Can Artificial Intelligence Technology Curb Carbon Emission Intensity?-Evidence from panel data on 277 prefecture-level cities in China

Jiaqi Yu[a], Ruihan Zhou[b,*], Oulun Yan[c], Weiyang Chen[d]

School of Humanities and Social Sciences, Beihang University, Xueyuan Road, Beijing, China

[a] yujiaqi@buaa.edu.cn, [b] zhouruihan@buaa.edu.cn, [c] yanoulun@buaa.edu.cn, [d] 21379113@buaa.edu.cn

*Corresponding author

Keywords: Artificial Intelligence, Carbon Emission Intensity, Energy Use Efficiency, Green Innovation Efficiency, Threshold Effect

Abstract: Technology is an essential factor influencing the carbon emission intensity of cities, and artificial intelligence (AI) technology provides momentum for the transformation of cities to low-carbonization. Starting from the “dual carbon” goal, we empirically examine the impact, mechanism, and threshold effect of AI technology on the carbon emission intensity of Chinese cities, utilizing the data of 277 prefectural-level cities in China from 2011 to 2021. The study shows that: (1) AI technology can help reduce urban carbon emission intensity; (2) energy use efficiency and green innovation efficiency are two practical paths for AI technology to reduce carbon emission intensity; (3) heterogeneity test shows that AI technology has a more substantial carbon emission reduction effect in the central and western regions, non-provincial capitals, lower digitization levels and re-source-dependent cities; (4) threshold regression shows that the carbon emission reduction effect of AI has a marginal progressive effect on environmental regulation and the threshold effect of AI on carbon emission reduction is a significant factor for the reduction of carbon emission. Environmental regulation shows a marginal increasing trend while a marginal decreasing trend in Internet penetration. We provide a decision-making basis and policy inspiration for using AI technology to realize carbon emission reduction and promote low-carbon transformation of cities.

1. Introduction

Since reform and opening-up, China has made great progress. However, behind this are environmental problems. Under the “GDP-only” performance appraisal mechanism, regions have lowered environmental regulations. The climate warming caused by carbon dioxide is affecting people’s production and life. In 2021, China’s carbon emissions have reached 10.523 billion tons [1]. The “2021 China Green Low Carbon City Index TOP50” shows that as of 2020, China’s per capita carbon emissions amounted to 7 tons. Over half of the cities’ per capita carbon emissions exceeded the national average. The U.S. economic research company Rhodium Group announced the following: China’s urban carbon emissions are close to 80% of the national total, and cities have become the primary source of carbon emissions. So, how do we balance the contradiction between economic development and environmental protection to achieve higher quality and sustainable economic growth?

As a strategic technology for the scientific revolution, the deep integration of AI and industry provides momentum for the low-carbon transformation. Accompanied by a new round of scientific revolution, developed countries in the West formally put forward “Industry 4.0”, which combines AI with industrial development, provides a new way of low-carbon transformation of cities. Specifically, AI technology, analyzes and predicts carbon emissions of cities to optimize the carbon emission reduction decisions of the government and enterprises; it can be used to develop green technologies and help the people live a greener life. The World Conference on AI 2021 announced that China’s patent applications in AI are ranked first in the world. Therefore, with the help of AI technology to promote the low-carbon transformation, there is broad potential for application in China.

  DOI: 10.25236/meeit.2024.004

Driven by the "dual carbon" goal, how to realize carbon emission reduction has also become the focus of academic attention. The research on the factors that influence carbon emission reduction in China mainly focuses on two aspects. One is to analyze the factors that influence carbon emission from the perspectives of industries [2, 3]. The other is to, analyze the factors influencing carbon emission from a regional perspective [4, 5]. However, most existing studies on the factors affecting carbon emissions focus on the digital economy and only some focus on AI [6 ,7].

To make up for these shortcomings, we investigate the impact, mechanism of action, and threshold effect of AI on carbon emission intensity based on the panel data of Chinese cities from 2011 to 2021. It is found that, first, the development of AI significantly reduces carbon emission intensity of cities. Second, green innovation and energy use efficiency are important action mechanisms for AI to reduce carbon emission intensity. Third, AI has a more substantial inhibitory effect on carbon emissions in cities with lower digitization levels. In addition, AI has a more substantial inhibitory effect on carbon emissions in central and western regions, resource-dependent cities, and non-provincial capital cities. Fourth, the inhibitory effect of AI technology on carbon emission intensity has a threshold effect.

