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Do Artificial Intelligence Applications Affect Carbon Emission Performance?—Evidence from Panel Data Analysis of Chinese Cities

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Abstract: A growing number of countries worldwide have committed to achieving net zero emissions targets by around mid-century since the Paris Agreement. As the world's greatest carbon emitter and the largest developing economy, China has also set clear targets for carbon peaking by 2030 and carbon neutrality by 2060. Carbon-reduction AI applications promote the green economy. However, there is no comprehensive explanation of how AI affects carbon emissions. Based on panel data for 270 Chinese cities from 2011 to 2017, this study uses the Bartik method to quantify data on manufacturing firms and robots in China and demonstrates the effect of AI on carbon emissions. The results of the study indicate that (1) artificial intelligence has a significant inhibitory effect on carbon emission intensity; (2) the carbon emission reduction effect of AI is more significant in super- and megacities, large cities, and cities with better infrastructure and advanced technology, whereas it is not significant in small and medium cities, and cities with poor infrastructure and low technology level; (3) artificial intelligence reduces carbon emissions through optimizing industrial structure, enhancing information infrastructure, and improving green technology innovation. In order to achieve carbon peaking and carbon neutrality as quickly as possible during economic development, China should make greater efforts to apply AI in production and life, infrastructure construction, energy conservation, and emission reduction, particularly in developed cities.

Keywords: artificial intelligence; carbon emission; heterogeneity; mechanism

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1. Introduction

The emergence of big data and artificial intelligence has had a tremendous impact on technological development, production organization, business models, and social life. AI has become a major engine of global economic growth and industrial development. Governments in numerous nations have introduced policies to support the AI industry, including the UK's Artificial Intelligence 2020 National Strategy, Japan's Artificial Intelligence Industrialization Worksheet, the U.S. White House Office of Science and Technology Policy (OSTP) Special Committee on Artificial Intelligence's 2019 National Artificial Intelligence R&D Strategic Plan, and China's five departments' National New Generation Artificial Intelligence R&D Strategic Plan. However, as AI continues to liberate production, environmental issues arise. While AI has the potential to alleviate some of the stresses placed on environmental protection and climate change by increasing transportation efficiency, optimizing energy use, and innovating low-carbon materials, it also poses new challenges in the form of increased energy consumption and the production of electronic waste. Determining the precise environmental repercussions of the expansion of AI technology is, thus, a serious research concern.

Concurrently, worldwide attention and efforts to address climate concerns are growing. More than 70 nations have pledged to achieve net zero emissions by 2050 and to strengthen their international climate commitments under the Paris Agreement. As the greatest energy consumer and carbon producer in the world, China has set a clear target of reaching peak carbon emissions by 2030 and carbon neutrality by 2060. As a result, accomplishing the goals of carbon peaking and carbon neutrality concurrently with economic expansion has become a key concern for emerging economies today. Utilizing technologies related to energy efficiency and carbon reduction is essential for achieving sustainable development. Studies have demonstrated that AI technologies have a wide range of applications for improving renewable energy transmission in the grid [1], estimating energy use in the mining industry for energy-efficient operations [2], and optimizing energy control in buildings to reduce energy waste [3]. If it can reduce carbon emissions to reach carbon peaking and carbon neutrality, will the impact vary according to city size, infrastructure, or technological advancement? What are the mechanisms underlying AI's effect on carbon reduction? Understanding the role of AI, reaching carbon peak and carbon neutrality, and constructing a "human-centered" AI era all require in-depth examinations of the aforementioned concerns, yet there is still a dearth of relevant research in these areas.

AI-related carbon reduction studies have barely begun according to existing literature. A relevant study uses industrial robot data from 16 industries in China between 2006 and 2016 to examine the relationship between AI and energy intensity [4]. They discover that the application of AI technology in the industrial sector reduces energy intensity by increasing industrial output and reducing energy consumption. This is the only article that directly relates to the topic of this research. Other relevant literature about the use of AI to reduce carbon emissions falls into three categories. The first category relates to carbon emissions. Existing studies have measured carbon emission levels in various industries and regions [5–7]. These studies also categorized the factors influencing carbon emissions: fixed asset investment projects, particularly high energy-consuming and high carbon emission projects, are a significant source of rising carbon emissions; urbanization is associated with a rise in average temperature [8]; and government intervention [9]. The second category relates to AI-related characteristics. A study examined the influence of robotics applications on regional labor markets in the US using a general equilibrium model and established a measure of "robotics penetration" at the regional level in the US based on model results [10]. In this paper, we select the exposure of robots (ETR) as a proxy variable for the development level of artificial intelligence (AI) [10,11]. The application of robotics has been driving China's transformation from a "manufacturing power" to a "manufacturing superpower" and economy growth. According to the International Federation of Robotics (IFR), an industrial robot is a machine that can be automatically controlled, is reprogrammable, and includes multi-purpose machinery, a multi-joint manipulator, or multi-degree-of-freedom robots for industrial fields, which can be used in monotonous, time-consuming, and repetitive tasks. The study of the relationship between artificial intelligence and carbon emissions is the third category [12]. The third category of literature examines the economic implications of robotics. Some literature argues that the substitution effect of robots reduces labor demand [10,13,14] and some contends that technology advancements in robotics provide a substantial number of new jobs while displacing existing ones [15–17]. The literature also argues that the job promotion effect of robotics applications is larger than the substitution effect, and that the application of robots greatly increases industrial firms' labor force employment levels [18].

