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Does AI Application Matter in Promoting Carbon Productivity? Fresh Evidence from 30 Provinces in China

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Abstract: Artificial intelligence (AI) is an important force leading to a new round of scientific and technological revolution, as well as promoting the realization of the dual carbon goals of China. Determining how to take advantage of AI during the green industrial transformation and propelling participation in global value chains are of great importance to China. In this paper, we carefully study the influencing mechanism. The Batik Variable Method is then applied to measure robot penetration in the industries across 30 provinces in China from 2010 to 2019. Furthermore, intermediate and threshold effect models are constructed using three crucial variables. The estimates reveal critical findings: firstly, the application of AI has a significant positive effect on carbon productivity, and this conclusion is still valid after a series of robustness tests. Secondly, a heterogeneity test shows that, compared with the central and western regions, AI application in the east has a stronger and more significant effect on carbon productivity over time. Thirdly, the optimization of human capital and improvement of innovation level both play partial mediating roles in this process, and manufacturing agglomeration has a nonlinear adjustment effect on the positive relationship between AI application and carbon productivity. The conclusions of this study provide references for further optimizing and expanding the application scenarios of AI, thereby contributing to high-quality economic development in China.

Keywords: AI; carbon productivity; intermediate effect; nonlinear regulation effect; threshold effect model

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1. Introduction

Carbon emissions have become a "by-product" accompanying the success of human society, greatly heightening the severity of global warming [1]. However, despite important environmental considerations regarding this, fossil fuels will remain the world's primary energy source for the foreseeable future [2]. Using DICE-2023, a revised dynamic integrated climate and economy model (DICE) updated until 2023, Barrage et al. (2023) propose that the damage factor of rising global temperatures has nearly tripled compared to DICE-2016, resulting in a major increase in the social cost of carbon [3]. Especially in the post-COVID-19 era, countries worldwide are under enormous pressure for economic recovery, resulting in environmental regulations and taxes being rolled back in many countries [4]. This endangers the achievement of the Paris Agreement on climate change, as well as the related Sustainable Development Goals [5]. AI, characterized by high permeability, synergy, and multiplication, is often seen as a potential solution to address these challenges [6]. According to a report by the Boston Consulting Group, the use of AI helps reduce greenhouse gas emissions by 5–10% for a single organization, and if scaled globally, the reduction could be 2.6 to 5.3 billion tons of carbon dioxide equivalent [7]. The application of AI seems to provide a new approach to achieving green economic recovery [8].

China has maintained its position as the world's second-largest economy since 2010. At the same time, China's primary energy consumption has topped the world for 13 consecutive years by 2021, peaking at 157.65 EJ in the newest report, of which coal and oil account for 54.66% and 19.41%, respectively. The "high-carbon" character of economic growth is obvious. In response to this, China is promoting a change in the economic development mode to achieve sustainable growth, setting dual carbon targets of reaching the carbon peak by 2030 and carbon neutrality by 2060. According to the "CO_2 Emissions in 2022" report released by the IEA (International Energy Agency), although energy-related CO_2 emissions increased by 0.9% globally, China's carbon dioxide emissions in 2022 totaled 11,477 million tons, which was 0.2% lower than in 2021. However, from the perspective of China's economic development status and energy structure, realizing the dual carbon targets still needs advanced technical support to reduce uncertainty [9]. As a leading technology with "head goose" effects in a new round of scientific and technological revolution, AI is often seen as an important strategic starting point for China to transform from a manufacturing giant to a manufacturing power. Does the application of AI provide a new solution for the economic growth problem under the pressure of the dual carbon targets in China? Is there any heterogeneity in China? How does its internal mechanism work?

There have been many studies that focus on the economic benefits of AI application, providing both theoretical and empirical foundations for this study. Li et al. (2020) verified that AI application significantly enhances total factor productivity in China by promoting technological progress [10]. At the micro level of China A-share manufacturing listed companies, Fan et al. (2020) found that AI can significantly improve enterprise productivity through factors such as labor quantity, physical capital use efficiency, and innovation output [11]. Moreover, the impact of AI application on the job market is another research hot-spot. Acemoglu et al. (2018) believed that, from the perspective of science and technology history, the positive effects on jobs brought by technological progress are greater than the shock, a mechanism also applicable to the fourth industrial revolution represented by AI [12]. However, Cao et al. (2023) conducted research and pointed that the relationship between AI application and the manufacturing industry's employment in China is U-shaped [13]. Qiu et al. (2023) also proved that, although the application of AI has significantly reduced the employment scale of the labor force, the requirements for high-skilled labor have increased [14]. This is called the employment polarization effect, which means higher requirements are put forward for the level of human capital [15,16].

Another part of this research field examines the carbon emission effects brought about by AI application. Xue et al. (2017) argued that the rapid development of advanced technology, represented by AI, has had a huge impact on the traditional fossil-based environmental governance system [17]. Liu et al. (2022) indicated that, despite limitations in large-scale carbon neutrality transition using AI techniques, the future is still promising [18]. Based on panel data from 270 cities in China, Chen et al. (2022) empirically verified that AI application contributes to reducing carbon emissions by optimizing industrial structure, strengthening information infrastructure, and improving green technology innovation [19]. Xu et al. (2023) also proved that technological innovation led by AI plays an important part in carbon emission reduction [20]. Priya et al. (2023) proposed an AI framework for CO2 capture and storage [21]. In addition, as an important manifestation of advanced industrial development, industrial agglomeration contributes to the technology spillover effect, scale effect, and competition effect, all of which are significant for carbon emission reduction [22,23]. However, conclusions on this are not consistent. Some argue that with the exogenous technological progress brought by industrial agglomeration, firms would be stimulated to expand outputs, leading to a possible rebound effect of carbon emissions [24]. Moreover, once agglomeration rises beyond a certain threshold, the entry and growth of new enterprises are hindered, and the scale effect would be exceeded by the crowding effect, leading to an increase in carbon emissions [25].

