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Original Research

How Does AI Development Affect Pollution Emissions? A Regional Study of China

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Abstract

Using provincial panel data of China from 2011 to 2022, this study constructs an evaluation index system to measure regional AI development and empirically examines its nonlinear impact on regional pollution emissions. The findings show the following: there is a significant U-shaped relationship between AI development and regional pollution emissions, with the effect transmitted through an inverted U-shaped relationship with green technology innovation and energy efficiency. Heterogeneity analysis further shows that the U-shaped relationship is only pronounced in regions southeast of the "Hu Huanyong Line". It exhibits greater marginal effects in areas with lower levels of marketization. This study provides useful references for effectively empowering regional green development through AI.

Keywords: artificial intelligence, pollution emissions, green technology innovation, energy efficiency

Introduction

Currently, China remains the world's largest energy consumer and emitter of carbon dioxide. According to the International Energy Agency (IEA), global carbon dioxide emissions reached a record high of 37.4 billion tons in 2023, with China contributing 12.6 billion tons, accounting for 33.69% of the global total. To address the challenges posed by environmental pollution, the Chinese government is actively taking measures to reduce various types of pollution emissions, including carbon emissions, while promoting the green transformation of production methods. The advancement of next-generation information technologies, particularly artificial intelligence, is significantly influencing the transformation of enterprise production models and the upgrading of industrial structure. For instance, AI-driven industrial robots enhance automation levels, optimize production processes, and improve product quality [1]; Digital twin technology enables enterprises to optimize decision-making, minimize disruptions, and reduce costs through real-time data analysis and model prediction [2]; Blockchain technology, when applied to supply chain management, traceability, and regulatory compliance, enhances transparency, security, and efficiency [3]; Moreover, as a representative breakthrough in AI technology, ChatGPT can perform various scenario-based tasks, enhance production efficiency, and even revolutionize production models through dataset pre-training, fine-tuning for specific scenarios, and reinforcement learning in specialized domains. Overall, artificial intelligence serves as a core driving force for industrial technological innovation, facilitating the modernization

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and intelligent transformation of production methods, improving resource utilization efficiency, optimizing energy structure allocation, and promoting industrial transformation and upgrading, thereby presenting new opportunities for reducing pollution emissions [4].

By reviewing the existing literature on artificial intelligence and environmental development, it is evident that there is no consensus in the academic community regarding the impact of artificial intelligence on the environment. Most studies argue that AI can promote green technological advancements, enhance production efficiency and resource allocation, reduce pollution emissions, and foster green economic development [5]. For instance, intelligent manufacturing creates opportunities for cost-effective green technology innovation, helps to eliminate obsolete equipment, mitigates pollution, and plays a crucial role in environmental protection [6]; AI investment improves energy efficiency and enables cleaner production [7]; the adoption of industrial robots enhances energy efficiency, strengthens pollution control technologies, and reduces regional pollution emission intensity [8]; and industrial robots contribute to environmental improvement by reducing the ecological footprint [9]. However, some studies contend that the application of artificial intelligence entails substantial energy consumption, emits toxic substances in the production process, and leads to environmental pollution [10]. In addition, while the widespread adoption and deep integration of AI technology have improved energy efficiency, they have also led to increased energy demand, giving rise to the “scale effect” and “rebound effect” [11]. Research shows that the use of industrial robots has enhanced productivity and energy efficiency; however, it has also amplified production and consumption, increasing total energy consumption, leading to a deterioration of air quality [12]. Meanwhile, existing research indicates that the development of artificial intelligence has a significant negative spatial spillover effect on carbon emission efficiency. Specifically, the findings indicate that artificial intelligence impedes green technological progress, reduces energy consumption efficiency, and consequently fails to contribute positively to green total factor productivity [13].