Using panel data from 270 prefectural cities in China from 2011–2017 matched with CO_2 emissions data, this paper examines the impact of AI on carbon emissions in terms of direct impact, heterogeneity, and impact mechanism. We use instrumental variables to address endogeneity variables, and we conduct robustness tests by reconstructing explanatory variables, adding dimensional time trend terms to the baseline model, and including outliers of observations. Here are three areas where this study differs from others. First, from a research standpoint, this study focuses on the influence of AI on carbon emission and presents substantial empirical data, as opposed to the established studies that focus on the economic consequences of AI on industrial structure and productivity. Second, in terms of data, unlike existing studies that take the carbon emission perspective of industries [4], the carbon emission in this paper is at the city level, providing a new and more rigorous perspective for studying the impact of artificial intelligence on carbon emission. At the same time, we examine city-level heterogeneity further. Due to vast variances in size, infrastructure, and technology, the severity of AI's impact on carbon emissions varies significantly between cities. Consequently, city features give crucial information for the establishment of distinct and effective AI policies in each city. Thirdly, this article also investigates the mechanism of AI's function in reducing urban carbon emission intensity by optimizing industrial structure, enhancing information infrastructure, and enhancing the green technology innovation. Fourth, in a practical sense, under the dual constraints of facing economic development and environmental pressure, this paper provides empirical evidence for further development of the AI industry and provides a new scientific basis for government policies to achieve the goal of carbon neutrality (zero emissions) as soon as possible.

The remainder of the our work is organized as follows: Section 2 reviews relevant literature on similar topics; Section 3 presents the empirical design and data description; Section 4 presents the empirical results and analysis, focusing on the model's basic regression results, robustness, and heterogeneity; Section 5 examines the mechanism by which AI contributes to the reduction in urban carbon emission; Section 6 concludes the paper.

2. Literature Review

2.1. Impact of AI on Carbon Emissions

Studies on the effects of AI on carbon emissions are mixed. Widespread opinion holds that AI has a positive impact on carbon reduction [19,20]. First, technical progress may promote economic development, energy structure adjustment, and industrial structure upgrading, which can lower carbon emission efficiently [21]. AI technology may leverage vast data from many sources to solve complicated issues, hence boosting productivity and reducing CO_2 emissions per unit of GDP. Second, artificial intelligence, as a cutting-edge technology, increases productivity and generates knowledge and information spillover, which enables carbon-neutral technologies. A study jointly published by Microsoft and PwC states that "the use of AI technology to environmental protection is predicted to increase global GDP by 3.1 to 4.4 percent by 2030, while reducing global greenhouse gas emissions by 1.5 to 4.0 percent". Thirdly, AI enables more accurate detections and predictions of company pollution, which contribute to the development of a robust carbon emissions trading market, which further decreases CO_2 emissions [22].

However, other scholars argue that technological advancements brought about by AI not only reduce energy consumption, but also result in lower energy prices and energy surplus, which may further stimulate energy use and transition, thereby reducing the anticipated energy savings of the technology. This phenomenon is known as the "rebound effect" [23,24]. AI is also relatively energy-intensive for industry, as machine learning and industrial robotics are far more energy-intensive than human labor. In recent years, the computational power required for major AI technologies such as DeepMind's AlphaZero Go program has doubled roughly every 3.4 months, tripling between 2012 and 2018. Deep learning-based AI in particular is becoming the largest engine of corporate growth in data centers throughout the world, and if the energy consumption and carbon emissions it generates are not handled seriously, it will cause a "butterfly effect" catastrophe. In the meantime, the European Union has issued a warning that the AI industry's greenhouse gas emissions could climb sevenfold to 14% over the next two decades.

Therefore, this article empirically indicates that it is of major importance to find whether the implementation of artificial intelligence in China has a positive or negative effect on carbon emissions.

2.2. AI Reduces Carbon Emissions by Optimizing Industry Structure

Industrial structure upgrading is a major driving force for energy conservation and pollution reduction [25,26]. With the improvement of industrial structure, production factors gradually migrate from sectors with low marginal efficiency to sectors with high marginal efficiency. The resource allocation tools of artificial intelligence economy can reallocate labor, capital, and other resource factors to promote the industrial structure to the high end of the industrial chain, which is conducive to improving energy efficiency and reducing pollution emissions [27].

From the macro perspective, the advanced information and data represented by artificial intelligence, as a new production factor, stimulate the rapid growth of AI vehicles, industrial robots, and other new industries, effectively promote the reallocation of production factors, and optimize industrial institutions.