However, empirical studies that combine economic as well as carbon emission benefits are notably lacking, and this may lead to a deviation in policy orientation. The application of AI injects new momentum into our entire society, and sustainable development should be a part of the process. For China, the high-quality development task also asks for an environmentally friendly economy. Therefore, the concept of carbon productivity should be attached to overcome these limitations, and the influencing mechanism should also be identified. To sum up, this paper attempts to make breakthroughs in the following aspects. Firstly, a new integrated unified analysis framework is constructed that focuses on the internal mechanism of AI application and carbon productivity. Secondly, based on panel data from China, the effects of AI application on carbon productivity are demonstrated empirically. Thirdly, the intermediate effects of human capital and the innovation level, as well as the nonlinear regulation effect of manufacturing agglomeration, are further tested. This work provides theoretical support for AI-related policies in China.

The layout of this work is as follows: Section 2 explains the theoretical hypotheses. Section 3 describes the model, framework, variables, and data sources. Section 4 presents the empirical results. Section 5 provides discussion and limitations. Section 6 presents the conclusion, respectively.

2. Theoretical Analysis and Hypothesis

2.1. Direct Impact of AI Application on Carbon Productivity

From Alpha Go's "human–machine chess" to Chat GPT's "human–machine dialogue", AI technology, which takes machine learning as its core, is constantly refreshing human cognition. The impact of AI application on carbon productivity mainly works through the following aspects: (1) AI application injects new momentum into social production. On one hand, the use of AI helps to automate complex tasks, transparentize the production processes [26], and rationalize resource allocations, thereby improving production efficiency [10]. On the other hand, the real-time data collection and matching functions of AI facilitate the integration and supply of fragmented information for enterprises [27]. This helps to realize accurate matching between upstream and downstream industrial chains as well as enhance coordination and reduce redundancy [28]. (2) AI is an important support for increasing carbon productivity. In addition to providing technical support, AI also promotes source governance and industrial transformation in traditional high-consumption and high-emission key industries [29]. Meanwhile, the constantly updated end-treatment methods of carbon capture and reuse have greatly contributed to the pushing of cleaner production [30]. (3) AI technology improves the adaptability of the dual carbon policy. With the updating of algorithm technology and theory in big data, cloud computing, and other related fields, AI has already been embedded into the government and can be used to follow and analyze the carbon footprints in all links in the value chain [31]. These have become important means for AI to drive the green economy. Thus, Hypothesis 1 is proposed.

H1. *AI application helps increase carbon productivity.*

2.2. Intermediate Transmission Mechanisms of AI Application That Affect Carbon Productivity

According to the analysis above, the use of AI has a promoting effect on carbon productivity, and this effect may be transmitted through different intermediaries. Based on the existing literature, this paper further discusses this concept from the following two perspectives.

Firstly, the rapid development of AI will inevitably shock employment. This will first be manifested as the "substitution effect". That is, due to the "procedural bias" characteristic of AI, repetitive work is the work most easily replaced [32]. New work tasks and employment opportunities can also be created with the use of new technology [31], which is named the "job creation" effect; however, the employment effect of AI in China is still mainly manifested as the substitution effect at present [33]. This means that intense competition and higher requirements coexist in the Chinese labor market. A study by Kang et al. (2021) [34] confirmed that the use of AI promotes the upgrading of China's employment structure. As a traditional production factor itself, investment in high-level labor can optimize production and technology transformation efficiency and can thus promote the improvement of carbon productivity [35]. Therefore, Hypothesis 2a is proposed.

H2a. *AI application has a positive impact on carbon productivity by improving human capital.*

Secondly, according to the creative destruction theory by Schumpeter (1934) [36], technological progress is the basic force driving economic growth in the long term. As an innovative shared technology, AI can eliminate obsolete production methods, promote new business forms and new models, and automate complex tasks [29]. In addition, the spillover and demonstration effects of innovation activities themselves further stimulate the motivation of R&D in enterprises, forcing enterprises to absorb, develop, and utilize new technologies [37]. Studies have proven that technological innovation has a significant effect on the growth of carbon productivity [38]. Accordingly, Hypothesis 2b is proposed.

H2b. *AI application has a positive impact on carbon productivity by improving innovation levels.*

2.3. Nonlinear Regulating Effect of Manufacturing Agglomeration on AI Application and Carbon Productivity

Manufacturing agglomeration and the dual carbon commitment are essential for China's manufacturing power construction and sustainable development, respectively. Therefore, manufacturing agglomeration needs to be considered when exploring the impact of AI application on carbon productivity. Firstly, the externality theory by Marshall (1890) holds that firm clusters are conducive to promoting a specialized division of labor [39]. Secondly, according to the Core and Periphery Theory by Krugman (1991), industrial agglomeration is a spatial organization that has the joint drives of both internal centripetal and centrifugal forces [40]. It performs both innovation resource spatial convergence and economic activity spatial expansion. Thus, a scale effect, competitive advantage effect, and knowledge spillover effect are generated, which effectively reduce the production or transaction costs among enterprises in a cluster and improve the utilization and reuse of resources [41,42]. Moreover, technological progress and competitive pressure also force enterprises to engage in green production behaviors, which are necessary to enhance differentiated competitive advantages and social reputation [43]. However, agglomeration does not necessarily lead to the improvement of carbon productivity [44]. This is because when the agglomeration exceeds a certain degree, it causes a series of negative congestion effects [45], such as rising factor costs, traffic congestion, and structural rigidity, all of which lead to increased energy consumption, ecological environment deterioration, and other problems [46]. These issues hinder the improvement of carbon productivity and are not conducive to the sustainable development of the social economy. Based on the analysis above, Hypothesis 3 is proposed, and the theoretical framework is shown in Figure 1.