The marginal contributions of our research are the following three aspects. First, we analyze the mechanism of the role of AI technology from the perspectives of energy use efficiency and green innovation efficiency. Second, we pay special attention to the carbon emissions at the city level, embedding factors such as cities' location, administrative level, digitalization level, and resource endowment into the global logic framework of artificial intelligence technology and carbon emission intensity. Third, it is important to introduce internet penetration rate and environmental regulations to examine the threshold effect of artificial intelligence on carbon emission intensity from the two aspects of application conditions of artificial intelligence technology.

2. Theoretical Analysis and Research Hypotheses

Currently, AI and industrialization are undergoing organic integration [8]. As AI presents positive and negative effects in the process of task replacement and labor substitution [9]. According to the existing literature, the dynamic changes in economic development and labor employment in turn triggers the evolution of energy consumption and pollution emission patterns [10]. So, will the development of AI also significantly impact the carbon emissions?

2.1. Direct Impact of AI Technologies on Carbon Emission Intensity of Cities

Existing literature has reached mixed conclusions about the impact of AI on carbon emissions. Some studies point out that applying AI technology may exacerbate carbon emissions [11, 12]. However, most of the literature suggests that AI has a carbon emission reduction effect and can reduce the intensity of carbon emissions [13, 14]. AI technology is a significant change in the era of the digital economy, which can reduce the intensity of carbon emissions of cities. In enterprise and government management, AI can help enterprises and governments carry out technical inspection and track carbon footprints and realize accurate energy management to reduce energy waste and lower carbon emission intensity. In the field of transportation, AI technology can optimize traffic routes and traffic signal control to reduce congestion and ineffective driving [15]. In the construction of carbon emissions trading market, AI can also provide technical support for carbon emissions trading to help to make decisions in the carbon emissions trading market and to promote the goal of carbon emission reduction [16]. Based on this, we propose the following research hypotheses:

Hypothesis 1 (H1). AI technologies can help reduce the carbon emission intensity of cities.

2.2. Indirect Impacts of AI Technologies on the Carbon Emission Intensity of Cities

The indirect impact path of AI on cities' carbon emission intensity includes reducing energy consumption and green innovation. On the one hand, the main goal of carbon emission reduction is to reduce fossil energy consumption [17]. With the technical support of AI, enterprises acquire relevant production data through intelligent technology, comprehensively consider energy distribution and use in multiple fields, and then optimize the energy management system to improve energy use efficiency. AI can reduce energy consumption in the building sector by automating lighting, heating, ventilation, and air conditioning systems to ensure that buildings and equipment are better adapted to actual demand and environmental conditions. Critical energy-consuming parts such as cooling systems in data centers will also be intelligently controlled, significantly saving energy consumption. On the other hand, an essential means to solve economic and environmental problems is technological progress [18]. AI, as an innovation-driven high-precision technology, can improve the efficiency of green innovation. AI technology supports green technology research by collecting dynamic environmental information in real-time and efficiently acquiring a large amount of primary data such as air quality, water quality, and temperature. Compared with the green innovation supported by traditional technology, AI enhances the effect of green technology use in the process of R&D design and technology application and improves the efficiency of green innovation technology use in energy saving and environmental protection, ecological protection and restoration, which has far-reaching impacts on the suppression of cities' carbon emission intensity. Based on the above theoretical analysis, we propose the following research hypotheses:

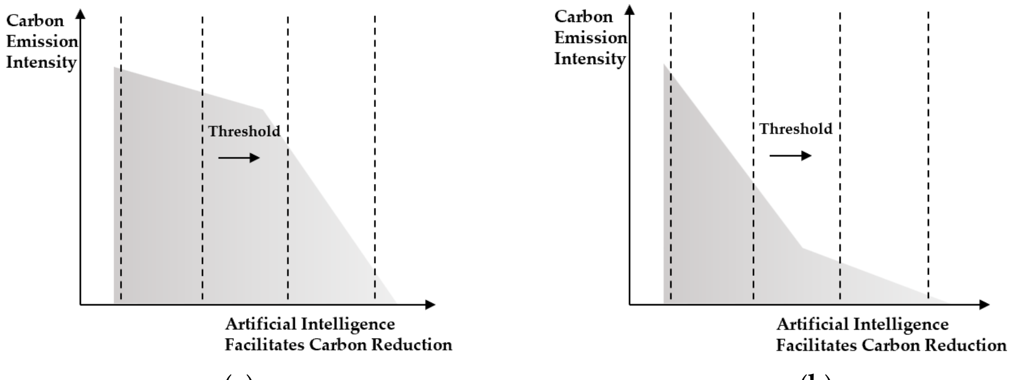
Hypothesis 2a (H2a). AI technology can reduce carbon emission intensity of cities by improving energy use efficiency.

Hypothesis 2b (H2b). AI technology can reduce the carbon emission intensity of cities by improving the efficiency of green innovation.

2.3. Threshold Effect of AI Technology on Carbon Emission Intensity of Cities

Existing studies have proved that external policy changes [19] and the degree of AI development has different effects on carbon emission intensity of cities. The application conditions of AI technology and environmental governance are important factors affecting the carbon emission reduction effect. In the primary stage of AI development, vigorously increasing the Internet penetration rate are important factors in fuelling the development of AI. The climb of AI technology also naturally affects carbon emission intensity. As the level of digitalization increases, the marginal effect of infrastructure development is no longer obvious, and the marginal increase in the saturation of Internet penetration may mean that those Internet users who have not been trained may use AI technology inefficiently, and the carbon emission reduction effect of AI technology may be lower than the carbon emission effect, leading to the reverse threshold effect; government environmental regulation as an important factor to stimulate the carbon emission reduction effect of AI can induce the emergence of more green professional technology, and improved carbon emission reduction effect of AI. When the marginal carbon emission reduction caused by the application of green technology promoted by AI technology is greater than the marginal carbon emission increased by AI technology, the carbon emission reduction effect of AI shows a marginal incremental trend. Although AI technology has a tendency to inhibit carbon emission intensity, the impact shows stage differences. Based on this, we propose the following hypotheses:

Hypothesis 3 (H3). There is threshold effect of AI technology on carbon emission intensity of cities (Figure 1).



(a) (b)

Figure 1 AI for Carbon Reduction Threshold Effect.

3. Research Design

3.1. Modeling

To test the impact of AI technology on carbon emission intensity, based on theoretical analysis, we construct the following benchmark regression model to test Hypothesis 1 (**H1**):

$$lnco_{i,t} = \beta_0 + \beta_1 ai_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \tag{1}$$

Where i and t represent cities and years, respectively. The logarithmic value of carbon emission intensity of city i in year t, and $ai_{i,t}$ is the number of city AI patent applications, $X_{i,t}$ is series of control varia; μ_t, δ_i and $\varepsilon_{i,t}$ are year fixed effects, city fixed effects, and random perturbation terms, respectively.

3.2. Selection of Variables and Descriptive Statistics

(1) Carbon emission intensity (*lnco*) is measured by the ratio of carbon emissions to GDP, and carbon emissions per capita are tested for robustness [20].

(2) Referring to the practice of Peng et al [21], AI technology (*ai*) is measured by AI patent data.

(3) Energy use efficiency (*ene*) is measured by energy consumption per unit of GDP, while green innovation efficiency of cities (*gre*) is measured by the SBM model.

(4) Control variables. Referring to the study of Yu et al. [22], we select the following control variables: government expenditure on science and technology (*edu*), level of financial development (*fin*), foreign direct investment (*fdi*), urbanization rate (*urban*) and population density (*pden*).

Through data cleaning, we finally use the panel data of 277 prefecture-level cities from 2011-2021 for the empirical test. To prevent the quantile from affecting the regression results, all data are standardized. Among them, the data on AI patents are from the Patenthub database. The data on carbon emissions, mediating variables, and control variables are from the previous years' *China Urban Statistical Yearbook*, *China Energy Statistical Yearbook*, etc.

Table 1 presents the descriptive statistics of the main variables.

Table 1 Variable selection and descriptive statistics.

