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# Smarter and Sustainable Development: Evaluating the Impact of Artificial Intelligence on Energy Conservation and Emission Reduction

Siyu Ren [a], Wenchao Bu [b, *]

[a] *School of International Business, Shanghai University of International Business and Economics, Shanghai, China*

[b] *Center for Transnationals' Studies of Nankai University, Nankai University, Tianjin, China*

## ABSTRACT

Improving energy conservation and emission reduction (ECER) efficiency is a virtuous cycle of economic development and environmental protection, promoting countries around the world towards sustainable development. As a strategic technology leading a new round of technological revolution and industrial transformation, the large-scale application of artificial intelligence (AI) is driving the transformation of manufacturing production methods, which is increasingly essential for improving the effectiveness of environmental governance. This study aims to analyze the impact of AI technology on ECER in the manufacturing industry, as well as the specific impact paths and heterogeneity. We contribute to previous literature by measuring ECER of Chinese manufacturing sector using the EBM model. The mediation effect model is used to analyze the impact mechanism between AI technology and ECER. The results indicate that AI promotes the ECER efficiency in the manufacturing sector. The positive effects are attributed to the development of energy consumption structure and technological innovation. The impact of AI on ECER exhibits an evident heterogeneous effect across industries with different pollution intensity, R&D intensity and labor intensity, and ownership dominant industry. Additionally, higher levels of environmental regulation lead to an increase in the positive effects of robot promotion on ECER. The research conclusions provide important reference for understanding the relationship between AI technology and ECER, and contribute a new way to promote environmental governance and carbon neutrality.

## KEYWORDS

Artificial Intelligence; Energy Conservation and Emission Reduction; Technological Innovation; Sustainable Development

* Corresponding author: Wenchao Bu
E-mail address: buwenchao420@163.com

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## 1. Introduction

Green development has become the mainstream option for countries who seek to change their development philosophy and production methods (Ozturk et al., 2019; Lin et al., 2022). As an important measure to promote green growth and achieve compatible co-existence between man and nature, the “double carbon” strategy has attracted much attention (Lin et al., 2023; Xie et al., 2023). With a country's rapid economic growth, history has repeatedly shown that the problem of high carbon emissions caused by production activities has become increasingly serious and is restricting the country's sustainable development process (Bu and Ren, 2023a). As the largest developing country, China is experiencing severe ecological degradation. China's carbon emissions have reached 11.9 billion tons in 2021, accounting for 33% of the global total. This situation presents a critical juncture for balancing sustainable transformation and economic growth. The prevailing consensus is that extensive environmental regulation is required to make a tangible contribution to climate action. China has committed to the goal of carbon neutrality in accordance with the purposes of the International Climate Conference. The key to achieving carbon peaks is to improve energy efficiency (Du et al., 2022; Wu et al., 2020). Therefore, improving the efficiency of ECER is a significant approach for China's future development if the goal of carbon neutrality is to be achieved. The ongoing new industrial revolution is transforming production technologies worldwide, giving rise to emerging digital technologies such as artificial intelligence. The breakthrough development of such technologies provides new technical foundations for environmental pollution control. On the one hand, the seminal “Porter Hypothesis” posits that technological advancement enhances firms’ energy efficiency, optimizes energy consumption structure in production, and achieves simultaneous pollution mitigation and profit growth. On the other hand, AI technologies can optimize energy storage and distribution, enhancing sustainability and cleanliness. As such, AI harbors the potential to become a novel impetus for ECER.

Air pollution mainly comes from the production activities of the manufacturing industry. One of its effective means of prevention and control is to improve the efficiency of ECER (He, 2015; Zhang et al., 2020). The driving factors of ECER have been argued bymany existing literatures, which indicate explicitly that the improvement of ECER requires green technology, industrial upgrading, green industry chain, clean energy substitution (Yang et al., 2021). Moreover, some scholars have discussed the driving force of ECER, considering economic systems and policies such as market segmentation, and official corruption (Yao et al., 2021). Regrettably, the previous literatures have ignored artificial intelligence such as robot applications, big data, energy internet in digital economy era.

With the rise of AI, the use of robots in manufacturing processes is increasingly widespread. The intelligent industry represented by robotics has become an iconic symbol of technological innovation in the digital era. According to the statistics of the IFR, the industrial robots running in factories around the world has reached 3 million units in 2020, of which the output of Chinese industrial robots is 168,400 units, making China the largest producer of industrial robots in the world. Besides, China has enacted some encouraging industrial policies to support the development of intelligent industries. At the end of 2021, China proposed to accelerate the development of 5G, industrial robots, energy internet, internet of things, and other infrastructural advancements. Additionally, AI and green manufacturing have been advocated in the government work report for four consecutive years. The vigorous development of industrial intelligence showed by robot has made China the biggest market for industrial robots for six consecutive years. From the data in Figure 1, it reveals that the stock and installation of industrial robots in China showed a gradual upward trend from 1998 to 2019. Industrial robots are also growing rapidly in the European market. In 2022, for example, nearly 72,000 industrial robots were installed in the EU, a 6% year-on-year increase, according to data released by the European Federation of Robotics (IFR), of which Germany is by far the largest robotics market in Europe, with around 26,000 installations in 2022, accounting for 37% of the total EU installations. Germany, Italy, and France account for nearly half of the total robot installation in the European Union. Industrial robots are widely used in a variety of fields, including automotive manufacturing, electronic equipment manufacturing, and plastic product manufacturing. AI technologies play a crucial role in green development. First, AI can substantially improve efficiency and accuracy. Through big data analytics and machine learning, firms can make more precise predictions and decisions to optimize resource allocation and production processes, reducing waste and emissions. Second, AI provides innovative solutions to challenges that conventional methods struggle to address. For instance, deep learning and computer vision can help firms more accurately detect and diagnose environmental issues, and propose more effective solutions. In addition, AI facilitates sustainable development by enhancing energy efficiency in smart energy management and transportation systems, lowering energy consumption and carbon footprints. Likewise, adopting AI strengthens firms' competitiveness to meet consumer demand for green products, enabling more eco-friendly and sustainable production and services, garnering consumer trust.