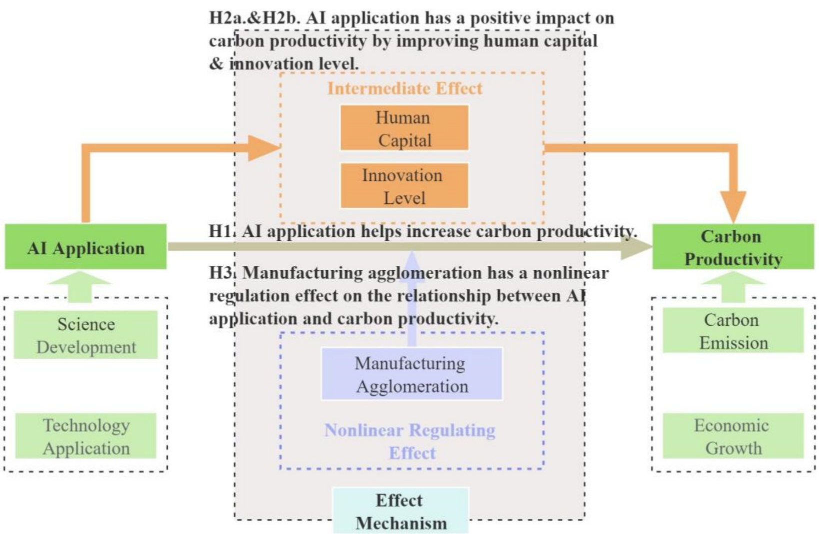

Figure 1. Conceptual theoretical diagram. This figure was created by the authors.

H3. *Manufacturing agglomeration has a nonlinear regulation effect on the relationship between AI application and carbon productivity.*

3. Materials and Methods

3.1. Empirical Model Construction

The theoretical framework states that the application of AI affects carbon productivity, and that this process is further affected by intermediate and nonlinear regulating effects. Based on the theoretical analysis, this study establishes the following regression equations to test our hypotheses:

$$CP_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Con_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

where *CP* denotes the carbon productivity. The prefixes *i* and *t* demonstrate the province and the year, respectively. *AI* represents the level of AI application, which is the core explanatory variable in this paper. *Con* is the control variable group. λ and μ are added to the model to capture the fixed effects of the province and year. β and ε are a parameter to be estimated and a random error term, respectively.

Equation (1) shows the immediate impact of AI application on carbon productivity. Referring to the causal stepwise regression method proposed by Baron and Kenny (1986) [47], the variables of human capital and the innovation level are then added to the accompanying intermediate effect model as mediation variables (*Meds*) to further study the possible implicit impact pathways.

$$Med_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 Con_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (2)$$

$$CP_{it} = \phi_0 + \phi_1 AI_{it} + \phi_2 Med_{it} + \phi_3 Con_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (3)$$

To further examine the nonlinear effects of manufacturing agglomeration on the relationship between AI application and carbon productivity, the method proposed by Hansen (1999) [48] is adopted to construct the threshold effect model.

$$\begin{aligned} CP_{it} = {} & \varphi_0 + \varphi_1 AI_{it} \times I(Mad_{it} \le \theta_1) + \varphi_2 AI_{it} \times I(\theta_1 < Mad_{it} \le \theta_2) + \cdots \\ & + \varphi_n AI_{it} \times I(\theta_{n-1} < Mad_{it} \le \theta_n) + \varphi_{n+1} Con_{it} + \lambda_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (4)$$

where *Mad* represents the threshold variable. $I(\cdot)$ denotes the indicator function, and its value is 1 if the condition in parentheses is met; otherwise, the value is 0.

3.2. Variable Definitions

3.2.1. Explained Variable: Carbon Productivity (CP)

By referring to Sun et al. (2020), the ratio of the provincial GDP to the total carbon emissions is used to represent the carbon productivity [49]. The equation is shown in Equation (5).

$$CP_{it} = \frac{GDP_{it}}{TC_{it}} \quad (5)$$

where the prefixes *i* and *t* demonstrate the province and year, respectively. *GDP* and *TC* are the Gross Domestic Product and total carbon emissions at the provincial level. By referring to the calculation method of the IPCC (Intergovernmental Panel on Climate Change, 2006) [50], the consumption of eight kinds of energy (*EC*), including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, is measured and multiplied by carbon emission coefficients (*COs*). Then, the final carbon emissions can be obtained by adding up all these results. The equation is shown in Equation (6).

$$TC = \sum_{n=1}^{8} TC_n = \sum_{n=1}^{8} EC_n \cdot CO_n \quad (6)$$

Using the drawing software of Origin 2021, Figure 2 indicates that China's carbon productivity enjoyed a steadily increasing trend during the study period, with the highest growth rate occurring in 2013. Since 2015, the growth rate has declined. Meanwhile, despite the positive trend in carbon productivity, the spatial differences are significant. Figure 3 illustrates that the high-carbon-productivity areas are mostly concentrated in the southeast coastal and middle reaches of the Yangtze River, while northern provinces generally have lower carbon productivity. The maximum value appears in Beijing, which is nearly 17 times the minimum value. This may be because the northern region is rich in coal, steel, and other resources, making it a major hub for China's old heavy industries. In particular, the Yellow River Basin is known as the "energy basin" and used to have a tradition of extensive use and excessive consumption of resources. However, facing a situation of declining energy quality and strict environmental regulation, these provinces must determine how to achieve sustainable economic development goals. While relying on the advantages of the reform and opening-up policy, provinces in the southeast coastal and middle reaches of the Yangtze River have continuously improved economic and technological levels. In particular, the Yangtze River Delta and Pearl River Delta are gradually eliminating low-end production and processing and are moving toward high-end manufacturing links such as research and development. It is also worth noting the outstanding performance of Beijing in carbon productivity. As the capital of China, as well as its political and economic center, Beijing's economic development is characteristic of tertiary industry. Combining strict and perfect carbon control measures, such as updating general manufacturing enterprises, eliminating old motor vehicles, and promoting new energy vehicles, has contributed to the unique advantage of Beijing.

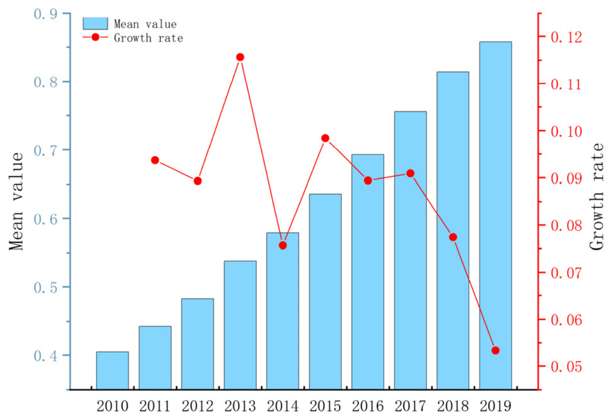

Figure 2. The mean value and growth rate of carbon productivity from 2010 to 2019 in China. This figure was created by the authors.