Existing research has examined the impact of artificial intelligence on environmental development from multiple perspectives, providing a strong theoretical foundation for this study. However, there remains a lack of a systematic evaluation index system to measure the level of regional AI development. Additionally, few studies have conducted nonlinear analyses on the relationship between AI development and regional pollution emissions or provided an in-depth examination of its internal transmission mechanisms. To address these gaps, this study employs the entropy method to construct a comprehensive evaluation index system for regional AI development by selecting indicators across 4 key dimensions: environmental construction, inputs, outputs, and applications. Based on this framework, the AI development level of each province (autonomous regions and municipalities) in China is measured, and their evolutionary trends and spatial distributions are analyzed. Furthermore, using panel data from 30 provinces in China from 2011 to 2022, this study investigates the internal transmission mechanisms through which AI development influences regional pollution emissions. Specifically, it examines 2 key pathways: the green technology innovation mechanism and the energy efficiency mechanism. The findings aim to provide valuable insights into how artificial intelligence can effectively contribute to high-quality regional development.

This study makes several key contributions. First, it develops a comprehensive evaluation index system for regional AI development based on 4 dimensions – environmental construction, inputs, outputs, and applications – providing a quantitative foundation for assessing regional disparities in AI development and analyzing its evolution and spatial distribution. Second, it explores the nonlinear relationship between AI development and regional pollution emissions, challenging the prevailing linear assumptions in existing research on AI’s environmental impact. Third, from the theoretical perspectives of “green technology-driven” and “green technology gap”, as well as “energy efficiency improvement” and “energy demand growth”, this study provides a dialectical analysis of the internal transmission mechanisms through which AI development influences regional pollution emissions.

Theoretical Analysis and Hypotheses

AI Development and Regional Pollution Emissions

Amid the rapid development of the digital economy, artificial intelligence has emerged as a leading technology in boosting the new quality productivity, serving as a powerful engine for regional green technology innovation and pollution reduction. This implies that AI development exerts a “green technology-driven effect”. Green technology innovation facilitates energy structure optimization and enhances energy efficiency, thereby reducing regional energy consumption and pollution emissions. However, technological advancements often yield unintended side effects, which are typically proportional to the anticipated side effects [14]. One such expected side effect is the inherent link between technological progress and increased energy consumption. Large-scale AI applications, in particular, may lead to a greater energy demand and pollution emissions. As AI technology reaches maturity and becomes widely adopted, large-scale automation and a substantial increase in output may result in a significant surge in energy consumption. With the completion of the technological leap, the popularization and application of artificial intelligence will lead to a large-scale replacement of traditional human labor and a significant expansion of production output, ultimately driving a substantial increase in energy consumption. In addition, the information overload caused by AI development could lead to a "green technology gap", that is, the fractured interaction between excessive data elements and traditional enterprise factors ultimately impedes green technology innovation, leading to the misallocation of energy resources or a decline in efficiency, which in turn exacerbates regional pollution emissions. Based on the above analysis, we propose:

Hypothesis 1: There exists a significant U-shaped relationship between AI development and regional pollution emissions.

Green Technology Innovation Mechanism

Artificial intelligence primarily promotes green innovation activities and reduces pollution emissions through three main channels. First, the application of AI technology can reduce information asymmetry and lower transaction costs [15]. Experts and scholars across industries can interact and exchange knowledge through AI platforms, facilitating the commercialization of green technology outcomes and thereby accelerating the adoption and dissemination of green technologies [16]. Second, AI technology can automate important but repetitive and time-consuming tasks, optimizing green technology development systems through rapid model generation and simulation [17]. This approach shortens the development and evaluation cycle of new green technologies while enhancing their application speed and market adaptability [18]. Finally, AI technology strengthens the connections between various stages of green innovation, breaking the chain-like characteristics of knowledge accumulation, development, application, and conversion production in traditional innovation processes, and forming a networked green innovation model that accelerates the iteration process of green innovation [19]. The significant reduction in energy intensity brought about by technological innovation has been widely confirmed [20, 21]. Green technological innovation is a key driver of process technology advancement and reduced coal resource consumption, directly leading to decreased pollution emissions [22].