From the meso perspective, AI embedded in traditional industries provides informational driving force. For example, in the manufacturing industry, AI can be used to establish an intelligent manufacturing system, improve the efficiency of the use and allocation of production factors, promote manufacturing upgrades, and reduce resource losses and pollution emissions [28]. Artificial intelligence can create a new virtual workforce to replace the workforce performing programmed tasks [10,29], thus enabling "intelligent automation".

From the micro perspective, big data are widely distributed, changing rapidly [5], and gradually become a decision-making resource for people to obtain deeper knowledge of things, especially the deep integration of artificial intelligence technology and big data which provides powerful tools for modeling and analysis of complex decision-making problems (Yu Hong et al., 2020).

2.3. AI Reduces Carbon Emissions by Enhancing Information Infrastructure

As a byproduct of the Internet age, artificial intelligence will not only stimulate traditional information infrastructure such as fiber optics, but also encourage new information infrastructure such as data centers and supercomputers. Statistics from the Ministry of Industry and Information Technology indicate that by the end of May 2022, a total of 1.7 million 5G base stations were built and opened in China, and more than 650,000 new 5G base stations were built in the previous year. Furthermore, 5G users accounted for more than a quarter of the total, with 428 million households using the technology. In addition, the 2022 Government Work Report states:

> Promote digital economy. Improve the overall digital China construction. Construct a digital information infrastructure, a national integrated big data center system, promote the deployment of 5G, encourage the digital transformation of industries, and develop smart cities and digital villages. Accelerate the growth of the industrial Internet, cultivate and expand integrated circuits, artificial intelligence, and other digital sectors, and improve technical innovation and the supply capacity of essential software and hardware.

Information infrastructure, which is ecologically friendly with fewer negative externalities, encourages dematerialization of economic activity and minimizes carbon emissions [30]. Moreover, information infrastructure encourages businesses to invest in information technology, which reduces carbon emission activities. Moreover, the information infrastructure facilitates better articulation and communication between upstream, midstream, and downstream enterprises in the industry chain, as well as the dissemination of information and data between the productive service and manufacturing industries, thereby achieving the separation of the production link from the service link and a cleaner and more efficient production and operation model [31,32].

2.4. AI Reduces Carbon Emissions by Enhancing Green Technology Innovation

Technological progress and innovation are seen as significant elements in energy conservation and emission reduction [33–35]. Technology diffusion enables the promotion of cleaner manufacturing processes and green technology in environmentally polluted regions, which has a favorable impact on energy and carbon emission performance [27]. Artificial intelligence is a crucial vehicle for the introduction and spread of technology.

The new industries represented by artificial intelligence provide conventional industries with a high-tech bonus, which is helpful to decreasing R&D clichés in industrial sectors, supporting the transition of industries toward intelligence and greening, and increasing industrial added value. AI may also foster the growth of an innovation ecosystem and the building of R&D and innovation capabilities to boost productivity significantly [36]. In addition, AI contributes to the advancement of green technology through the economies of scale and technology spillover effects. As the number of users increases, the marginal cost sink of artificial intelligence input decreases, yielding a considerable economy of scale effect.

3. Materials and Methods

3.1. Identification Strategies

This article investigates the impact of artificial intelligence on carbon emissions. The baseline model is

$$CEI_{c,t} = \alpha + \beta \ln AI_{c,t} + \lambda X_{c,t} + u_c + \mu_t + \varepsilon_{c,t}, \tag{1}$$

where $CEI_{c,t}$ denotes the carbon emission intensity of city c in year t; $AI_{c,t}$ measures the AI development level of city c in year t; $X_{c,t}$ is a set of control variables; u_c and μ_t denote the area fixed effect and time fixed effect; $\epsilon_{c,t}$ is the error term. The coefficient β, the net effect of the level of AI development on carbon emission intensity, is the key coefficient in this paper. A significant negative β indicates a reduction in carbon emission intensity as a result of improved AI development. Either an insignificant or a positive β indicates an insignificant impact of AI development on carbon emission.

3.2. Variables

3.2.1. Dependent Variable (Carbon Emission Intensity)

This paper focuses on urban industrial carbon emissions due to the fact that AI applications are currently geared toward businesses. This paper divides urban industrial carbon emissions into two categories: direct emissions that come from energy use such as natural gas and LPG, and indirect emissions that come from electricity utility in urban industries. Inspired by a relevant study [37], the carbon emission is calculated as follows:

$$CE = C_1 + C_2 + C_3 = \alpha_1 E_1 + \alpha_2 E_2 + \alpha_3 (\eta E_3) \tag{2}$$

$$CEI = CE/GDP, \tag{3}$$

where CE denotes the total CO_2 emissions; CEI denotes the carbon emission intensity; C_1 and C_2 denote the CO_2 emissions from natural gas and LPG, and C_3 is the CO_2 emissions from the whole society's electricity consumption; E_1, E_2, E_3 denote the consumptions of natural gas, LPG, and industrial electricity, respectively; α_1, α_2 denote the CO_2 emission factors of natural gas and LPG (carbon emission factors come from IPCC2006 Guidelines for National Greenhouse Gas Emission Inventories); α_3 is the greenhouse gas emission factor of the coal power fuel chain, and η denotes the proportion of coal power generation to total generation.