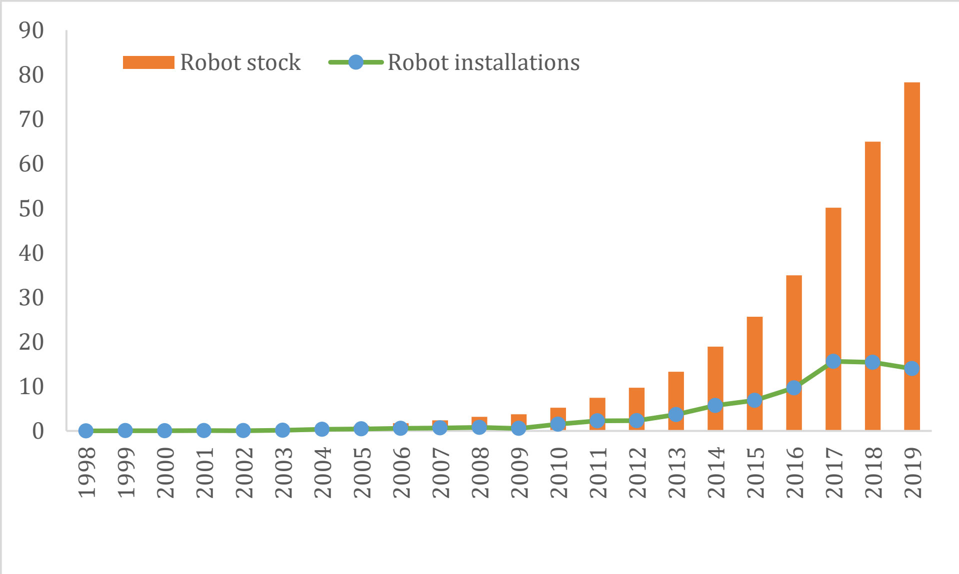


**Figure 1.** China's robot stock and installation in 1998-2019.

Previous literature has discussed the promotion role of robots on GDP growth and found that the application of robots improves economic value. This relationship has been attributed to the improvement in productivity and TFP (Graetz and Michaels, 2015, 2018). Other studies involved the conclusion that robots may reduce employment and wages (Klarl, 2022). Unlike the findings, some conclusions suggest robot did not significantly reduce total employment (Dauth et al., 2017), but they reduced low-skilled workers' employment share (Graetz and Michaels, 2018). Besides, although some literature studies the internet and environmental governance (Wu et al., 2021a; Yang et al., 2020), there is little literature on the impact of AI on ECER. As a quintessential achievement of the technological revolution, the industrial robots have triggered a series of changes in production and organization. It is an essential promote force for the economic growth, and low-carbon development of the global economy. Additionally, AI inspires companies to increase R&D expenditures, promotes technological progress, and reduces energy consumption (Jaiprakash et al., 2017; Lee et al., 2022; Nabila et al., 2021). Robot applications improve production efficiency and raw material utilization, and automated operation performance reduces energy loss and waste (Li et al., 2022). The robots increases the overall technology of enterprises, which makes the production process more intelligent than before and reduces energy consumption (Hassan et al., 2020). However, the impact mechanism of robotic applications on ECER efficiency has not been systematically discussed in the existing literature.

As global climate change and environmental degradation intensify, ECER have become imperative. However, traditional methods for quantifying energy and emission savings do not account for unexpected outputs. Hence, exploring novel and more efficient approaches is warranted. Examining the nexus between artificial intelligence and energy and emission efficiency can furnish an in-depth understanding of how artificial intelligence optimizes energy utilization, offering specific guidelines and technical support for practice. This enriches theoretical development and provides practical recommendations for policymakers and technology developers. Despite permeating applications across domains, the interface of artificial intelligence with ECER remains an underexplored direction. Such inquiry can stimulate the deployment of artificial intelligence technologies in sustainability to nurture harmonious symbiosis between technological advancement and environmental well-being. Therefore, this paper examined the effect mechanism of AI on ECER using the China manufacturing data. The contributions are reflected: (1) Research perspective: we innovatively analyzed the role of artificial intelligence in ECER, proposing a novel view for follow-up research on industrial green development. (2) To enhance the understanding on the mechanisms through which AI, we further proposed two potential channels, including technological innovation and energy structure transformation, and validated them by empirical analysis. (3) We revealed the heterogeneity of robot effects. Specifically, we divided the full sample by industry ownership, R&D intensity, factor input type, and industry characteristics, and perform analysis on each subgroup. Heterogeneity analysis demonstrated a complete picture of the green effect of AI. Therefore, our findings not only make up for the insufficiency of existing research, but also provide important references for developing countries in environmental distress to achieve the “carbon neutrality”.

## 2. Literature review

### *2.1. Literature study on ECER*

Energy is the foundation of industrial growth and a critical determinant of life quality. The demand for energy is becoming scarcer, which has a obvious negative response on sustainable development as the population and economy growth (Bu and Ren., 2023b). Thus, the optimization of energy efficiency (EE) is considered as major strategy to achieve low-carbon growth (Zhou et al., 2022). Single EE ignores other production factors, and is often used due to the simple measurement method (Shao et al., 2016). To overcome the limitations of single EE, the new concept of the total factor EE was proposed. With the increasingly severe climate extremes, the efficiency of ECER has become an important issue for researchers. This is an effective framework to improve green development, and get rid of the resource curse and reduce the energy crisis. Wu et al. (2021b) proposed a measurement framework of ECER using SBM model, which considers input variables and undesired outputs. This framework outperforms traditional efficiency assessments as it considers multiple input and output variables. The methods used to assess ECER can be divided into parametric (SFA) and non-parametric (DEA) methods. SFA has major merits in the application of maximum likelihood estimation and technical inefficiency assumption. Furthermore, Song et al. (2013) raised the Bootstrap DEA model. This model described above are an essential reference for measuring EE. In addition, regarding the improvement path of ECER, many studies have summarized that the efficiency of ECER benefits from technological progress. Vigorously developing energy-saving technologies and improving energy conversion and utilization efficiency can effectively increase the economic output effect of polluting gas emissions.

### *2.2. Literature study on artificial intelligence*

The fourth technological revolution represented by AI is gradually emerging around the world. Some literature on AI analyzed the effect of robot on employment rate, wage and employment distribution (Giuntella and Wang, 2019). Their analytical conclusions are not uniform, and some analysis conclusion suggests that AI improves labor productivity and produces employment substitution effects (Acemoglu and Restrepo, 2018; David, 2017).

Compared with manual labor, the application of robot has a comparative advantage in product production, which results in the reduction of labor demand of enterprises (Carbonero et al., 2020; Dottori, 2021). Acemoglu and Restrepo (2020) based on the data of robot in 19 industries from 1990 to 2007, and concluded that the employment population would decrease by about 0.18% -0.34% for every 1,000 people adding one robot. Another part of the scholars suggests that AI mainly exerts the employment creation effect rather than the substitution effect (Dixon et al., 2020). In reality, although the application of industrial robot, digital technology and computers has replaced part of the labor force, robots are also constantly creating new jobs. On the one hand, technological development leads to efficiency improvement and industrial expansion to a certain extent, which generates more labor demand and creates many new labor positions (Berg et al., 2018). On the other hand, the intelligent production technology caused by robots reduces production costs, which is beneficial for enterprises to expand production scale and create mountains of new labor positions (Acemoglu and Restrepo, 2019). Oschinski and Wyonch (2017) focused on the Canadian labor market and concluded automation did not cause mass unemployment. Berg et al. (2018) suggested that the development of robotics primarily exerted the job creation inpact and created a lot of works. The internal mechanism is that the application of new technologies increases productivity, breeds new industries, and increases labor demand.