Type	Name	Symbol	Obs	Min	Max
Explained variable	Carbon emission intensity	*lnco*	3047	-3.0630	2.8155
Explanatory variable	AI patent applications	*ai*	3047	-0.2106	20.3946
Mediating variable	Energy use efficiency	*ene*	3047	-0.9265	15.3492
	Green innovation efficiency	*gre*	3047	-1.6837	1.7285
Control variable	Government expenditure on science and technology	*edu*	3047	-0.9467	9.4573
	Level of financial development	*fin*	3047	-1.4263	13.6456
	Foreign direct investment	*fdi*	3047	-0.7053	12.1194
	Urbanization rate	*urban*	3047	-2.4727	2.9874
	Population density	*pden*	3047	-1.3598	4.3551

3.3. Characterizing Facts

As shown in Figure 2, China's total carbon emissions have shown a rising trend since 2011, which is consistent with the results of existing studies [23]. Carbon emission intensity decreased after 2010, with a brief rebound in 2016 and 2020. In recent years, the central government has issued several policies to push forward the development of AI technology. Based on this, we speculate that the important reason for the decline in carbon emission intensity is the in-depth development of AI technology. Figure 2 also presents that the carbon emission intensity of China's eastern, central, and western regions shows a synchronized downward trend. Among them, the carbon emission intensity of cities in the West is the highest, followed by the center, and the east is the least, which is consistent with existing research results [11]. From the viewpoint of AI industry agglomeration, AI technology is more developed in the eastern region with a higher degree of economic development, while AI technology is more backward in the central and western regions, which further adds reasonableness to the speculation of our research.

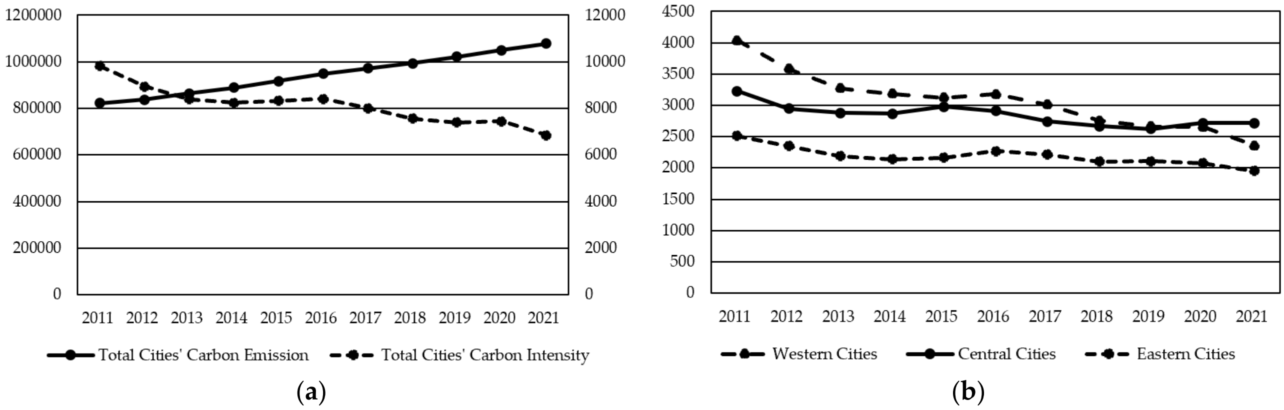


Figure 2 Trends in carbon emission intensity of cities.

4. Empirical Results and Analysis

4.1. Baseline Regression Analysis

The benchmark regression results are as shown in Table 2. Column (1) is a random effects regression of only AI patent applications and carbon emissions, column (2) introduces control variables on top of that, column (3) introduces city fixed effects, and column (4) then adds year fixed effects. By adding control variables and various fixed effects, the coefficient on AI patent applications is always negative at the 5% significance level. This suggests that AI technology effectively suppresses carbon emission intensity, validating Hypothesis 1 (**H1**).