However, once AI technology undergoes a leap forward and resource allocation efficiency peaks, the marginal returns of green technology innovation begin to decline. As a result, AI's role in promoting green technology innovation may diminish or even reverse. Moreover, the continuous development of AI could exacerbate the "green technology gap", which is a structural mismatch caused by the rapid accumulation of data and algorithms generated by AI that cannot be effectively integrated with traditional production factors (such as capital, labor, and infrastructure). Under the influence of the "green technology gap", the decoupled interaction between excess data elements and traditional enterprise elements causes a mismatch or decrease in the efficiency of energy resources, thereby increasing pollution emissions. Based on the above analysis, we propose the following hypothesis:

Hypothesis 2: AI development influences regional pollution emissions through an inverted U-shaped relationship with green technology innovation.

Energy Efficiency Mechanism

AI development plays a significant role in improving energy efficiency, which can be observed in three key aspects. First, the effect on resource allocation: driven by intelligent algorithms, artificial intelligence systems can formulate optimal energy allocation plans, optimize energy resource allocation, and improve energy efficiency [23]. In addition, artificial intelligence systems can also issue warnings about excessive resource consumption, thereby reducing energy consumption and avoiding unnecessary waste of resources [24]. Second, knowledge spillovers: the knowledge diffusion resulting from AI development accelerates the integration of intelligent technology into energy production, fosters imitation and learning among enterprises, and promotes the intelligent trading, production, and processing of energy resources, thereby improving energy efficiency while simultaneously reducing energy consumption and pollution emissions. Third, the complementary effect of technology: artificial intelligence enhances human labor capabilities in the production process, improving energy efficiency and overall productivity while reducing energy intensity and pollutant emissions [25]. The introduction of artificial intelligence has improved energy efficiency, preventing resource waste and reducing pollution emissions [26].

However, as the AI development level surpasses a critical threshold, the negative impacts of the rebound effect, substitution effect, and scale effect on energy consumption begin to manifest, gradually outweighing its energy efficiency benefits and ultimately leading to an increase in regional pollution emissions. Specifically, the "Jevons paradox" suggests that technological advancements may enhance energy efficiency yet simultaneously drive an increase in energy consumption [27]. As AI development exceeds a critical threshold, the substantial rise in energy demand may eventually outstrip the energy savings it generates, exacerbating pollution emissions – this phenomenon corresponds to the "rebound effect" of energy consumption [28]. Additionally, AI-driven improvements in energy efficiency reduce production costs, leading to declining energy prices, which incentivize firms to substitute higher-cost factors such as labor and capital with energy-intensive production methods [29], thus increasing overall energy consumption and pollutant emissions, a mechanism known as the "substitution effect". Finally, artificial intelligence enhances total factor productivity, stimulates economic growth, and expands aggregate demand for goods and services. Higher consumption may, in turn, lead to increasing demand for energy and, consequently, increasing pollution emissions

– this represents the "scale effect" of AI development. Based on the above analysis, this paper proposes:

Hypothesis 3: AI development can affect regional pollution emissions through an inverted U-relationship with energy efficiency.

Materials and Methods

Sample Selection and Data Sources

This study selects data from 30 provinces in China from 2011 to 2022 as research samples[1]. Missing values in the dataset were addressed using the interpolation method, resulting in a final dataset of 360 observations. The primary data sources for this study include the China Statistical Yearbook, China Energy Statistical Yearbook, China High-tech Industry Statistical Yearbook, and the National Bureau of Statistics. Additionally, provincial (autonomous regions and municipalities) statistical yearbooks and the EPS database were utilized.

