the same time, all levels embed the thinking mode of risk-taking and innovative development to cultivate a corporate culture with digital vision and genes. Second, we should carry out "online + offline" digital training and create a scientific training evaluation system. Intelligent manufacturing enterprises should drive data-driven enterprise learning and set up personalized and specific training courses. At the same time, using various management software and data analysis functions, these enterprises should establish a scientific training evaluation system, link the training content with employee performance, and fully mobilize employees' enthusiasm to integrate into the digital age. Third, we should pay attention to individual value and realize the symbiosis of enterprise and employee value. Intelligent manufacturing enterprises should pay attention to organizational performance goals and consider the value of employees in the organization. Enterprises should establish a value platform shared by employees and organizations, constantly strengthen the communication between employees and other high-tech enterprises, improve the cognitive level of employees, and achieve the goal of matching the development speed of enterprises and employees.

(4) Considering the role of carbon emission trading in promoting TFEE, it is necessary to continue to speed up the construction of the carbon emissions trading market in pilot areas and improve the national unified carbon trading market system. When the government provides a good platform for trading subjects, it should also handle the relationship between the government and the market. Based on emphasizing fairness, we should give play to the role of the market mechanism, not interfere

with the implementation of the carbon emission trading system, give play to the dominant position of enterprises in the market, use the market mechanism to guide the rational allocation of factors, save energy and improve energy utilization efficiency. To implement a carbon emission trading system, we should not only fully consider each region's historical cumulative carbon emissions but also fully measure each region's natural endowment and economic development to improve TFEE effectively. A differentiation strategy can be implemented.

### 7.3. Limitations

This study has certain limitations. (1) The statistical sample used in this study was China's provincial panel bureaus. The granularity of the data is large. In future studies, artificial intelligence or data from publicly traded energy companies could be used to study the topic at a more microscopic level. (2) It is well known that finding a strictly exclusive instrumental variable is very difficult. In the causal inference method, using the instrumental variable method to solve the endogeneity problem may need to be improved. In future studies, differential analysis or breakpoint regression can be used to identify the causal relationship between the two based on relevant policy pilots. (3) Accurately measuring TFEE is very difficult. In future studies, SFA and DEA methods can be organically combined to measure TFEE by using more flexible and accurate stochastic non-parametric envelopment of data (Sto NED).

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