Table 2 Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
	lnco	*lnco*	*lnco*	*lnco*
ai	-0.0809*** (0.0263)	-0.0449*** (0.0141)	-0.0430*** (0.0134)	-0.0207** (0.0085)
Controls	No	Yes	Yes	Yes
City FE	No	No	Yes	Yes
Year FE	No	No	No	Yes
Constant	-0.1638*** (0.0546)	-0.1422*** (0.0483)	-0.1425*** (0.0018)	0.1503*** (0.0171)
N	3047	3047	3047	3047
adj. R^2	0.0551	0.2882	0.2868	0.4861

Note: *, **, and *** are significance levels of 10%, 5%, and 1%, respectively, and clustering robust standard errors at the city level are reported in parentheses, as in the table below.

4.2. Endogenous Processing

4.2.1. Exogenous Policy Shocks

From the perspective of empirical method, the benchmark regression model may have endogeneity problems due to missing variables and reverse causality In this regard, we refer to Yu et al. [24], using Smart City pilots as exogenous policy shocks. From 2012 to 2014, China released three batches of smart city pilot lists. Since the smart city policy as an exogenous shock can effectively represent the level of AI development, we utilize the multi-period DID method to test the causal effect of AI in suppressing carbon emission intensity. The model is set explicitly as follows:

$$lnco_{i,t} = \beta_0 + \beta_1 smart_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \tag{2}$$

Where $smart_{i,t}$ is a dummy variable for smart city pilot. The regression results, as shown in Table 3, consistently indicate that the regression coefficients for smart city policies are significantly negative at the 5% significance level regardless of the inclusion of control variables. This suggests that AI still has a significant carbon reduction effect after exogenous policy shocks are used to address endogeneity.

4.2.2. Two-stage Least Squares

The instrumental variables constructed for AI are as follows: first, we can refer to the practices of Bartik [25] and Yi et al. [26], and use a lagged first-order AI patent application volume and the product of the first-order difference of AI patent application volume over time to construct instrumental variables; second, we can refer to the practices of Fisman [27] and Zhang et al. [28], and use the removal of the mean of AI patent application volume in other cities within the same province as an instrumental variable. The two-stage least squares regression was conducted, and the results are shown in column (2) of Table 3. At a 1% significance level, the regression coefficient for the AI patent applications still remains negative. This suggests that after accounting for potential endogeneity issues, AI technology is still effective in suppressing carbon emission intensity of cities, consistent with the baseline regression findings and again validating Hypothesis 1 (**H1**).

Table 3 Endogenous processing results.

Variable	(1)	(2)	(3)
	lnco	*lnco*	*lnco*
smart	-0.0276** (0.0120)	-0.0088** (0.0041)	
IVai			-0.1693*** (0.0052)
Controls	No	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	0.3868*** (0.0133)	-0.0327 (0.0242)	-1.0895*** (0.0374)
N	3047	3047	3047
adj. R^2	0.4781	0.7724	0.9712

4.3. Robustness Tests

Table 4 Endogenous processing results.

Variable	(1)	(2)	(3)
	lnco	*lnco*	*lnco*
ai	-0.0450*** (0.0098)	-0.0205** (0.0082)	-0.0251** (0.0104)
lowco		-0.0461** (0.0186)	
smart		-0.0396* (0.0233)	
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Constant	-0.2291*** (0.0165)	0.1508*** (0.0171)	0.1269*** (0.0190)
N	3047	3047	3047
adj. R^2	0.4445	0.4886	0.4419

To further verify the reliability of the benchmark results, we conducted robustness tests as follows. First, replacing the explained variable. Following the practice of existing literature, we used per capita carbon emissions to measure the carbon emission intensity of cities. Second, excluding policy interference. We controlled for low-carbon pilot city policies and smart city pilot policies, incorporating both into the regression equation to as much as possible eliminate policy interference. Third, shortening the sample years. Considering the impact of the 2020 COVID-19 outbreak on carbon emission intensity of cities, this study excluded research samples from 2020 and beyond, thus shortening the original sample range to the years 2011 to 2019. The test results are shown in Table 4. Combining the above three methods, the regression coefficients of AI technology are still significantly negative, indicating that the conclusion that AI technology suppresses carbon emission intensity has strong robustness and reliability.