3.2.2. Core Independent Variable (AI Development Level)

In the era of digital economy, artificial intelligence is widely used in various fields of the economy and society, and manifests itself in a variety of ways. However, there is a lack of indicators that directly measure its development level. This paper selects industrial exposure to robots (ETR) as a proxy variable for the development level of artificial intelligence. According to ISO 8373:2012, a robot is a programmable device that has two or more degrees of freedom, and traverses its surroundings to complete a preset mission. Therefore, ETR would be an excellent indicator of the extent of AI progress.

Inspired by a relevant study [10], this paper uses a method similar to the "Bartik instrument" [38,39] to construct the ETR for city c in year t as

$$ETR_{c,t} = \sum_{i \in \emptyset} \gamma_{c,i} \cdot APR_{it} \tag{4}$$

where $\gamma_{c,i}$ denotes the proportion of employment in industry i in the manufacturing sector in city c in the base year (2011), $APR_{i,t'}$ denotes the robot penetration in year t in industry i at the country level, $\gamma_{c,i}$ and $APR_{i,t}$ are calculated by

$$\gamma_{c,i} = \frac{L_{c,i,2011}}{L_{c,2011}} \tag{5}$$

$$APR_{i,t} = \frac{RN_{i,t}}{L_{i,2011}} \tag{6}$$

where $L_{c,i,2011}$ denotes the employed population in industry i in city c in the base year (2011), $L_{c,2011}$ denotes the employed population in the manufacturing sector in city c in the base year (2011); $RN_{i,t}$ denotes the stock of industrial robots in year t in industry i country-wide, $L_{i,2011}$ denotes the employed population in industry i in the base year (2011).

Since city-level employment data for manufacturing subsectors are unavailable, this paper generates an alternative parameter $\widetilde{\gamma_{c,i}}$ for $\gamma_{c,i}$ from the Chinese Industrial Enterprises Database, which contains all state-owned industrial enterprises and non-state-owned industrial enterprises. The statistical scope, which is mainly for manufacturing enterprises, covers the extractive industry, manufacturing industry, and electricity, gas, and water production and supply industry. Since the database provides information on each firm's province, city, and number of employees at the end of the year, and the sample firms cover nearly all local manufacturing enterprises, the alternative parameter $\widetilde{\gamma_{c,i}}$ can be built as follows:

$$\widetilde{\gamma_{c,l}} = \frac{\sum_{j=1}^{n} L_{cij,2011}}{\sum_{i=1}^{11} \sum_{j=1}^{n} L_{cij,2011}} \tag{7}$$

where $L_{cij,2011}$ denotes the employed population in firm j of city c in industry i in the base year (2021). The total employed population in industry i in city c is the summation of the year-end 2011 employees of all firms in industry i in city c from the Database of Chinese Industrial Enterprises; the total employed population in the manufacturing sector is the summation of the year-end 2011 employees of all firms in city c.

3.2.3. Instrumental Variables

Similar to China over the sample period, the growth of industrial robots in the United States can reflect the trend of technological progress, and its impact on China's carbon emissions satisfies the endogeneity assumption of instrumental variables. At the same time, changes in the US industrial robot stock do not correlates with variables affecting China's carbon intensity, satisfying the exogeneity assumption of instrumental variables. Therefore, we use US industrial robots as an instrumental variable for the exposure to Chinese industrial robots:

$$ETR_{c,t}^{IV} = \sum_{i \in \emptyset} \frac{L_{ci,2011}^{CN}}{L_{c,2011}^{CN}} \cdot \frac{RN_{it}^{US}}{L_{i,1990}^{CN}}, \tag{8}$$

where RN_{it}^{US} denotes the US industrial robot stock in industry i in year t.

3.2.4. Control Variables

The control variables in this present work are fixed asset investment ($invest$), which is denoted as the ratio of the city's total fixed asset investment to regional GDP; financial development level (fin), which is denoted as the proportion of the city's year-end loan balance of financial institutions to the regional GDP; urbanization ratio ($urban$), which is expressed as the population share of the municipal district; and government intervention (*expenditure*), which is expressed as the ratio of the city's general public budget expenditure to the regional GDP.

3.3. Data Source

This research examines the impact of AI development on carbon emissions using panel data for 270 prefecture-level cities in China from 2011 to 2017. Publicly accessible statistics from the China City Statistical Yearbook, International Federation of Robotics (IFR), China Industrial Enterprises Database, China Labor Statistics Yearbook, EPS Data Platform, and China Research Data Service Platform (CNRDS) are the primary sources of research data. Table 1 contains the descriptive statistical analysis of the variables.

Table 1. Variables and descriptive statistics.