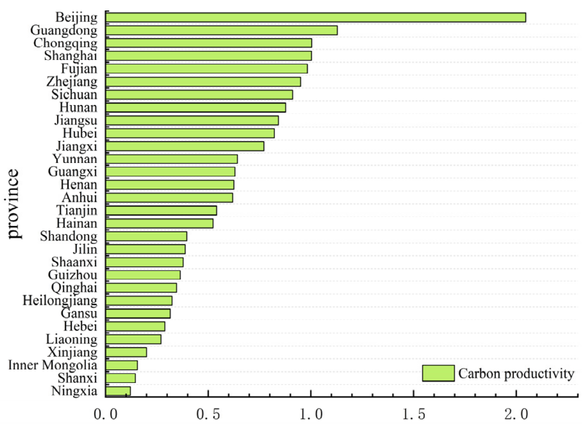

Figure 3. The mean values of carbon productivity from 2010 to 2019 in 30 provinces of China. This figure was created by the authors.

3.2.2. Core Explanatory Variable: AI Application (AI)

As a representation of AI application, AI penetration is an expression of AI density [51]. Therefore, based on the works by Acemoglu et al. (2020) [33] and Wang et al. (2020) [52], the Batik Variable Method is adopted to construct China's provincial-level industrial robot penetration as a proxy variable for AI application. The basic process is as follows. First, the classification system of the IFR (International Federation of Robotics) is matched with the Classification of National Economic Industries (GB/T4754-2011). By referring to Yan et al. (2021) [43], this paper divides the industries into six categories. Industries not specified by the IFR are not included in industry matching, and data of robot stock and employment of corresponding industries that cannot be clearly classified are excluded. Then, taking the employment situations of different industries in each province as weights, the industrial robot penetration at the provincial level is further calculated. Specific equations and the decomposition are shown in Equations (7) and (8):

$$AI_{it} = \sum_{j=1}^{n} \left(\frac{L_{ijt}}{L_{it}} \times R_{jt}\right) \tag{7}$$

$$R_{jt} = \frac{Rob_{jt}}{L_{jt}} \tag{8}$$

where AI denotes AI penetration; the prefixes i, j, and t represent the province, industry, and year, respectively; and n represents the collection of industries. L_{ijt}/L_{it} is the employed proportion of industry, j, in the total number of urban employment, which is used as the weight to measure the contribution of the penetration of different industries. R_{jt} is the robot density of industry, j, equal to the ratio of robot ownership (Rob_{jt}) and employment (L_{jt}).

In order to further explore the spatio-temporal evolution characteristic of AI penetration, taking the years 2013, 2016, and 2019 as examples, the Natural Breaks Method of Arc MAP10.8 software is used to make a spatial visualization mapping of AI penetration, as shown in Figure 4. From the perspective of time evolution, the development level of China's AI penetration is gradually improving overall. The minimum value of AI penetration increased from 1.042 in 2013 to 13.798 in 2019, and the maximum value increased from 16.0589 in 2013 to 119.344 in 2019. From the perspective of spatial evolution, China's AI penetration shows a decreasing trend from east to west. High-AI-penetration areas are mostly concentrated in the east coastal and middle reaches of the Yangtze River, while provinces in the west generally have lower AI penetration. As the leading area of China's opening up, the regions in the east have advantages in factors and institutional endowments, creating a good environment for cultivating and applying AI technology. Industrial optimization and core competitiveness, shaping motivations, are always strong in this area. However, the central and western regions, constrained by resource allocation and industrial base, have relatively limited use of AI. For the time evolution, the provinces with AI penetration in the high- and low-value regions are relatively stable. Specifically, Shanghai, Guangdong, Tianjin, and Jilin are almost always in the high-value areas, indicating that these areas have long been at the forefront of AI application in China. The Yangtze River Delta and the Pearl River Delta, as windows of China's opening up, undoubtedly have unique advantages in technology introduction and research and development. Tianjin and Jilin, being both early adopters and big industrial provinces in northern China with strong industrial foundations, prominently use AI with the support of policies and funds. The AI penetration in Hubei and Chongqing is maintained at the level of the middle- and high-value areas, making them leaders in AI application in the central and western regions of China. This is closely related to the industrial characteristics of the two provinces, oriented towards automobile manufacturing and production research and development.

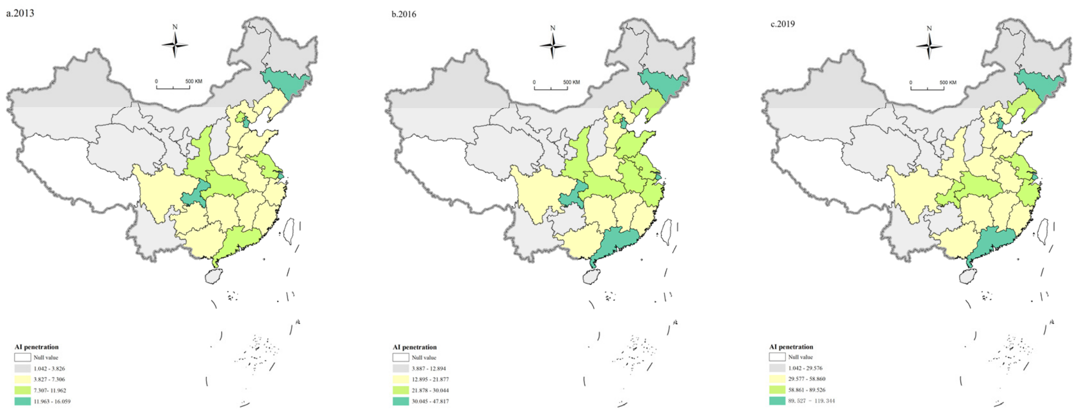

Figure 4. Spatial distribution of AI penetration in China. This figure was created by the authors.

3.2.3. Mediating Variables

Human capital (*HC*): college students with higher education are an important source of high-quality labor for China, determining the level of the labor force to a large extent [53]. Therefore, *HC* is represented by the number of students enrolled in ordinary colleges and universities.