Different from the above findings, some studies confirm that robots has a heterogeneous impact on labor with different skills (Furman and Seamans, 2019). Industrial robots, as a skill-based technological advance, substitute for low-skilled workers but augment the demand for high-skilled workers. For example, Graetz and Michaels (2018) suggested AI poses no prominent threat to the overall employment rate. However, other studies have found that industrial robot, unlike general technological advances, may reduce the demand for labor of all skill levels (Acemoglu and Restrepo, 2020). Industrial robot on labor demand is mainly determined by the combination of the replacement and the productivity effect. Some literatures also discussed the influence of robots on enterprise productivity (Kromann et al., 2020; Acemoglu and Restrepo, 2019), global value chains, economic growth (Gasteiger and Prettner, 2022), firms added value (Graetz and Michaels, 2018). Gordon (2013) suggested that the development of information technology only provides new consumption opportunities and does not promote the upgrading and development of the macro economy.

Previous studies have the following limitations. First, previous literature has focused on energy efficiency measurement and influencing factors, but little literature has focused on energy efficiency and emission reduction efficiency in the manufacturing sector. Second, for the measurement of energy saving and emission reduction efficiency, some literature does not consider the impact of non-desired outputs. Third, previous studies rarely analysed the impact of AI technology on energy efficiency and emission reduction, ignoring the role of AI technology in energy efficiency improvement and environmental governance. Some similar studies did not elaborate on the impact mechanisms and heterogeneity between the two.

## 3. Mechanism analysis

With breakthroughs in basic layer technologies such as data processing capabilities, and algorithms, AI has entered the stage of technological upgrading and large-scale application. Under the trend of the integration and wide application of AI and big data, the mode and means of ecological environment governance will inevitably undergo subversive changes. On the one hand, robotics alleviates the trade-off between economy and environment by improving resource utilization and refined environmental management. On the other hand, it also provides a new technological tool for real-time environmental detection and cross regional collaborative pollution control.

AI mainly contribute to emission reduction as follows. Firstly, from the perspective of production, the artificial substitution effect produced by robots improves the production efficiency and decreases the energy consumption per unit of output (Atkinson, 2019). The high-speed evolution of AI and robotics has alleviated the serious pollution that is unpreventable by manual operations (Vänni and Korpela, 2015). Robot operation requires less raw materials than manual operation at the same output, which improves material utilization and reduces pollution emissions. Relying on the support of AI technology, enterprises can accurately grasp changes in production efficiency and improve their ability to deal with environmental pollution. Robot can autonomously perceive high-pollution and high-energy-consumption production links, optimize production processes, and improve environmental precision management (Lee et al., 2022). Second, the networked collaborative production mode formed by AI improves production efficiency. AI helps enterprises build a closed-loop network system covering the whole life cycle of products such as R&D design, equipment production, transmission and assembly, etc. (Liu et al., 2020). It enables enterprises to have the ability to respond quickly and dynamically optimize. Moreover, the application of robot can drive upstream and downstream enterprises to carry out green transformation of process design and transportation services, and increase supply chain efficiency (Liu et al., 2022). Finally, with the blessing of industrial robots, manufacturers can design product recycling and reuse processes following user preferences, thereby effectively reducing resource and energy consumption.

Hypothesis 1: The AI can increase the efficiency of ECER.

As an important aspect of the fourth industrial revolution, AI significantly promotes structural adjustment (Chen, 2018), and structure adjustment is conducive to environmental performance (Li et al., 2022; Dhanabalan and Sathish, 2018). The influencing mechanism is summarized into three aspects. (1) The AI promotes the transformation of resource-intensive industries, and promotes the industrial structure towards advanced sustainable development (Javaid et al., 2022). Meanwhile, driven by government policies and economic development, green, low-carbon, high-tech, information-based, and high-value-added industries with strong profitability and promising development prospects are more likely to attract labor and capital, which promotes the industrial structure upgrade and optimization. (2) AI promotes change to all internet energy market transactions and product types, increases renewable energy utilise, promotes the clean and efficient use of fossil energy (Lange et al., 2020). (3) As a major aspect of digital technology, informatization, and industrialization, the AI has significantly promoted the progress of green technology. Information technology is a central driver of EE and green technology innovation. Additionally, AI reduce information asymmetry and transaction costs, and improve energy system management (Ahmad et al., 2021). On the other hand, AI advances technology spillover through the network association effect and interaction effect. The diffusion of green energy technology among economic actors is promoted through imitation and learning (Yi et al., 2020). Meanwhile, AI has also promoted collaborative industry–university–research–user innovation, advancing the progress of green technology (Wang et al., 2019).

Hypothesis 2: The application of robot can improve the ECER efficiency by improving technological innovation.

The AI promotes energy transformation by improving energy efficiency of enterprises from the production side. Fossil fuel is regarded as the direct source of pollution (Shao et al., 2019). Due to technological limitations, China faces enormous difficulties and challenges in improving EE. AI can increase the direct clean technology of coal combustion and the technology of converting coal into clean fuel, improve energy efficiency, and reduce corporate pollution emissions. AI can also address the complexity of energy transition and improve system efficiency, thereby reducing costs and speeding up energy transition. Moreover, AI helps to accelerate the penetration and use of renewable energy and renewable equipment. With the gradual introduction of intelligent technology into industrial production workshops, outdated technological processes and inefficient fossil energy will gradually be eliminated. This promotes the application of clean energy and renewable energy, reduces the proportion of traditional energy, and optimizes the energy consumption structure.

Hypothesis 3: AI can improve the ECER efficiency by improving energy consumption structure.

Industrial robot is considered to be a revolutionary product of the continued development of software and the internet in the information technology era. In the initial stage of industrial intelligence investment, the acquisition and feedback costs of information and knowledge are relatively high, and the diffusion ability of intelligent equipment is relatively weak. At the beginning of economic development, industrial robot's effect on the efficiency of industrial green development is small, or even negative. This is attributed to the power of industrial robots mainly comes from electrical energy, which increases energy consumption. The enforcement intensity of environmental policies is the key to reducing pollutant emissions. However, environmental regulation policy promotes firm to change production equipment and improve intelligent production processes to avoid high punishment costs. With the continuous advancement of industrial intelligence, the analysis and decision-making costs of smart factories and smart equipment will gradually decreased, leading to a continuous increase in the green contribution of intelligent systems. When investment in industrial intelligence exceeds a certain scale, the efficiency of the connection between the R&D, design and application departments of the enterprise and the market demand side will gradually improve, and the information linkage in the industrial chain will become more closely.

Hypothesis 4: The marginal effect of AI on ECER increases in the industry of stricter environmental regulations.