Variables	Variable Symbols	Mean	Standard Deviation	50th Percentile	Min.	Max.
Carbon emissions intensity	CEI	0.0300	1.020	−0.270	−1.450	6.200
Exposure to robot	$\ln ETR$	2.380	0.870	2.380	−0.0700	5.370
Financial development	fin	0.790	0.290	0.760	0.0900	2.200
Fixed asset investment	$invest$	0.370	0.240	0.300	0.0500	1
Percentage of population in urban areas	$Urban$	0.0800	0.0500	0.0700	0.0100	1.270
Government intervention	$Expenditure$	11.94	1.030	11.82	8.130	16.08

4. Results

4.1. Basic Regression Results

This study employs a two-way fixed effects model, controlling for temporal and area-level fixed effects, to examine the connection between AI development and carbon emissions intensity. The results of the baseline regressions are shown in Table 2. Column (1) displays the results of regression with the level of AI development as the sole explanatory variable, whereas column (2) displays the results of regression with the addition of control variables. As seen in Table 2, each 1% improvement in AI development reduces carbon intensity by 0.0027%, which is statistically significant at the 1% level. The estimated coefficients become smaller when control variables are included, but are still significant. This demonstrates that the development of artificial intelligence has a statistically significant positive effect on reducing the intensity of carbon emissions.

In addition, this paper investigates the disparate impacts of AI development level on cities with varying carbon emission levels. Cities with carbon emission intensity greater than the 50 percent quantile are in the high-CEI group, whereas those with less than the 50 percent quantile are in the low-CEI group. Columns (3) and (4) show the grouping regression results. Developing AI considerably lowers the carbon emission intensity of both groups of cities, with the absolute value of the estimated coefficients being greater for cities in the low-CEI group, indicating better carbon reduction impacts. The reason for this could be that cities with lower carbon emission intensities are more productive overall and are better able to make use of artificial intelligence tools to boost efficiency and cut down on carbon output.

Although the baseline regression shows a significant result, there may be endogeneity issues. The regression model in this paper only controls for factors such as financial development level, fixed asset investment, urbanization level, and government intervention. It does not control for variables that affect carbon emission intensity, and there may be unobservable variables, such as culture or institutions, that lead to omitted variable bias. Furthermore, there may be reverse causality as reduced carbon emission intensity frequently implies an enhanced urban environment, and a good urban environment may also be a factor in attracting AI technological expertise. To address potential endogeneity and reverse causality issues, this research introduces an instrumental variable for AI development in China using data on the stock of industrial robots in the United States during the sample period.

Table 2. Baseline model.

Variables	(1)	(2)	(3) Low CEI	(4) High CEI
$\ln ETR$	−0.2720 ***	−0.2389 ***	−0.0296 *	−0.1809 ***
	(0.0306)	(0.0336)	(0.0154)	(0.0574)
fin		0.0852 **	−0.0309 *	0.1836 ***
		(0.0373)	(0.0171)	(0.0628)
$invest$		0.0937	0.2343 ***	0.2307 **
		(0.0708)	(0.0373)	(0.1039)
$urban$		−0.9216 ***	−0.2271 ***	−0.9533 ***
		(0.0804)	(0.0430)	(0.1344)
$expenditure$		2.0483 ***	−0.7688 ***	1.3422 ***
		(0.3446)	(0.2863)	(0.4475)
Constant	0.6761 ***	0.5837 ***	−0.5593 ***	0.8422 ***
	(0.0739)	(0.1004)	(0.0483)	(0.1628)
Observations	1890	1614	735	840
Adjusted R-squared	0.6586	0.6815	0.4286	0.5961
F statistics	79.20	43.35	45.95	15.24
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%.

The outcomes of the 2SLS regression with instrumental variables are displayed in Table 3. The estimated coefficient of stage 1 in column (1) is 0.9432, which is significant at the 1% level, showing that the instrumental variables are highly correlated with China's urban exposure to robots. The estimated stage 2 coefficient in column (2) is negative and statistically significant at the 1% level. The absolute value of the estimated second-stage coefficient of IV is significantly greater than the OLS regression results, indicating a reverse causal effect in which the reduction in urban carbon emission intensity has a dampening effect on the application of AI, thereby causing the OLS regression to underestimate the carbon reduction effect of AI. The instrumental variable test indicates that the model does not have unidentified and weak instrumental variables. Specifically, the Anderson canon. corr. LM statistic is 1420.719 with a p-value of 0.0000, which rejected the null hypothesis of unidentifiability; the Cragg–Donald Wald F statistic value is 12,000, which exceeds the empirical judgment of 10 and passes the weak instrumental variable test.

Table 3. IV regression model.

Variables	(1) First Stage	(2) Second Stage
$\ln ETR^{IV}$	0.9432 ***	
	(0.0086)	
$\ln ETR$		−0.2594 ***
		(0.0716)
Cragg–Donald Wald F	2659.34	12,000
Anderson canon. corr.		1420.719
F statistics	2659.34	
Observations	1629	1614
Adjusted R-squared	0.9648	0.0990
Year FE	YES	YES
Province FE	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%.

4.2. Heterogeneity Analysis

On a full-sample basis, the preceding study showed that AI development significantly reduces carbon emissions. However, the impact of AI development on carbon emissions may also vary by city size.