Innovation level (*Inn*): enterprises are important innovation subjects [54]. Enterprises above designated sizes tend to pay more attention to technology in order to further enhance their advantages [55]. *Inn* is expressed as the expenditure of industrial enterprises above a designated size to develop new products.

3.2.4. Moderator Variables

The agglomeration degree of the manufacturing industry (*MA*) is measured using the location entropy proposed by Combes (2000) [56]. The specific equation is shown in Equation (9):

$$Mad_{it} = \frac{ML_{it}/L_{it}}{ML_t/L_t} \tag{9}$$

where ML_{it}/L_{it} and ML_t/L_t denote the proportion of manufacturing employees in the total number of employees in province, i, and the whole country, respectively.

3.2.5. Control Variables

To alleviate endogeneity problems related to missing variables, this paper adds the following control variables to the empirical model, referring to relevant studies [57]. The urbanization level (*Urb*) is expressed as the share of the urban population in the total population [57]. The economic development level (*PGDP*) is represented by the per capita GDP [58]. The degree of opening up (*Ope*) is measured using the total export–import volume [59]. The level of industrialization (*Ind*) is represented by the ratio of industrial added value to GDP [60]. Education support (*Edu*) is measured using education spending [61].

3.3. Study Area, Data Sources, and Software

This paper adopts 30 provinces of China as the research object (Tibet, Macao, Hong Kong, and Taiwan are not considered for the time being due to serious data deficiencies). The original data of the industrial robot stock comes from the IFR. Employment-related data are derived from the China Labor Statistics Yearbook. Data on carbon emissions are mainly obtained from the China Energy and Environmental Statistical Yearbook. In addition, data for other variables come from the official website of the National Bureau of Statistics, the China Statistical Yearbook, and provincial statistical yearbooks. In this paper, all the economic variables are adjusted for constant prices based on 2010, and missing values of individual data points are estimated using an interpolation method. In addition, although the IFR data on China's industrial robots began in 2006, the relevant data showed a relatively obvious upward trend only after 2010, so the study period of this paper is set from 2010 to 2019. To eliminate the effect of heteroscedasticity, the innovation level, opening up, and education support are logarithmically processed. Table 1 includes the data sources and measurement units.

Table 1. Data sources and measurement units.

Variable Types	Abbreviations	Definition	Unit	Source
Explained variable	*CP*	Carbon productivity	10 million yuan per thousand tons	Statistical Yearbook
Core explanatory variable	*AI*	AI penetration	per 1 million people	IFR Statistical Yearbook
Mediating variables	*HC* Ln*Inn*	Human capital Innovation level	per thousand people 10 thousand yuan	Statistical Yearbook
Moderator variables	*MA*	Manufacturing agglomeration	/	
Control variables	*Urb* *PGDP* Ln*Ope* *Ind* Ln*Edu*	Urbanization level Economic development Opening up Industrialization Education support	/ 10 thousand yuan 10 thousand yuan / 10 thousand yuan	

Table 2 reports the descriptive statistics for all variables. The average carbon productivity (*CP*) is 0.620, ranging from 0.112 to 3.082, with a standard deviation of 0.444. The overall level of carbon productivity in China is relatively low, with notable disparities among provinces [62]. The average AI penetration (*AI*) is 19.096, ranging from 0.607 to 119.334, with a standard deviation of 22.283, suggesting high volatility. According to Zhou's study (2022), AI penetration in China has increased steadily every year and is positively correlated with the economic development degree of each province [63]. At the provincial level, both human capital (*HC*) and the innovation level (Ln*Inn*) have notable standard deviations, highlighting significant differences among sampled provinces. With the in-depth implementation of strategies, such as "strengthening the country with talents" and "rejuvenating the country with science and technology," the quality of human capital and R&D expenditure in China are on the rise. However, at the same time, the quality of human capital in the east is significantly higher than that in the central and western regions, and the distribution of innovation factors is unbalanced and insufficient [64,65]. The average manufacturing industry (*MA*) is 0.835, ranging from 0.292 to 1.824, with a standard deviation of 0.346. Although promoting advanced manufacturing agglomeration is one of the important means for China to realize high-quality economic development, regional differences are also noteworthy [66]. Other control variable characteristics align with the current literature [57–61].

In addition, Stata 16, a data processing software that allows the creation of models by typing in commands accordingly, will be used to study the variables as parameters. It is seen as the best and least demanding method available to date [67]. Therefore, data are processed via Stata 16 software in the following empirical analyses. Moreover, as an efficient geographic information processing instrument, Arc MAP10.8 software is employed to draw maps, and the Natural Breaks Method is mainly used in this paper. Other figures are created using Origin 2021 software.

Table 2. Descriptive statistics.

Abbreviations	(1) OBS	(2) Mean	(3) Sd	(4) Min	(5) Max
CP	300	0.620	0.444	0.112	3.082
AI	300	19.096	22.283	0.607	119.344
HC	300	1.354	2.962	0.001	25.994
Ln*Inn*	300	14.261	1.392	10.41	17.47
MA	300	0.835	0.346	0.292	1.824
Urb	300	0.577	0.126	0.338	0.896
PGDP	300	1.259	0.781	0.476	4.712
Ln*Ope*	300	17.189	1.56	12.837	20.392
Ind	300	0.330	0.085	0.113	0.556
Ln*Edu*	300	15.950	0.690	13.810	17.711

3.4. Preliminary Empirical Observation

Before analyzing the estimation results, a trend chart of carbon productivity and AI application was first drawn by Stata 16 (Figure 5). It was found that the correlation between carbon productivity and AI application was visibly positive.