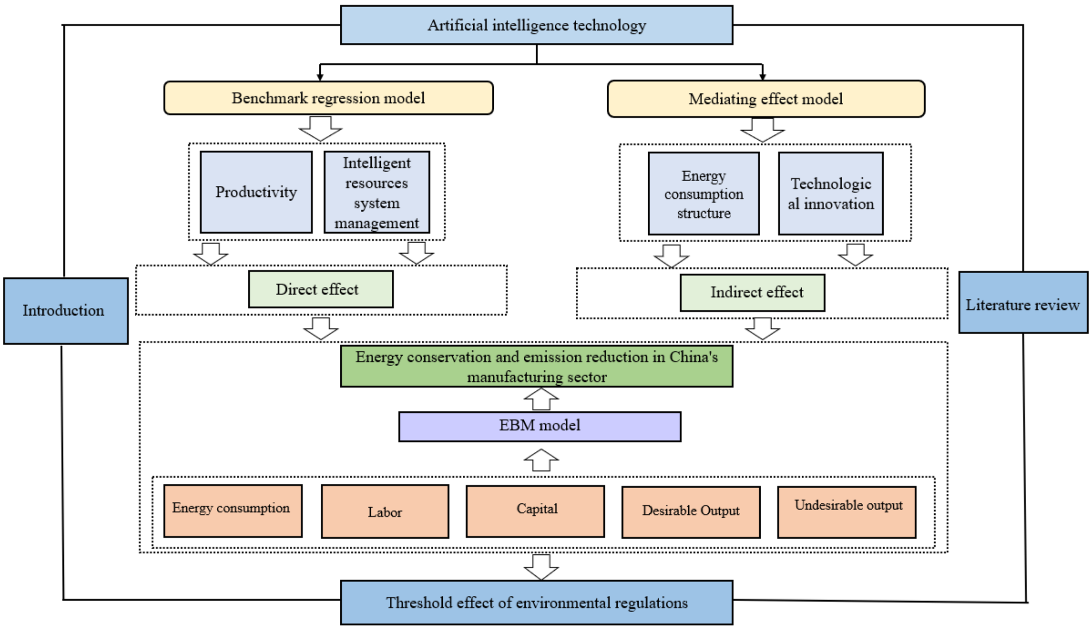


**Figure 2.** Research framework.

## 4. Methodology and data

### *4.1. Model*

#### 4.1.1. Benchmark model

We set the following model to explore the impact of AI and ECER:

$$ECER_{it} = \alpha + \beta_1 robot + \eta X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

Where $i$ represents the industry, $t$ is the time. The independent variable ($robot_{it}$) represents the AI. $X_{it}$ is a set of control variables. $\varepsilon_{it}$ is the random disturbance term. $\beta_1$ means the substitution elasticity of industrial robot use for ECER efficiency.

#### 4.1.2. Mediation effect models

To explore whether the AI improve the ECER through technological innovation and energy consumption structure, we propose a mediation effect model with equation (2). When considering the effect of the independent variable $robot_{it}$ on the dependent variable $ECER_{it}$, $Med_{it}$ is called to be the mediation variable if $robot_{it}$ affects $ECER_{it}$ through the influence variable $Med_{it}$. The effect of $robot_{it}$ on $ECER_{it}$ through the mediation variable $Med_{it}$ is the mediation effect.

$$Med_{it} = \vartheta_0 + \vartheta_1 robot_{it} + \eta X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$ECER_{it} = \vartheta_0 + \vartheta_1 robot_{it} + \vartheta_2 Med_{it} + \eta X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

Among them, $Med_{it}$ is the mediating variables (technological innovation and energy consumption structure). Formula (2) estimates the effect of AI on mediating variables.

4.1.3. Threshold panel model

Furthermore, this study investigates whether the AI and ECER have a nonlinear relationship with environmental regulation? However, the empirical model presented above makes it difficult for nonlinear nexus analysis. Additionly, this study tests that environmental regulation is anticipated to increase the role of the AI in the growth of the green economy. Finally, this paper considers cross-sectional drivers of environmental regulation as threshold variables. If $\beta_1$ and $\beta_2$ are significantly positive, and $\beta_2$ is greater than $\beta_1$, it indicates that as the intensity of government environmental policies increases, the role of AI in ECER is greater. As a particular setting, the model is as follows.

$$ECER_{it} = \beta_0 + \beta_1 robot_{it} \bullet I(eri_{it} \le \gamma) + \beta_2 robot_{it} \bullet I(eri_{it} > \gamma) + \beta_3 X_{it} + \lambda_i + \varepsilon_{it} \quad (4)$$

## *4.2. Variables selected*

4.2.1. ECER efficiency

The evaluation of ECER is one of the most frequently applied scenarios of the DEA model. To measure the diversity and interdependence between variables, the EBM model adds the exponent ε (Tone and Tsutsui, 2010). It has a more substantial superiority in recognizing the efficient decision-making unit (DMU). In recent years, the EBM model has become a popular efficiency evaluation method in light of its ability to account for bad output factors. The specific formula is as follows:

$$\gamma^* = min\theta - \epsilon_x \sum_{i=1}^{m} \frac{W_i S_i}{X_{i0}}$$

$$s.t. \begin{cases} \theta_{X_0} - X\lambda - s = 0 \\ \lambda Y \ge 0 \\ \lambda \ge 0 \\ 0 \le \gamma^* \le 1 \\ s \ge 0 \end{cases}$$

Where, $W_i$ is the input weight and meets $\sum_{i=1}^{m} W_i = 1$ ($W_i \ge 0$), X = $\{x_{ij}\} \in R^{m\times n}$ is the input vector, Y = $\{x_{ij}\} \in R^{s\times n}$ is the output vector. The GML index is incorporated into EBM model.

$$GML^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1}) = \frac{1 + \vec{D}^G_{EBM}(X^t, Y^t, B^t)}{1 + \vec{D}^G_{EBM}(X^{t+1}, Y^{t+1}, B^{t+1})}$$

**Table 1.** ECER efficiency measurement in China.

| Attribute layer | First-class index level |
|---|---|
| Input variable | Capital stock (K)<br>labor (L)<br>Energy consumption (E) |
| Desirable outputs variable | Industrial sales output value |
| Undesirable output variable | Chemical oxygen demand (COD)<br>SO2 emissions (SO2)<br>Carbon emission (CO2)<br>Solid waste emissions |

ECER is decomposed into green technology efficiency (GTE) and technology progress (GTP). Results indicate the average values of ECER, GTE, and GTP for China's manufacturing are 1.020, 0.988, and 1.037, respectively. Therefore, the green transformation of China's manufacturing is attributed to the GTE. The reasons are as follows: first, the Chinese government has promulgated a variety of environmental regulation laws and regulations and directly intervened in high energy consumption in the form of government administrative orders. These policies force enterprises to implement energy conservation standards and reduce energy consumption. Second, the continuous implementation of supply side structural reform has raised the environmental access threshold of traditional fossil energy, which directly affects the entry and exit decisions of high pollution enterprises and shifts to green development. Third, strict environmental regulations stimulate enterprises to increase investment in clean energy and energy-saving technology research and development to achieve energy-saving goals.