According to the Chinese government's classification of city size, cities with a permanent urban population of less than 500,000 are small cities, those with more than 500,000 and less than 1 million are medium cities, those with more than 1 million and less than

5 million are large cities, and those with more than 5 million and less than 10 million are megacities. According to these criteria, this study divides cities into three groups: small and medium-sized cities, large cities, and megacities and supercities. Table 4 exhibits the outcomes of grouped regressions for cities of various sizes, with columns (1), (3), and (5) showing the outcomes of regressions using the level of AI development as the independent variable, and columns (2), (4), and (6) showing the outcomes of regressions with control variables. According to the regression results, the impact of AI on carbon emission intensity is not significant in small and medium-sized cities, but it is significant at the 1% level in large cities, megacities, and supercities, and the absolute value of the coefficients grows as city size increases. This may be due to the properties of artificial intelligence technologies. The inputs for artificial intelligence technologies are primarily software, with zero marginal cost of use but stringent data size constraints. The larger a city's population, the easier it is for economic activities to generate large-scale data, the stronger the foundation for AI applications, and the greater its impact on reducing the intensity of carbon emissions.

Table 4. Heterogeneity analysis: city size.

Variables	**City Size**					
	Mega- and Supercities		**Large Cities**		**Medium and Small Cities**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ln ETR	−0.2526 ***	−0.1484 ***	−0.2138 ***	−0.1877 ***	−0.0475	−0.3022
	(0.0354)	(0.0414)	(0.0447)	(0.0475)	(0.1786)	(0.2801)
Controls	NO	YES	NO	YES	NO	YES
Observations	648	554	1163	993	79	67
Adjusted R-squared	0.6347	0.6668	0.6695	0.7051	0.9169	0.9686
F statistics	50.82	23.54	22.90	30.34	0.0707	19.83
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for mega- and supercities; columns (3) and (4) indicate the regression results for large cities; columns (5) and (6) indicate the regression results for medium and small cities. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. *t*-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%.

The application of artificial intelligence technology depends not only on the production of massive amounts of data, but also on the level of technologies and infrastructures such as the Internet. The more established traditional infrastructure construction for data collecting and transmission makes it more feasible to apply AI technology to optimize the consumption and distribution of energy, which improves energy efficiency.

This research then proceeds to group regressions for cities with varying levels of infrastructure. Table 5 displays the results of the regression by infrastructure grouping. The regression outcomes in columns (1) and (2) indicate that the development of AI has no significant effect on the carbon emission reduction in cities with inadequate infrastructure. The regression results in columns (3) and (4) indicate that, for cities with better infrastructure, the application of AI technology reduces carbon emission, and the absolute value of coefficient is greater than the baseline regression, which is consistent with our hypothesis.

Table 5. Heterogeneity analysis: infrastructure.

Variables	Traditional Infrastructure			
	Poor Infrastructure		**Better Infrastructure**	
	(1)	**(2)**	**(3)**	**(4)**
ln ETR	−0.0073	−0.0221	−0.3059 ***	−0.2190 ***
	(0.0517)	(0.0528)	(0.0334)	(0.0350)
Controls	NO	YES	NO	YES
Observations	917	821	973	792
Adjusted R-squared	0.7203	0.7446	0.6162	0.6836
F statistics	0.0202	22.91	83.78	44.31
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for cities with poor traditional infrastructure; columns (3) and (4) indicate the regression results for cities with better traditional infrastructure. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%.

Artificial intelligence, as a knowledge-intensive frontier technology, is highly associated with the local technological level. As the two fundamental components of AI, algorithms and processing power are not only essential for the ongoing development of AI, but also for assessing AI's effectiveness in practical applications. The algorithm determines the theoretical productivity in software, whereas the arithmetic power ensures the actual productivity in hardware, both of which are affected by the technological level.

The results of grouped regressions for various technological levels are presented in Table 6. According to the regression results in columns (1) and (2), the development of AI has no statistically significant effect on carbon emissions in cities with modest levels of technology. Lower technological level does not support the application of AI, and AI-capable talent may be scarce; hence, substantial reductions in carbon emissions cannot be attained. The regression results in columns (3) and (4) indicate that the deployment of AI can significantly reduce carbon emissions in cities with a higher technological level. These cities have greater human resources to make algorithmic breakthroughs and greater financial resources to construct hardware facilities that rely on the development and application of AI technologies, such as data centers and supercomputers.

Table 6. Heterogeneity analysis: technology.

Variables	Regional Technology Level			
	Low-Tech		**High-Tech**	
	(1)	**(2)**	**(3)**	**(4)**
ln ETR	−0.0513	−0.0377	−0.2221 ***	−0.1483 ***
	(0.0561)	(0.0538)	(0.0294)	(0.0352)
Conrols	NO	YES	NO	YES
Observations	912	826	964	775
Adjusted R-squared	0.6930	0.7382	0.5770	0.6131
F statistics	0.834	29.61	57.23	26.68
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for low level of technology; columns (3) and (4) indicate the regression results for high level technology. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively.

4.3. Robustness Tests

This paper has addressed the endogeneity issue through instrumental variables, and to further verify the robustness of the benchmark regression results, the following aspects are tested by reconstructing the independent variables, adding dimensional time trend terms to the benchmark model, and considering outliers of the observations, and the results are presented in Table 7.