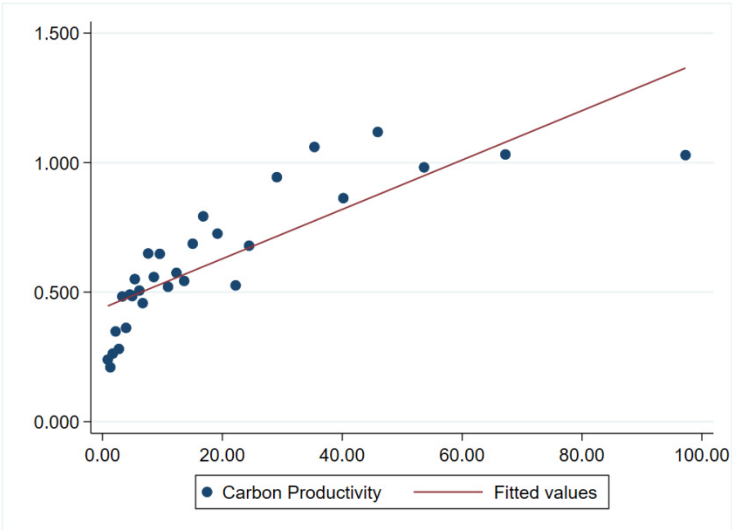

Figure 5. The relationship between AI application and carbon productivity. This figure was created by the authors.

4. Empirical Results

4.1. Baseline Regression

First of all, the variance inflation factor (VIF) test should be conducted to avoid multicollinearity since high correlation of the independent variables in the regression model would make the estimation effect unstable [68]. Then, the F test and Hausman test follow, aiming to verify whether fixed effects or random effects are more applicable to make the results more credible [69]. Using the data processing software STATA 16.0, the VIF test results are 4.07 (<10), which mean that the collinearity of the index is acceptable. The results of the F test and Hausman test in Table 3 show that all the null hypotheses were rejected at the 1% level, meaning the time-individual fixed effect model was the optimal choice. Then, *AI* was further used as the core explanatory variable, and Stata16 was again employed to estimate the parameters of the time-individual fixed effect model as well as those of the OLS and FE models. The results are shown in Table 3. Columns (2)–(7) are the results of the fixed effect stepwise regression method. They indicate that the significance and influence degrees of the core explanatory variable, as well as the control variables, had no significant change after adding the control variables one by one. Column (7) shows that after adding all control variables, for each unit increase in *AI*, the *CP* will change by 0.002 units, and this is significant at the 1% level. This means that improving the use level of AI will significantly improve carbon productivity. In terms of control variables, Column (7) of Table 2 shows that all control variables had a significant impact on carbon productivity. The effect of the urbanization level was negative, and the others were positive.

The study results strongly confirm that H1 is valid.

Table 3. Baseline regression results.

Variables	**OLS**	**FE**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
AI	0.005 *** (5.21)	0.004 *** (4.85)	0.002 ** (2.08)	0.003 *** (3.92)	0.002 *** (2.95)	0.002 *** (3.12)	0.002 *** (2.89)
Urb	−1.341 *** (−4.43)		−2.869 *** (−4.59)	−1.315 *** (−2.78)	−1.907 *** (−3.71)	−1.717 *** (−3.34)	−2.265 *** (−3.83)
PGDP	0.440 *** (9.53)			0.860 *** (14.77)	0.827 *** (14.05)	0.885 *** (14.23)	0.818 *** (11.43)
ln*Ope*	−0.001 (−0.03)				0.080 *** (2.75)	0.074 ** (2.57)	0.078 *** (2.72)
Ind	−0.744 *** (−3.17)					0.641 *** (2.65)	0.632 *** (2.62)
ln*Edu*	0.240 *** (5.11)						0.190 * (1.85)
Constant	−2.829 *** (−5.51)	0.394 *** (15.73)	1.888 *** (5.78)	0.064 (0.24)	−0.923 ** (−2.06)	−1.231 *** (−2.69)	−3.865 ** (−2.58)
Province FE	NO	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES	YES	YES
Observations	300	300	300	300	300	300	300
R_squared	0.607	0.595	0.625	0.797	0.803	0.808	0.811
F test				64.54 ***			
Hausman test				19.41 ***			

Note: the values between parentheses are the standard errors of regression coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2. Robustness Test

The existence of the endogeneity problem can make results biased and inconsistent. In order to verify the reliability of the baseline regression results, referring to relevant studies [70,71], the following three methods are used to test robustness, and the results are shown in Table 4. Method 1: Winsorization (W). In this paper, the explained variable and core explanatory variable were tailored at the 1% level to mitigate the potential impact of extreme samples on the global regression results. The results are shown in Column (1). Method 2: replacing the core explanatory variable (RCE) and the explained variable (RE), respectively. To replace the core explanatory variable, referring to the seven types of international patent classification methods for AI in the Reference Relation Table of Strategic Emerging Industries Classification and the International Patent Classification (2021) issued by the China State Intellectual Property Office, this paper manually collected and determined the number of AI patent applications in each province from 2000 to 2019. As a proxy indicator for AI application, the regression results are shown in Column (2). To replace the core explanatory variable, industrial added value was used to replace GDP, and then carbon productivity was recalculated. The regression results are shown in Column (3). Method 3: the instrumental variable method (IV). Considering that there may be a lag in the effect of AI application on carbon productivity, this paper adopted the lag phase of AI penetration as the explanatory variable, and the research results are shown in Column (4).

Table 4. Robustness check.

Variables	Method 1 W (1)	Method 2 RCE (2)	RE (3)	Method 3 IV (4)
AI	0.003 ***	0.012 ***	0.001 ***	0.002 ***
	(4.13)	(3.07)	(0.00)	(2.98)
Urb	−1.686 ***	−2.434 ***	0.242 *	−2.440 ***
	(−3.03)	(−4.40)	(0.15)	(−4.04)
PGDP	0.615 ***	0.695 ***	0.127 ***	0.734 ***
	(9.15)	(9.20)	(0.02)	(10.70)
ln*Ope*	0.073 ***	0.099 ***	0.020 ***	0.052 *
	(2.69)	(3.63)	(0.01)	(1.84)
Ind	0.408 *	0.570 **	0.277 ***	0.583 **
	(1.80)	(2.37)	(0.06)	(2.54)
ln*Edu*	0.290 ***	0.173 *	0.071 ***	0.274 ***
	(2.99)	(1.67)	(0.02)	(2.69)
Constant	−5.286 ***	−3.684 **	−1.651 ***	−4.115 ***
	(−3.76)	(−2.46)	(0.37)	(−2.83)
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	300	300	300	270
R_squared	0.807	0.811	0.716	0.968

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The results above show that the regression results of these test methods were basically consistent with the baseline regression, indicating that the positive effect of AI application on carbon productivity in Chinese provinces is robust.