**Table 2.** The average value of ECER efficiency from 2006-2017.

| Industry code | ECER | GTE | GTP | Industry code | ECER | GTE | GTP |
|---|---|---|---|---|---|---|---|
| M1 | 0.996 | 0.955 | 1.048 | M15 | 1.037 | 0.998 | 1.040 |
| M2 | 0.986 | 0.971 | 1.027 | M16 | 0.957 | 0.968 | 1.020 |
| M3 | 1.004 | 0.978 | 1.028 | M17 | 1.029 | 0.984 | 1.047 |
| M4 | 1.000 | 1.000 | 1.000 | M18 | 1.049 | 0.996 | 1.053 |
| M5 | 1.013 | 0.966 | 1.052 | M19 | 1.050 | 1.002 | 1.072 |
| M6 | 1.017 | 0.982 | 1.040 | M20 | 1.030 | 0.984 | 1.048 |
| M7 | 0.993 | 0.977 | 1.030 | M2 | 1.008 | 0.969 | 1.042 |
| M8 | 1.002 | 0.999 | 1.005 | M22 | 1.052 | 1.001 | 1.050 |
| M9 | 1.006 | 1.000 | 1.006 | M23 | 1.048 | 1.004 | 1.043 |
| M10 | 1.013 | 0.978 | 1.037 | M24 | 1.066 | 1.006 | 1.071 |
| M11 | 0.976 | 0.988 | 0.993 | M25 | 1.061 | 1.000 | 1.061 |
| M12 | 1.001 | 1.000 | 1.001 | M26 | 1.053 | 1.000 | 1.053 |
| M13 | 1.004 | 0.967 | 1.055 | M27 | 1.030 | 1.000 | 1.030 |
| M14 | 1.055 | 0.996 | 1.060 | | | | |

4.2.2. Artificial intelligence

Industrial robot data was collected from the IFR consortium. The database provides industry-level robot operations per country and is widely used in the issue on industrial robot (Giuntella and Wang, 2019). IFR has provided China's annual industrial robot stock data by industry since 2006. According to China's industry classification and IFR's industry classification of robot stock, this paper classifies and counts the operation volume of industrial robot by 27 industries. The type of AI in this article mainly covers industrial robotics. It is an important component in the field of intelligent manufacturing that automates the tasks on the production line and improves productivity and product quality.

4.2.3. Control variable

To avoid the effect of missing variables on the estimated results of this paper, this paper adds factors that affect industry ECER to the benchmark model. The industry size (size) is measured by the logarithm of the number of enterprises in each industry. Environmental regulation (eri) is measured by the ratio of the sum of the annual operating costs of wastewater and waste gas to the industry sales output value. Capital structure (cst) is measured by the ratio of foreign capital to paid-in capital. Property rights structure (prst) is measured by the ratio of the total assets of state-owned enterprises in the industry to the total assets of industrial enterprises in the industry. Import structure (imst) is measured by the ratio of the import value of different industries to the industrial sales output value. Data sourced from UN commtrade. Among them, the industry import value is converted into China's industrial sector classification according to the SITC. Other data are mainly from China Industrial Statistics Yearbook 2007-2018. The Chinese manufacturing sector is the dataset used for this research discussion and adoption. These data, while reflecting economic activity in the manufacturing sector to some extent, may not capture the impact on other industrial sectors. In addition, it may not reflect the latest developments in the industry in real time due to the way and time constraints of data collection. The descriptive characteristics of the main variables are displayed in Table 3.

**Table 3.** Descriptive statistics of variables.

| Variable | Definition | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Green energy efficiency | *GTFP* | 324 | 1.2080 | 0.3119 | 0.5162 | 2.1704 |
| Artificial intelligence | *robot* | 324 | 5.2861 | 3.8839 | 0 | 12.7139 |
| Industry size | *size* | 324 | 9.0543 | 1.1023 | 4.8040 | 10.5891 |
| environmental regulation | *eri* | 324 | 1.4674 | 1.8364 | 0.0216 | 8.3773 |
| Capital Structure | *cst* | 324 | 0.2776 | 0.1490 | 0.0005 | 0.7638 |
| property rights structure | *prst* | 324 | 0.1670 | 0.2206 | 0.0030 | 0.9949 |
| Import structure | *imst* | 324 | 0.1129 | 0.2190 | 0.0009 | 1.7231 |

## 5. Empirical results

### *5.1. The benchmark regression*

Columns (1) - (8) of Table 4 report the impact of AI on ECER. Columns (1) - (2) only control the year fixed effect or the industry fixed effect. Column (3) controls the both industry and the year fixed effect, and the estimated coefficient for robot is positive. Furthermore, we gradually increase the control variables in the model in columns (4) - (8). It illustrated that the AI still increases the ECER of the industry after considering the influence of the control variables. It is similar to the research conclusions of Yu et al. (2022), but different from those of Luan et al. (2022). Their conclusions indicate that the widely used robots improve productivity and energy efficiency, expand enterprise production scale, thereby increasing total energy consumption and exacerbating environmental pollution.

**Table 4.** Basic regerssion results.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *robot* | 0.0216*** | 0.0793*** | 0.0261*** | 0.0267*** | 0.0259*** | 0.0260*** | 0.0265*** | 0.0262*** |
| | (5.2595) | (15.8624) | (2.9305) | (2.9822) | (2.8446) | (2.8489) | (2.9146) | (2.8828) |
| *size* | | | | -0.0413 | -0.0405 | -0.0286 | -0.0491 | -0.0433 |
| | | | | (-0.6516) | (-0.6382) | (-0.4166) | (-0.7032) | (-0.6196) |
| *eri* | | | | | -0.0082 | -0.0077 | -0.0121 | -0.0132 |
| | | | | | (-0.5802) | (-0.5450) | (-0.8390) | (-0.9149) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *cst* | | | | | | 0.0907 | -0.0953 | -0.0572 |
| | | | | | | (0.4627) | (-0.4095) | (-0.2434) |
| *prst* | | | | | | | -0.6701 | -0.6881 |
| | | | | | | | (-1.4789) | (-1.5187) |
| *imst* | | | | | | | | -0.1366 |
| | | | | | | | | (-1.1495) |
| *cons* | 1.0941*** | 0.7890*** | 1.0702*** | 1.4404** | 1.4497** | 1.3154** | 1.6683** | 1.6273** |
| | (41.9506) | (28.2005) | (22.3895) | (2.5263) | (2.5387) | (2.0514) | (2.4428) | (2.3809) |
| Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fe | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes |
| *Ajusted* $R^2$ | 0.763 | 0.763 | 0.763 | 0.763 | 0.763 | 0.763 | 0.763 | 0.763 |
| N | 324 | 324 | 324 | 324 | 324 | 324 | 324 | 324 |

*Note: *** p<0.01, ** p<0.05, * p<0.1. () are the t-values. This note applies to the following table.*

### *5.2. Robustness test*

(1) Instrumental variables (IV)

Considering that there may be an endogenous problem between the use of robots and the efficiency of ECER, it may make the estimation results of the least squares method biased or inconsistent. The normal method of improvement is to find a variable that is closely associated with the deployment of industrial robots in China but independent of the efficiency of ECER as an IV for 2SLS estimation. This study selects the average of robot usage in the United States, Japan, South Korea and Australia as an IV for industrial robots in China. The primary reason is that the industrial robots of these countries are less affected by Chinese economy, and do not directly affect China's green ECER. Therefore, using the average robot usage of the four countries as an IV of Chinese industrial robot usage satisfies the exogenous and correlation conditions, and better solves the endogeneity problem.