First, because of China's "poor oil, rich coal, and little gas" resource endowment, thermal power generation makes up more than 70% of the electricity, making coal combustion the primary source of carbon emissions in China. This research reconstructs the independent variables using sulfur dioxide emission intensity (ratio of sulfur dioxide emissions to regional GDP) because the consumption of coal frequently entails the emission of sulfur dioxide. The regression results in column (1) of Table 7 reveal that the regression coefficient using sulfur dioxide emission intensity as the independent variable is still negative and significant at the 1% level, implying that the application of AI technology reduces environmental pollution significantly.

Second, there is a significant latitudinal gradient in China, with urban centers spread out across the country from alpine regions to tropical regions. Wintertime heating needs in alpine cities will have a considerable impact on carbon emission intensity. In contrast, with China's economic growth and technical development, carbon emissions will likewise vary over time. Then, we introduce the interaction term $latitude * year$ for city dimension and year in the benchmark model to investigate whether there is an interactive effect of both time and region on the carbon reduction effect of AI. The regression findings in column (2) of Table 7 indicate that the regression coefficient of AI with the interaction term is -0.2437 and is statistically significant at the 1% level. The coefficient of regression for the interaction term $latitude * year$ is considerably positive at the 1% level.

Finally, we regress the baseline model after customizing the samples of explanatory factors, explained variables, and control variables to exclude the probable influence of outliers in the sample observations on the regression findings; the resulting regression results are shown in (3) in Table 7. The estimated coefficient of AI following the tailoring process is -0.2370, which is largely consistent with the benchmark regression while significant at the 1% level, indicating that the results of the benchmark regression are robust to outliers.

Table 7. Robustness test.

Variables	**Reconstructing the Dependent Variable**	**Adding Dimensional Time Trend Terms**	**Drop Outliners**
	Sulfur Dioxide Emission Intensity	CEI	CEI
	(1)	**(2)**	**(3)**
$\ln ETR$	−0.1587 ***	−0.2437 ***	−0.2370 ***
	(0.0463)	(0.0334)	(0.0340)
$latitude * year$		1.8579 ***	
		(0.3827)	
Controls	YES	YES	YES
Observations	1597	1614	1614
Adjusted R-squared	0.4183	0.6860	0.6872
Year FE	YES	YES	YES
Province FE	YES	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%.

5. Mechanism Test

This paper's empirical study demonstrates that the application of AI can reduce urban carbon emissions economically and statistically. The results are still significant after excluding endogeneity issues with instrumental variables. Reconstructing the explanatory variables and accounting for outliers verified the robustness of the baseline regressions. The following section of this research will investigate the potential mechanisms by which AI reduces carbon.

5.1. Industrial Structure Effect

AI plays a significant role in the new industrialization process and can promote the upgrading of traditional manufacturing industries [40], thereby enhancing production efficiency, economic efficiency, and total factor productivity. Artificial intelligence redistributes labor, capital, and other factors of production in the manufacturing industry via algorithm, which entails the needs of the service nature of artificial intelligence. On the other hand, AI technologies with big data and machine learning as tools transform traditional service industries such as finance, law, education, logistics, and new service industries such as Internet and health, opening up various application scenarios of "AI+service industry" and promoting the rapid development of service industries [41,42]. Therefore, AI may change the industrial structure by promoting the development of tertiary industries such as the service industry, which will have the effect of reducing emissions.

We use the ratio of tertiary industry to GDP as the dependent variable and the level of AI development as the independent variable for regression to examine the optimization effect of AI on industrial institutions. The results in column (1) of Table 8 indicate that AI has a positive effect on industrial structure optimization, which implies that AI reduces carbon emission by promoting industrial structure upgrading.

Table 8. Mechanism test: industrial structure effect.

Variables	Industrial Structure (1)	Information Infrastructure (2)	Number of Green Inventions Applied for That Year (3)	Number of Green Utility Models Applied for That Year (4)
$\ln ETR$	0.7469 ***	0.4490 ***	0.8477 ***	0.7375 ***
	(0.2721)	(0.0591)	(0.0603)	(0.0518)
Controls	YES	YES	YES	YES
Observations	1628	1629	1595	1603
Adjusted R-squared	0.7457	0.5675	0.6053	0.6748
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
F statistics	338.1	194.5	202.4	203.3

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

5.2. Information Infrastructures

As a byproduct of the Internet era, the application of artificial intelligence not only promotes traditional information infrastructures such as optical fiber, but also stimulates new information infrastructures such as data centers and supercomputers, which is environmentally friendly. Meanwhile, it accelerates information and knowledge dissemination, and encourages businesses to invest in information technology, thereby lowering carbon emissions.

This research uses four information infrastructure-related indicators to measure the level of infrastructure development, namely: the number of Internet users per 100 people, the proportion of computer service and software employees in urban employment, the total number of telecommunication services per capita, and the number of cell phone users per 100 people. All these data are also obtained from the China Urban Statistical Yearbook. This study employs principal component analysis (PCA) to standardize and downscale the above indicators, and then produces the complete information infrastructure index as a proxy variable for digital infrastructure, denoted by Inf.