4.4. Impact Mechanism Testing

We refer to the mediating effect test framework proposed by Wen et al. [29], and constructs the model as follows by using the stepwise regression method:

$$lnco_{i,t} = \beta_0 + \beta_1 ai_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (3)$$

$$M_{i,t} = \beta_0 + \delta ai_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (4)$$

$$lnco_{i,t} = \beta_0 + \theta ai_{i,t} + \tau M_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (5)$$

In model (3) to (5), $M_{i,t}$ represents the mediating variable, $\beta_1$represents the total effect of AI, θ represents the direct effect, and $\delta\tau$ represents the mediating effect. Column (1)-(2) of Table 5 shows that AI technology can significantly reduce energy consumption and improve energy utilization efficiency and the reduction in energy consumption also has a significant impact on reducing carbon emissions intensity of cities, validating hypothesis 2a (**H2a**). Column (3)-(4) of Table 5 illustrates that green innovation efficiency has a significant impact on carbon emissions intensity of cities. Although the impact of AI technology on green innovation efficiency is not significant based on model (4), further Bootstrap tests, as per the approach of Peng et al. [30], resulted in an interval of [-0.1892752, -0.0503849], validating hypothesis 2a (**H2b**).

Table 5 Impact mechanism test.

Variable	(1)	(2)	(3)	(4)
	Energy consumption		Green innovation efficiency	
	ene	*lnco*	*gre*	*lnco*
ai	-0.0853*** (0.0283)	-0.0149** (0.0070)	0.0143 [1] (0.0529)	-0.0213*** (0.0065)
ene		0.0665*** (0.0149)		
gre				0.0450*** (0.0112)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-0.1948*** (0.0361)	0.1604*** (0.0160)	-0.4185*** (0.0449)	0.1735*** (0.0163)
N	3047	3047	3047	3047
adj. R^2	0.4861	0.5059	0.4861	0.4977

[1]The direct effect of AI on green innovation efficiency is not significant, but according to the testing process, we can confirm the existence of a mediation effect after further Boostrap tests.

5. Further Discussion

5.1. Heterogeneity Analysis

5.1.1. City Location

To explore whether the carbon emission reduction effect of AI technology is different in different regions, the sample is divided into East, Central, and West. The results show that the strength of AI technology in reducing carbon emission intensity is more muscular in the central and western regions. This is mainly due to differences in economic and industrial structures between regions.

5.1.2. Administrative Level

We divide the sample into provincial capital cities and non-provincial capital cities. It examines the effects of AI technology on carbon emission intensity in cities at different administrative levels in groups. The results in Table 6 show that AI's carbon emission reduction effect is significant in non-capital cities while not in capital cities. This may be due to the smaller size of non-provincial cities and the relatively simple economic structure, which makes it easier to achieve carbon reduction through AI technology.

Table 6 Heterogeneity analysis of city location and administrative level.

Variable	(1) Eastern	(2) Central	(3) Western	(4) Provincial Capital	(5) Non-provincial Capitals
ai	-0.0277*** (0.0092)	-0.0552** (0.0222)	-0.0466** (0.0224)	-0.0019 (0.0082)	-0.0132** (0.0062)
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Constant	-0.0506*** (0.0164)	0.1726*** (0.0252)	0.3092*** (0.0537)	-1.1612*** (0.0961)	0.2983*** (0.0247)
N	1155	1078	814	286	2761
adj. R^2	0.8118	0.7864	0.6439	0.6973	0.4625

5.1.3. Level of Digitization

We apply principal component analysis to measure the digitization level of each city [31] and divides the sample into two groups for estimation according to the mean value. The results show that the carbon reduction effect of AI is more extraordinary in cities with lower levels of digital economy development. These cities usually have a more significant potential to reduce emissions and a higher demand for new technologies.

5.1.4. Resource Endowment

We divide the sample into resource-dependent and non-resource-dependent cities to empirically test AI's carbon emission reduction effect. The results in Table 7 show that AI can more effectively promote carbon emission reduction in resource-dependent cities, indicating that the application of AI technology is more likely to find entry points in industries such as heavy industry and resource development and achieve significant carbon emission reduction.

Table 7 Heterogeneity analysis of digitization levels and resource endowments.