On this basis, we perform parsimony regression using the average robot usage of the four countries as an explanatory variable. The results of columns (1) and (2) in Table 5 illustrate that the estimated coefficient of *robot_m* is positive at the statistical level of 1%, which indicates that robots can improve the efficiency of ECER. Every 1% increase in robot usage can lead to an increase of 0.2457% in ECER efficiency in the industry. Columns (3) - (4) reflect the results of 2SLS method. We test the correlation between IV and endogenous variables, and perform an under-identification test and a weak identification test. The corresponding Wald F statistics are all bigger than 10, indicating that IV is related to endogenous variables. So the instrumental variables we choose are reasonable, and the estimation results are reliable. Columns (3) - (4) mainly report the results of the second stage. After controlling for the year and industry fixed effects of the regression in column (3), variable *robot* is positive. Column (4) adds a set of control variables based on column (3), and the *robot* is still positive.

**Table 5.** Robustness test (1).

| Variables | Simple regression | | IV 2SLS | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *robot* | | | 0.1278*** | 0.1534*** |
| | | | (4.4920) | (5.0941) |
| *robot_m* | 0.1841*** | 0.2457*** | | |
| | (5.6349) | (7.1051) | | |
| *size* | | -0.0758 | | -0.1477 |
| | | (-1.1591) | | (-1.5735) |
| *eri* | | -0.0209 | | 0.0176 |
| | | (-1.5677) | | (0.8819) |
| *cst* | | -0.0015 | | -0.0923 |
| | | (-0.0069) | | (-0.3018) |
| *prst* | | -1.2814*** | | -0.9479 |

| | | | | |
|---|---|---|---|---|
| | | (-2.9624) | | (-1.5985) |
| *imst* | | -0.4042*** | | -0.0899 |
| | | (-3.4632) | | (-0.5799) |
| *cons* | 0.0198 | 0.5993 | | |
| | (0.0937) | (0.9184) | | |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year Fe* | Yes | Yes | Yes | Yes |
| *F value* | | | 47.43 | 51.37 |
| | | | (0.00) | (0.00) |
| *Under-identification test* | | | 46.229 | 50.230 |
| | | | (0.00) | (0.00) |
| *Weak identification test* | | | 47.433 | 51.373 |
| | | | (0.00) | (0.00) |
| *Ajusted R2* | 0.8069 | 0.8211 | | |
| *N* | 324 | 324 | 324 | 324 |

(2) Replace the explanatory variables

In the benchmark regression, AI is measured by the stock of industrial robots. Furthermore, the installed amount of industrial robots (*robot_m*) is represented the AI for empirical analysis to make the results credible. It reflects that industrial robots installation promote ECER efficiency, indicating that the above regression results are robust.

(3) Eliminate financial crisis interference

The 2008 financial crisis disrupted the economic development of all countries. After the financial crisis, the affected countries in the world gradually began to adjust and upgrade their industrial structures to improve their ability to address a new potential crises. To examine whether the impact of robot use on ECER is different after the financial crisis, we introduce the interaction term of financial crisis (stock) and robot usage in the model. At the time point before 2008, stock = 0, after 2008, stock = 1. Columns (3) - (4) in Table 6 show that the interaction term *robot*stock* is significantly positive. It reflects that since the financial crisis, the positive effect of robot use on ECER has been significantly improved. Therefore, AI can alleviate the negative role of the financial crisis and improve emission reduction efficiency of the industry.

**Table 6.** Robustness test (2) - (3).

| Variables | Robot installations | | Control financial crisis | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *robot*stock* | | | 0.0222*** | 0.0217*** |
| | | | (3.9759) | (3.7937) |
| *robot_install* | 0.0296*** | 0.0313*** | | |
| | (3.5664) | (3.7056) | | |
| *size* | | -0.0540 | | -0.0508 |
| | | (-0.7774) | | (-0.7339) |
| *eri* | | -0.0163 | | -0.0122 |
| | | (-1.1507) | | (-0.8555) |
| *cst* | | -0.0518 | | -0.0675 |
| | | (-0.2225) | | (-0.2903) |
| *prst* | | -0.7675* | | -0.4863 |
| | | (-1.7056) | | (-1.0814) |
| *imst* | | -0.1375 | | -0.1463 |
| | | (-1.1681) | | (-1.2448) |
| *cons* | 1.0753*** | 1.7385** | 1.1015*** | 1.6984** |
| | (28.1784) | (2.5628) | (39.2478) | (2.5089) |
| *Industry FE* | Yes | Yes | Yes | Yes |

| | | | | |
|---|---|---|---|---|
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.768 | 0.768 | 0.768 | 0.768 |
| N | 324 | 324 | 324 | 324 |

## *5.3. Influence mechanism*

In the mechanism analysis part, we propose that AI can affect the ECER of the industry by improving innovation and changing the energy structure. To test this research hypothesis, we construct technological innovation (rd) and energy structure (erst) indicators as explained variables for regression (Table 7). We find that coefficient of robot is positive with innovation as the explained variable, indicating AI significantly improves the technology innovation of the industry. Columns (3) and (4) display the results with the energy structure as the explained variable. It can be found that the AI significantly reduces the proportion of coal consumption and optimize energy structure.

**Table 7.** Impact mechanism results.

| Variables | Technological innovation | | Energy consumption structure | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *robot* | 0.0568*** | 0.0638*** | -0.0095*** | -0.0129*** |
| | (2.6860) | (3.2068) | (-2.7939) | (-4.0052) |
| *size* | | -0.6376*** | | 0.1118*** |
| | | (-4.1670) | | (4.5230) |
| *eri* | | -0.0222 | | -0.0122** |
| | | (-0.7046) | | (-2.3994) |
| *cst* | | -1.6311*** | | -0.1924** |
| | | (-3.1745) | | (-2.3177) |
| *prst* | | -3.0915*** | | -0.1879 |
| | | (-3.1183) | | (-1.1732) |
| *imst* | | -1.3904*** | | -0.1080** |
| | | (-5.3485) | | (-2.5711) |
| *cons* | 0.4283*** | 7.3229*** | 0.5028*** | -0.3767 |
| | (3.7689) | (4.8969) | (27.4765) | (-1.5595) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.942 | 0.942 | 0.942 | 0.942 |
| N | 324 | 324 | 324 | 324 |

## *5.4. Heterogeneity analysis*

This paper explores in detail the heterogeneity of industrial robot usage from four aspects: pollution intensity, labor intensity, R&D intensity, and the nature of ownership.