4.3. Heterogeneity Test

As a statistical concept, heterogeneity analysis is often used to evaluate and quantify differences within a study's results [72]. Though the spatio-temporal evolution analysis above, regional spatio-temporal differences in AI application and carbon productivity in China were determined to be significant. In particular, "accelerating the cultivation and expansion of emerging industries, including AI" was written into China's Government Work Report in 2017, followed by the rapid introduction of the New Generation of AI Development Plan, making the development of AI part of the national strategy. Based on these objective circumstances as well as the study by Huang et al. (2022) [73], this paper used 2017 as a boundary and divided the research period into two parts.

Moreover, given the significant regional differences in China's level of economic and technological development, the impact of AI application on carbon productivity is likely to be both temporally and regionally heterogeneous. Therefore, referring to the regional division method of the National Bureau of Statistics in China, this paper divided the research regions into two groups: the eastern and the central-western regions. A heterogeneity analysis was conducted for 2010–2016 and 2017–2019. The results are presented in Table 5.

As seen in Columns (1) and (3) of Table 5, during the period from 2010 to 2016, the regression coefficient of *AI* in eastern China was 0.002, but this was not significant. In central and western China, the regression coefficient was 0.008, and the positive effect was significant at the 1% level. Columns (2) and (4) show that for the period from 2017 to 2019, the regression coefficient of *AI* in eastern China not only increased to 0.006 but was also significant at the 5% level. At the same time, although the regression coefficient of *AI* in central-west China was still significant, it decreased to 0.002.

The results confirm that the regional and temporal heterogeneity of the impact of AI application on carbon productivity in Chinese provinces was obvious.

Table 5. Heterogeneity analysis.

Variables	East		Central–West	
	2010–2016 (1)	2017–2019 (2)	2010–2016 (3)	2017–2019 (4)
AI	0.002 (1.04)	0.006 ** (2.74)	0.008 *** (4.27)	0.002 * (1.98)
Urb	−4.123 *** (−6.93)	−2.933 (−1.12)	−0.623 (−0.53)	5.558 ** (2.52)
PGDP	1.042 *** (12.74)	0.362 ** (2.36)	0.820 *** (2.76)	−0.073 (−0.30)
ln*Ope*	−0.170 ** (−2.10)	0.749 * (1.99)	0.030 (0.92)	0.052 (1.12)
Ind	3.644 *** (7.69)	2.018 (1.75)	0.247 (0.82)	−0.974 (−1.32)
ln*Edu*	−0.109 (−1.21)	0.534 (1.22)	0.214 (1.45)	0.122 (0.53)
Constant	4.789 *** (2.92)	−21.230 ** (−2.68)	−3.908 * (−1.86)	−4.973 (−1.40)
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	77	33	133	57
R_squared	0.959	0.840	0.750	0.779

Note: provinces in the east are Beijing, Liaoning, Hebei, Shandong, Hainan, Tianjin, Jiangsu, Zhejiang, Fujian, Shanghai, and Guangdong. Provinces in central and western China are Liaoning, Hebei, Shandong, Hainan, Tianjin, Jiangsu, Zhejiang, Fujian, Shanghai, Guangdong, and Beijing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4. Intermediate Effect Test

To verify the mediating effect of human capital and innovation level, referring to Equations (2) and (3) as well as relevant studies [74], the intermediate effect test results are shown in Table 6. As seen in Columns (1) and (2), the effects of *AI* on *HC* were significantly positive at the 1% level, indicating that the application of AI can significantly encourage progress by improving human capital. According to regressions (3) and (4), the positive effects of *AI* on ln*Inn* were also significant at the 1% level, which means that the improvement of the innovation level greatly contributes to the promotion of carbon productivity.

Therefore, H2a and H2b are valid.

Table 6. Mediating effect tests.

Variables	Mediating Variable 1		Mediating Variable 2	
	HC (1)	***CP*** (2)	**ln*Inn*** (3)	***CP*** (4)
AI	0.146 *** (3.42)	0.001 ** (2.16)	0.006 *** (5.84)	0.001 * (1.90)
Med	—	0.003 *** (3.50)	—	0.096 ** (2.45)
Urb	133.510 *** (3.56)	−2.715 *** (−4.58)	0.006 *** (5.43)	−2.752 *** (−4.45)
PGDP	−10.227 ** (−2.25)	0.853 *** (12.06)	5.063 *** (5.28)	0.761 *** (10.19)
ln*Ope*	6.439 *** (3.54)	0.056 * (1.96)	0.597 * (1.7)	0.071 ** (2.47)
Ind	−46.755 *** (−3.05)	0.790 *** (3.29)	0.077 *** (3.8)	0.493 ** (2.01)
ln*Edu*	30.907 ** (4.73)	0.086 (0.82)	1.445 *** (3.09)	0.142 (1.37)

Table 6. *Cont.*

Variables	Mediating Variable 1 *HC* (1)	Mediating Variable 1 *CP* (2)	Mediating Variable 2 ln*Inn* (3)	Mediating Variable 2 *CP* (4)
Constant	−615.435 *** (−6.93)	−2.058 (−1.38)	−1.705 (−0.77)	−3.971 *** (−2.86)
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	300	300	300	300
R-squared	0.988	0.963	0.989	0.962

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.5. Nonlinear Regulating Effect Test

According to studies by Li et al. (2022) [46], along with the theoretical analysis and Equation (4), the threshold effect model is used to test the nonlinear regulating effect of manufacturing agglomeration on the relationship between AI application and carbon productivity. It is notable that before the official threshold regression, the existence and numbers of threshold effects should be tested. The test results are shown in Table 7. The single threshold was significant at the 1% level, while the double threshold was not significant. This means that there was a single threshold for the degree of manufacturing agglomeration, and the threshold value was 0.405.

Table 7. Threshold effect tests.