Variable	(1) Higher level of digitization	(2) Low level of digitization	(3) Resource-dependent	(4) Non-resource
ai	-0.0162** (0.0076)	-0.0274*** (0.0079)	-0.4805** (0.2126)	-0.0210*** (0.0073)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-0.0364 (0.1694)	0.1208*** (0.0235)	0.2192*** (0.0598)	0.0531*** (0.0135)
N	1749	1298	1111	1936
adj. R^2	0.3632	0.4814	0.3264	0.6191

5.2. Threshold Effect

To further examine the conditions for the realization of the carbon reduction effect of AI, we construct the following threshold model for estimation:

$$lnco_{i,t} = \beta_0 + \beta_1 ai_{i,t} \cdot I(T_{i,t} \leq \phi) + \beta_1 ai_{i,t} \cdot I(T_{i,t} > \phi) + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (6)$$

Where T is the threshold variable, $I(\cdot)$ is the indicator function segmented according to different thresholds, ϕ is the threshold to be estimated. The threshold variables are as follows: Internet penetration rate of cities is expressed as the ratio of the number of Internet broadband access users to the total population at the end of the year; the level of environmental regulation is measured by the frequency of "environmental protection" related terms in the government work report [32].

The results are shown in Table 8. First, the carbon emission reduction effect of AI is increased when the degree of environmental regulation exceeds a certain threshold, while the carbon emission reduction effect of AI shows a marginal increasing trend. Second, AI's carbon emission reduction effect will decrease when the Internet penetration rate crosses a certain threshold. But with the development of Internet infrastructure, the carbon emission reduction effect of AI technology shows a marginal decreasing trend.

Table 8 Threshold effect results.

Variable	(1) Level of environmental regulation	(2) Internet penetration
ai ($T \leq \phi$)	-0.0210*** (0.00485)	-0.301*** (0.0616)
ai ($T > \phi$)	-0.0524*** (0.0148)	-0.0215*** (0.00483)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Constant	0.284*** (0.0126)	0.267*** (0.0131)
N	3047	3047
adj. R^2	0.589	0.591

6. Conclusions and Recommendations

The results of our research show that: (1) AI technology can significantly inhibit carbon emissions of cities, a process realized through improving energy use efficiency and green innovation efficiency; (2) the heterogeneity test shows that AI has a more substantial carbon emission reduction effect in central and western regions, non-provincial capitals, regions with a lower level of digitization, and resource-dependent cities; (3) further use of the threshold regression finds that the carbon emission reduction effect of AI shows a marginal increasing trend in environmental regulation and a decreasing marginal utility in Internet penetration.

Based on the above conclusions, we make the following recommendations:

First, the strategic position of AI in promoting green and low-carbon development should be strengthened. Second, the deep integration of AI with green industries should be strengthened. Third, AI development strategies should be formulated according to local conditions. Fourth, the relevant regulations and standards system must be improved.

References

[1] Sun, P., Ge, L. (2021) The way to low carbon emission: Impact of high-speed railway on industrial carbon emissions. The Journal of World Economy, 10, 201-224.

[2] Han, F., Xie, R. (2017) Does the agglomeration of producer services reduce carbon emissions? Journal of Quantitative & Technological Economics, 34, 40-58.

[3] Chen, H., Yang, X., Wang, Z. (2024) The impact of digital economy on industrial carbon emission intensity and its spillover effect. Research of Environmental Sciences, 3, 1-20.

[4] Sun, H., Kim, G. (2021) The composite impact of ICT industry on lowering Carbon Intensity: from the perspective of regional heterogeneity. Technology in Society, 66, 101661.

[5] Xue, F., Zhou, M., Liu, J. (2022) The effect of digital infrastructure on reducing carbon emissions: quasi natural experiment based on “Broadband China” pilot. South China Journal of Economics, 10, 19-36.

[6] Acemoglu, D., Restrepo, P. (2020) Robots and jobs: Evidence from U.S. labor markets. Journal of Political Economy, 128, 2188-2244.

[7] Zhou, G., Ding, X. (2022) The effects of robotics application on income distribution of urban residents. Journal of Quantitative & Technological Economics, 39, 115-131.

[8] Wei, D., Gu, N., Han, Y. (2021) Does the artificial intelligence promote the upgrading of industrial structure? - Empirical research based on industrial robot data of China. Finance & Economics, 10, 70-83.