(1) Distinguish industry pollution intensity

Coal is the most dominant source of primary energy consumed in China. Therefore, this paper divides the industry into high-polluting and low-polluting industries according to the average coal consumption of the industry in 2009. The sub-sample results are displayed in Table 8. We found that compared with low pollution industries, AI have a greater effect on emission reduction in high pollution industries.

**Table 8.** Pollution intensity heterogeneity.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | High-pollution industries | | Low-pollution industries | |
| *robot* | 0.0648*** | 0.0763*** | 0.0103 | 0.0010 |

| | | | | |
|---|---|---|---|---|
| | (4.4060) | (4.6666) | (0.9464) | (0.0945) |
| *size* | | 0.0236 | | 0.0243 |
| | | (0.2624) | | (0.1903) |
| *eri* | | 0.0303* | | -0.0821** |
| | | (1.9263) | | (-2.4032) |
| *cst* | | -0.4006 | | -0.1630 |
| | | (-1.3527) | | (-0.3958) |
| *prst* | | 0.9537 | | -2.1144*** |
| | | (1.4593) | | (-3.1371) |
| *imst* | | -3.1930*** | | -0.1933 |
| | | (-4.9188) | | (-1.6506) |
| *cons* | 0.7812*** | 0.5244 | 1.1575*** | 1.3977 |
| | (7.8095) | (0.6129) | (26.1299) | (1.1011) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.759 | 0.759 | 0.759 | 0.759 |
| N | 156 | 156 | 168 | 168 |

(2) Distinguish labor intensity

To discuss whether the effect of robot use on ECER is affected by the labor intensity of the industry, we distinguish the sample into labor-intensive and non-labor-intensive industries (Table 9). Although the effect of AI on ECER is positive in both labor-intensive and non-labor-intensive industries, this impact has a greater positive effect in labor-intensive industries. Therefore, in order to improve the effectiveness of ecological environment governance, local governments should appropriately strengthen the external environmental regulatory pressure of labor-intensive industries, and force enterprises to accelerate the use of industrial robots to achieve green production transformation.

**Table 9.** Labor intensity heterogeneity.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Labor-intensive industries | | Non-labor-intensive industries | |
| *robot* | 0.0482*** | 0.0483*** | 0.0243** | 0.0235* |
| | (4.5236) | (3.6085) | (2.0787) | (1.9466) |
| *size* | | -0.1609* | | -0.0267 |
| | | (-1.8200) | | (-0.2904) |
| *eri* | | -0.0083 | | -0.0067 |
| | | (-0.4462) | | (-0.3468) |
| *cst* | | 0.2142 | | 0.1253 |
| | | (0.6169) | | (0.3892) |
| *prst* | | -2.3931** | | -0.0487 |
| | | (-2.3667) | | (-0.0764) |
| *imst* | | -0.4540 | | -0.0731 |
| | | (-0.3622) | | (-0.5041) |
| *cons* | 0.9997*** | 2.7875*** | 1.0742*** | 1.3174 |
| | (23.5702) | (3.0978) | (15.4623) | (1.4462) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.749 | 0.749 | 0.749 | 0.749 |
| N | 96 | 96 | 228 | 228 |

(3) Distinguish R&D intensity

To test whether the impact of AI on ECER is different in industries with different R&D intensity, we use the proportion of industry R&D investment in industry sales value to measure R&D intensity (Table 10). The classification basis of the industry is: it defines a high R&D intensity industry when the R&D intensity exceeds the median. The regression results show that AI promote ECER in industries with high and low R&D intensity, but this positive promotion is greater in industries with low R&D intensity.

**Table 10.** R&D intensity heterogeneity.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | High R&D intensity | | low R&D intensity | |
| *robot* | 0.0324** | 0.0415*** | 0.0386*** | 0.0468*** |
| | (2.3922) | (2.7185) | (3.9115) | (4.5259) |
| *size* | | -0.1392 | | -0.0324 |
| | | (-1.0386) | | (-0.3603) |
| *eri* | | -0.0043 | | -0.0380** |
| | | (-0.1988) | | (-2.0617) |
| *cst* | | -0.3208 | | 0.6197** |
| | | (-1.0228) | | (1.9867) |
| *prst* | | -0.5362 | | -0.4377 |
| | | (-0.8291) | | (-0.8142) |
| *imst* | | 0.3018** | | -1.2353*** |
| | | (2.2029) | | (-2.6951) |
| *cons* | 1.0672*** | 2.4183* | 0.9824*** | 1.2834 |
| | (12.0011) | (1.9688) | (23.3501) | (1.4445) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.802 | 0.802 | 0.802 | 0.802 |
| N | 156 | 156 | 168 | 168 |

(4) Distinguish the types of industry ownership

Furthermore, we divide the data samples into different property rights structures according to the industry ownership type. In this paper, the structure of property rights is measured by the ratio of the total assets of state-owned enterprises in the industry to the total assets of industrial enterprises in the industry. If the property right structure of the industry is greater than the median, it is a state-led industry; otherwise, it is a non-state-led industry. The results reflect that the ECER effect of AI is more prominent in the state-led industries (Table 11).

**Table 11.** Ownership heterogeneity.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | State-owned leading industry | | Non-state leading industries | |
| *robot* | 0.0531*** | 0.0299** | -0.0000 | -0.0094 |
| | (4.3259) | (2.1072) | (-0.0044) | (-0.8209) |
| *size* | | 0.2920** | | -0.3208*** |
| | | (2.0678) | | (-5.1675) |
| *eri* | | -0.0154 | | 0.0041 |
| | | (-0.7593) | | (0.2793) |
| *cst* | | -0.6252 | | 0.0778 |
| | | (-1.0963) | | (0.4107) |
| *prst* | | -0.4717 | | -0.7512 |
| | | (-0.7912) | | (-0.6076) |
| *imst* | | -0.4035** | | -0.3034 |
| | | (-2.1001) | | (-0.7136) |
| *cons* | 0.9197*** | -1.1735 | 1.2134*** | 4.2585*** |
| | (13.7441) | (-0.8883) | (21.3646) | (7.2475) |

| | | | | |
|---|---|---|---|---|
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Ajusted $R^2$* | 0.928 | 0.928 | 0.928 | 0.928 |
| N | 167 | 167 | 156 | 156 |

### *5.5. Dynamic threshold regression model*

Porter hypothesis holds that the rising level of regional environmental regulation (ER) will force enterprises to adopt cleaner production technologies to reduce emissions. Different industries will face different levels of environmental regulation in different areas of China, which is subject to different economic growth and industrial structure (Hao et al., 2022). Will this have different incentives for the industry to use industrial robots to achieve green emission reduction? The test of this problem can also verify whether the Porter hypothesis is tenable. In this paper, the cost of polluting equipment per 10000 yuan of industrial sales value is used to measure the environmental regulation, and based on sample self-sampling method (bootstrap), the sample is divided into two groups: high ER industry and low ER regional industry. The threshold model is used to test the nonlinear effect of AI on ECER. All variables are significant following to the Wald test and P-value. Hence, the threshold effect of environmental regulation exists. It indicates that the impact of AI on ECER has nonlinear characteristics. Specifically, the positive impact of AI on ECER is gradually increasing with the strength of ER. Strict ER force enterprises to increase investment in R&D of environmental protection technologies, which indirectly encourages the popularize of industrial robots and improves the effectiveness of environmental governance.