In column (2) of Table 8, the regression of AI on information infrastructure provides a significant coefficient of 0.449 at the 1% level. This suggests that there is a large positive correlation between the growth of AI and the information infrastructure, and that fostering AI promotes information infrastructure.

5.3. Green Technology Innovation Effect

Carbon emission intensity is the carbon emission per unit of GDP, which is a concept about efficiency and therefore pertains to technological innovation. The higher the technological innovation capacity of cities, the more it can lead to low-carbon technologies and environmental technologies, which curb carbon emissions. Can artificial intelligence, with big data and machine learning at its core, continually advance green technology innovation, therefore reducing the carbon intensity of industrial development?

Patent inventions are the output of R&D activities, which can directly reflect the level of urban innovation. To verify the effect of AI on green technology innovation, this paper uses the number of green inventions applied in the current year and the number of green utility models applied in the current year as proxy variables for green technology innovation. Green patents are obtained by eliminating non-green technology invention patents from the international green patent classification code.

The estimated coefficients in column (3) of Table 8 are significant at the 1% level, indicating that AI drives urban green technology innovation. The artificial intelligence technology is sufficiently universal to be linked with the green innovation business [43]. Based on the massive data and computing of artificial intelligence, the green technology innovation process can discover more innovation paths, and overlay at a faster rate, thereby improving green technology innovation, and reducing carbon emissions.

The improvement of information infrastructure level entails the enhancement of information network accessibility, and as a result of marginally decreasing network costs, it effectively reduces the information transmission cost of technological innovation mediated by the network and improves the flow of innovation factors and diverse information between regions. Information technology is continuously releasing technology spillover bonus in the industrial sector, which has a direct effect on raising urban green technology level, thereby giving a possible path for reducing carbon emission during industrial expansion.

6. Discussion and Conclusions

Artificial intelligence is a cutting-edge technology leading a new round of technical revolution and industrial transformation. A widespread application of AI in our economic activities invigorates economic growth. Despite the worldwide consensus on low-carbon production, the influence of artificial intelligence on carbon emissions has not yet been thoroughly investigated.This article empirically examines the impact of AI on reducing carbon emissions by creating a two-way fixed-effects model with a panel of 270 prefecture-level cities from 2011 to 2017. We show that (1) AI considerably reduces carbon emissions, as every 1% advance in artificial intelligence development will result in a 0.0024 reduction in carbon intensity. After regression of instrumental variables and a series of robustness tests, the conclusions still hold.(2) The effect of AI on carbon emission is heterogeneous. The effect of AI on carbon emission reduction is more significant in mega- and supercities, and cities with better infrastructure and a high technology level; conversely, the effect of AI on carbon emission reduction is not significant in small and medium cities, or cities with poor infrastructure and a low technology level. (3) The mechanism of AI reducing carbon emission is optimizing industrial structure, enhancing information infrastructure, and enhancing green technological innovation.

In order to reach the carbon peak and carbon-neutral goals as quickly as possible, to maximize the role of artificial intelligence in dealing with climate change, and to expedite the decoupling of China's economic growth from carbon emissions, this paper presents the following proposals. (1) Increase the use of artificial intelligence in manufacturing and daily life. Since carbon emissions are ubiquitous across all human activities and have a substantial impact on global climate change, the application of new technologies is one of the keys to mitigating climate change. AI technology, as an adaptive new technology, can significantly reduce carbon emissions from economic operations. The versatility of AI technologies enables their widespread application in combating climate change. (2) Provide more guidelines for the application of AI technologies. The impact of AI technologies on carbon reduction at the city level varies depending on city size, infrastructure development, and technological advancement. AI technologies should be applied first in places with superior infrastructure and technology, as these conditions are the most favorable to AI implementation. It also enables the AI technology's carbon reduction effect to be extended to more businesses and individuals, which will have a greater influence on reducing carbon emissions. (3) Pay close attention to the use of artificial intelligence technology in the development of green technologies. In terms of climate change, the significance of artificial intelligence technology is not only enhancing the efficiency of energy consumption in manufacturing activities to minimize carbon emissions, but also fostering the development of green technologies. The massive data mining and high-speed computing capabilities of artificial intelligence technology will considerably enhance the efficacy of green technology innovation and give additional opportunities for its development. In this light, the application of artificial intelligence in the sphere of technological innovation will be more crucial for reducing carbon emissions.

This research has some limitations and can be improved in the following ways: first, this study employs proxy variables to explain the general amount of AI growth; however, the measures of AI may vary among sectors. Using more diversified and precise AI explanatory factors for various economic activities will allow for more in-depth research. Second, due to the availability of data, this study calculates the exposure of industrial robots at the city level using the total number of employees of listed firms in city subindustries. The credibility of this study's findings would be strengthened by the availability of precise employment data for each city subsector. Lastly, the COVID-19 pandemic has expedited the digitization of productive life, hence expanding AI applications. How would non-technical external events, such as the pandemic outbreak, affect the carbon reduction effect of artificial intelligence technologies? To respond, additional study is required.

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