[9] Wang, Q., Wei, S., Jin, S. et al. (2022) A research on the effect of industrial intelligence on employment: Based on spatial econometric analysis of laborers’ skills and genders. Journal of Management World, 38, 110-126.

[10] Tan, Y., Dong, Z. (2022) Can industrial intelligence promote the improvement of carbon emission performance? - Based on empirical evidence at the urban level in China. Commercial Research, 5, 20-28.

[11] Xue, F., Liu, J., Fu, Y. (2022) The effect of artificial intelligence technology on carbon emissions. Science & Technology Progress and Policy, 39, 1-9.

[12] Henderson, P., Hu, J., Romoff, J. et al. (2020) Towards the systematic reporting of the energy and carbon footprints of machine learning. Journal of Machine Learning Research, 21, 1-43.

[13] Ding, T., Li, J., Shi, X. et al. (2023) Is AI associated with carbon emissions reduction? Case of China. Resources Policy, 85, 103892.

[14] Wang, Y., Tao, S. (2023) Study on the impact of industrial intelligence on the efficiency of industrial carbon emissions in China and its spatial effects. Journal of Technology Economics, 42, 130-140.

[15] Luo, L., Zhang, Z., Zhou, Q. (2023) Industrial intelligence and urban low-carbon economic transformation. Business and Management Journal, 45, 43-60.

[16] Chang, H., Xia, F. (2023) Empowerment of digital economy to low-carbon development: mechanism identification and spatial spillover. Science & Technology Progress and Policy, 40, 48-57.

[17] Chen, S. (2011) Fluctuating and declining patterns of carbon emission intensity in China and economic explanations. The Journal of World Economy, 34, 124-143.

[18] Shao, S., Li, X., Cao, J. et al. (2016) China’s economic policy choices for governing smog pollution management in China: Based on spatial spillover effects. Economic Research Journal, 51, 73-88.

[19] Huang, Z., Jiang, P. (2023) Digital low-carbon road: industrial robots and urban industrial carbon emissions. Journal of Finance and Economics, 49, 34-48.

[20] Lv, Q., Liu, H. (2020) Multiscale spatio-temporal characteristics of carbon emission of energy consumption in Yellow River Basin based on the nighttime light datasets. Economic Geography, 40, 12-21.

[21] Peng, D., Li, Y., Peng, X. (2021) The influence and mechanism of artificial intelligence on wage of floating population. Reform of Economic System, 3, 32-38.

[22] Yu, Z., Chen, J., Dong, J. (2020) The road to a low-carbon economy: the perspective of industrial plans. Economic Research Journal, 55, 116-132.

[23] Shao, S., Fan, M., Yang, L. (2022) Economic restructuring, green technology progress, and low-carbon transition development in China: An empirical investigation based on the Overall technology frontier and spatial spillover effect. Journal of Management World, 38, 46-69+4-10.

[24] Yu, D., Long, R., Wang, Chao. (2023) Digital economy and pollution control in border areas. Economic Research Journal, 58, 172-189.

[25] Bartik, T.J. (2006) How Do the Effects of Local Growth on Employment Rates Vary With Initial Labor Market Conditions. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, 11, 9-148.

[26] Yi, X., Zhou, L. (2018) Does digital financial inclusion significantly influence household consumption? Evidence from household survey data in China. Journal of Financial Research, 11, 47-67.

[27] Fisman, R., Svensson, J. (2007) Are corruption and taxation really harmful to growth? Firm level evidence. Journal of Development Economics, 83, 63-75.

[28] Zhang, X., Liu, B., Wang, T. et al. (2017) Credit rent-seeking, financing constraint and corporate innovation. Economic Research Journal, 52, 161-174.

[29] Wen, Z., Zhang, L., Hou, J. et al. (2004) Testing and application of the mediating effects. Acta Psychologica Sinica, 5, 614-620.

[30] Peng, L., Zhan, H., Wen, W. (2022) Entity enterprise financialization and technological innovation--Empirical evidence from non-financial listed companies. Economist, 4, 58-69.

[31] Zhao, T., Zhang, Z., Liang, S. (2020) Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. Journal of Management World, 36, 65-76.

[32] Zhang, J., Chen, S. (2021) Financial development, environmental regulations and green economic transition. Journal of Finance and Economics, 47, 78-93.