**Table 12.** The results for the threshold effect.

| Variables | *eri* |
|---|---|
| *L.ECER* | 0.9924*** |
| | (33.41) |
| *size* | 0.0197*** |
| | (2.63) |
| *cst* | -0.0350** |
| | (-2.47) |
| *prst* | -0.0042*** |
| | (-6.42) |
| *imst* | 0.0101*** |
| | (4.50) |
| *_con* | -0.0207 |
| | (-0.81) |
| $robot(ER \leq C)$ | 0.0015** |
| | (2.05) |
| $robot(ER > C)$ | 0.0042*** |
| | (2.77) |
| *AR(2)* | -1.33 |
| | [0.185] |
| *Hansen test* | 27.50 |
| | [0.976] |
| *Wald test* | 47207.47 |
| | [0.000] |
| *N* | 324 |

## 6. Discussion

AI can promote ECER efficiency of the manufacturing industry. As the latest achievement of modern information technology advancement, industrial robots have the advantages of high efficiency and continuity. Robot can realize programmed intelligent manufacturing of enterprises, and conduct real-time monitoring of energy consumption and pollution in product production, which can regulate excessive pollution caused by improper use of energy in enterprises. The combination of industrial robot and big data expand the spatiotemporal scope of environmental monitoring, greatly reducing the difficulty and cost of collecting environmental information. The combination of AI and robotics increases access to environmental information. This extensive search and analysis capability greatly improves human perception and observation of environmental conditions. Additionally, the development of robots has spawned a series of environmentally friendly products, which have realized the source control of pollutants, thereby effectively improving ECER.

AI significantly reduces the proportion of coal consumption and optimize energy structure. The application of industrial robots is setting off a new green innovation revolution on a global scale. The role of robots in technological progress is mainly attributed to two aspects. First, industrial robots have a substitution effect on low-skilled labor, which increases the number of management and R&D personnel who are familiar with automated production. On the other hand, AI eliminates unreasonable work allocation in the R&D department of firm, and monitor the progress of R&D tasks. In addition, the intelligent robots provide convenience for enterprises to acquire relevant knowledge and skills of green production. It helps to improve technical performance and innovation process, and enhance the ability of enterprises to innovate green technology. Industrial intelligence has spawned new formats and models, updated the intelligent equipment and processes of enterprises, and promoted the efficiency of technological innovation. Industrial robots enable enterprises to improve production efficiency with the lowest energy consumption. The application of industrial intelligence enables enterprises to select alternative energy sources for production based on energy costs and supply conditions, reducing the consumption of fossil fuels and promoting energy transformation.

## 7. Conclusions

This work analyzes the impact mechanism and heterogeneity of AI on ECER efficiency. The results show that the AI significantly contribute to ECER efficiency. Technological innovation and energy consumption structure upgrading are two important influence mechanisms. The result of the threshold model reported a obvious contribution of the AI on ECER when the coefficient of the environmental regulation crossed the threshold. There exists an evident heterogeneous effect across industries with different pollution intensity, R&D intensity and labor intensity, and ownership dominant industries.

Manufacturing enterprises may benefit from the widespread application of artificial intelligence technology. First, AI technologies confer salient advantages in corporate energy conservation and emission mitigation. Manufacturing firms can monitor and regulate energy consumption with higher precision by adopting AI, enhancing energy efficiency and eliminating unnecessary waste. It reduces the operating costs of enterprises, and meets the government's policy requirements for sustainable development. Second, AI technologies can assist companies in attaining more efficient and sustainable production and management paradigms. Manufacturing firms need to proactively develop and introduce AI to boost production efficiency, curb energy expenditure and emissions, and minimize environmental footprints. Superior corporate environmental performance enhances corporate image and reaps long-term economic gains. According to the entire research, some relevant policy recommendations have been proposed to improve the environmental governance effectiveness of AI.

First, enterprises actively increase the process of manufacturing intelligentization and help enhance the efficiency of industrial green transformation. Enterprises need to accelerate the construction of smart factories and the green application of smart devices, and promote the green transformation of the manufacturing industries to green optimization solutions based on collaborative production networks. Moreover, enterprises need to invest more funds in the R&D of industrial robots, and actively cultivate new formats and new models of industrial intelligence, thus promoting the large-scale application of green and intelligent technology in various fields of manufacturing. Further, government departments should also speed up the formulation of green development-oriented industrial intelligence development strategies. Under the strategic background of the international dual cycle, the government can use industrial intelligent technology to achieve efficient connection between supply and demand ends, form new competitive advantages in foreign trade, and promote industrial intelligent transformation (Yang and Khalid, 2023).

Second, government advocates the indirect driving role of technological innovation in ECER. On the one hand, relying on robots to increase the R&D process of industrial green energy-saving technology, improve the maturity of industrial green technology and realize large-scale application. This can realize the substitution of green technology for traditional technology on a large scale, and drive the great improvement of green technology innovation ability through institutional innovation. On the other hand, guide industrial intelligence to augment energy efficiency and speed up the process of replacing traditional energy with new energy. Moreover, it is necessary to promote the application of AI in green energy conservation, pay attention to the demand for mass customization of industrial products, and comprehensively improve energy efficiency.

At last, enterprises should increase the level of AI and improve the efficiency of resource utilization. Industrial robots are a strong driving force for industrial transformation and upgrading. Relying on industrial robots, enterprises should increase capital investment in improving resource utilization efficiency, and practice the concept of green development. In addition, enterprises should promote the development of AI, promote technological upgrading, and strengthen the application and promotion of green technologies. This is conducive to fundamentally making the low-carbon restraint effect greater than the driving effect. In addition, the government should guide energy structure adjustment through industrial policy and vigorously develop clean energy. Particularly, it is necessary to reduce excessive dependence on coal. Local governments should stimulate wind energy, biomass energy and other clean energy sources according to local conditions, vigorously advocate the use of clean energy.

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## Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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