Threshold Variable	Number of Thresholds	Threshold Value	*p*-Value	Critical Value 10%	Critical Value 5%	Critical Value 1%
Mad	Single	0.405	0.003	37.853	48.967	71.010
	Double	0.714	0.683	33.155	41.377	56.444

The results of the threshold regression are presented in detail in Table 8. It can be seen that with an agglomeration degree lower than 0.405, the estimated coefficient of *AI* was 0.016, and this was significant at the 1% level, indicating that AI application had a positive effect on carbon productivity. However, when the agglomeration degree was more than or equal to 0.405, the positive effect of AI application was still significant at the 1% level, but the regression coefficient dropped to 0.004. This means that when the level of manufacturing agglomeration is greater than or equal to the threshold value, manufacturing agglomeration will reduce the positive effect of AI application on carbon productivity.

Table 8. Threshold effect regression results.

Variables	OLS	Threshold Regression Model (*Mad* < 0.4025)	Threshold Regression Model (*Mad* ≥ 0.4025)
AI	0.002 *** (0.00)	0.016 *** (5.60)	0.004 *** (5.34)
Control variable	YES	YES	YES
Constant	−4.203 *** (1.49)	−4.480 *** (−3.81)	
Province FE	YES	YES	
Year FE	YES	YES	
Observations	300	300	
R-squared	0.814	0.815	

*** indicate significance at the 1%.

Therefore, manufacturing agglomeration has a nonlinear regulating effect on the relationship between AI application and carbon productivity, proving that H3 is valid.

The hypothesis testing results are summarized and shown in Table 9, proving that all the hypotheses are accepted.

Table 9. Hypothesis testing results.

Code	Hypothesis	Results
H1	AI application helps increase carbon productivity.	Accepted
H2a	AI application has a positive impact on carbon productivity by improving human capital.	Accepted
H2b	AI application has a positive impact on carbon productivity by improving the innovation level.	Accepted
H3	Manufacturing agglomeration has a nonlinear regulation effect on the relationship between AI application and carbon productivity.	Accepted

5. Discussion and Limitations

5.1. Discussion

The rapid development of AI technology is leading to profound changes in human society. Especially with the launch of Chat GPT, machine learning has greatly refreshed human cognition. The baseline regression indicates that an improvement in AI application increases carbon productivity, while regional and temporal heterogeneity is obvious. The wide application of AI contributes to cleaner production, as well as the improvement of productivity [75], which helps shift production patterns from energy-dependent to innovation-driven, making green and low-carbon economy development realizable [76]. Observed regional and temporal heterogeneity may be due to the fact that economic growth in the eastern region has long been at the cost of carbon emissions. When replacing and improving the original production mode using AI, the "sunk costs" and "pain period" effects are obvious in the initial stage [77]. Regions in the east, focusing on economic quality improvements combined with good economic and technological foundations, have created huge opportunities for improving carbon productivity [78]. This is expressed through the wide usage of advanced green technologies, improvements in resource use efficiency, and so on [79,80]. In central and western China, AI application is mainly reflected in increasing output and expanding production scales, resulting in a lack of momentum for improving carbon productivity [81].

The results of intermediate effect test confirm that human capital, as an essential input factor in endogenous economic growth theory, helps to improve the efficiency of resource usage [82]. This phenomenon is especially prominent in China, since the expansion of graduate enrollment has greatly contributed to the cultivation of high-level talents, providing great support for the development of a green economy [83]. It is also confirmed that human capital in China has spatial agglomeration and spillover effects, which makes production greener and is thus conducive to a green economy [84]. Technological innovation, affecting carbon productivity through optimizing input–output structure and improving energy utilization efficiency [85], helps achieve clean production from the source. Furthermore, innovation directly enhances resource recycling efficiency and weakens undesirable output, reducing pollutant emissions from the terminal at the same time [86]. These factors have made technological innovation an important means of carbon reduction [38]. The nonlinear regulating effect test further reveals that manufacturing agglomeration, to a certain degree, improves carbon productivity by promoting technology diffusion and improving energy efficiency [25]. Agglomerated enterprises are encouraged to share pollution abatement equipment as well as adopt energy-saving and emission reduction technology [87]. Moreover, agglomeration promotes innovation in governance concepts, and as a result, leads to improved levels of ecological efficiency [88]. However, beyond a certain threshold, scale benefits are offset by increased costs, and crowding effects emerge [46]. Problems such as air and soil pollution, water environment deterioration, and element competition become serious, and consequently, environmental supporting ability declines [89], inevitably leading to diseconomies of scale.

5.2. Limitations and Future Research Directions

There are still some limitations that point to future research directions. First, considering that carbon emissions are derived from eight kinds of energy, this may result in an underestimation of carbon emissions. More comprehensive carbon emissions data, such as night light data, can be used. Secondly, this study only focused on the overall effect, and the impact of AI applications in different industries on carbon productivity is worth watching. Additionally, while the optimization of human capital and progress in innovation both play partial mediating roles in this process, other possible mediating mechanisms should be discussed in future research. Finally, this paper concerns the relationship between AI application and carbon productivity in China. Comparative studies of countries at different levels of development, such as America, Japan, Europe, and the ASEAN (Association of Southeast Asian Nations), can be explored.

6. Conclusions

This research aimed to identify the relationship between AI application and carbon productivity and explore the internal influence mechanism. By constructing the theoretical framework of the impact of AI application on carbon productivity, this study conducted an empirical study of the internal mechanism based on large-dimensional data from the period from 2010 to 2019 in 30 provinces of China. Conclusions are as follows: (1) the application of AI has a significant positive effect on carbon productivity, and this conclusion is still valid after a series of robustness tests. Meanwhile, improvements in economic development, industrialization, opening up, and the strengthening of education support all have promoting effects on carbon productivity. (2) The heterogeneity test shows that, compared with the central and western regions, the AI application in the east has a stronger and more significant effect on carbon productivity over time. (3) The optimization of human capital and the improvement of the innovation level both play partial mediating roles in this process, and manufacturing agglomeration has a nonlinear adjustment effect on the positive relationship between AI application and carbon productivity. That is, when the manufacturing agglomeration level is lower than the threshold value, it is conducive to enhancing the positive effect. Otherwise, the positive effect of AI application will be reduced.

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