Variable Definitions

Explained Variable

Regional Pollution Emissions (Poll). Environmental pollution is commonly assessed using the "three wastes" framework, which includes wastewater, waste gas, and solid waste. This paper employs three proxy indicators for pollution emissions [30]: (1) general industrial solid waste generation/real GDP, (2) sulfur dioxide emissions/real GDP, and (3) chemical oxygen demand emissions in wastewater/real GDP. The entropy method constructs optimal weights by quantifying the contribution of various factors within the overall system. This approach effectively captures the utility of information entropy while minimizing human-induced bias. Therefore, this study employs the entropy method to develop a comprehensive index system for environmental pollution, enabling a robust assessment of pollution emission levels across provinces. The specific steps are as follows:

There are m provinces and n evaluation indicators; X_{ij} is raw data, where I = 1, 2, 3, ..., m; j = 1, 2, 3, …, n.

Step 1: Standardize x_{ij}:

$$x_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}}, \text{ } X_{ij} \text{ is a positive indicator} \quad (1)$$

$$x_{ij} = \frac{X_{max} - X_{ij}}{X_{max} - X_{min}}, \text{ } X_{ij} \text{ is a negative indicator} \quad (2)$$

where X_{max} and X_{min} represent the maximum and minimum values of indicator j, respectively, and x_{ij} denotes the normalized data.

Step 2: Calculate the probability of occurrence of x_{ij}:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

Step 3: Calculate the information entropy e_j of x_{ij}:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln P_{ij} \quad (4)$$

Step 4: Determine the weights W_j of x_{ij}:

$$W_j = \frac{1 - e_j}{\sum_{j=1}^{n} \left(1 - e_j\right)} \quad (5)$$

Step 5: Calculate the score S_j

$$S_j = \sum_{j=1}^{n} W_j x_{ij} \quad (6)$$

Furthermore, the 3 selected indicators are positively processed, so that the higher the score, the higher the pollution emission level of the region.

Explanatory Variables

AI Development Level (AI). The indicator system construction method is a commonly used approach for measuring the level of artificial intelligence development [5, 31]. Zhou et al. [13] employ the entropy value method to construct a comprehensive AI development indicator system comprising 3 primary indicators, 7 secondary indicators, and 16 tertiary indicators. Referring to their approach, this study constructs an evaluation index system for regional AI development levels using 6 second-level indicators and 13 third-level indicators across four dimensions: regional artificial intelligence environmental construction, inputs, outputs, and applications, as presented in Table 1. Using the constructed evaluation index system and provincial data, calculations were performed using the entropy method[2]. To facilitate interpretation, the index scores were uniformly scaled by multiplying by 100, yielding the final comprehensive AI development scores for

[1] Tibet and Hong Kong, Macao and Taiwan samples were excluded due to missing data.

[2] The calculation steps have been elaborated in detail in the measurement of pollution emissions, and thus will not be repeated here.

Table 1. Regional AI development level evaluation indicator system.

Primary Indicators	Secondary Indicators	Measurement Indicators	Unit
Environmental Construction	Scientific Research Institutions	Number of R&D activities in industrial enterprises above a designated size	Count
		Number of legal entities, scientific research, and technical services	Count
	Technicians	Number of employed people in scientific research and technical services in urban units	10,000 people
		Number of employed people in urban units in the information transmission, software, and information technology services industry	10,000 people
		Number of employees in high-tech industries	10,000 people
	Infrastructure	R&D expenditures of industrial enterprises above a designated size	100 million yuan
		Fiber optic cable line length	Kilometer
		Number of Internet broadband access ports	10,000
Inputs	Capital operations	R&D investment intensity	Ratio
Outputs	Direct Outcomes	Artificial intelligence patents	Count
		Software business revenue	100 million yuan
		Number of new product projects of industrial enterprises above designated size	Count
Applications	Application Revenue	Total profit of high-tech enterprises/number of high-tech enterprises	100 million yuan/ enterprise

each province. A higher comprehensive score indicates a more advanced level of AI development in the region.

Mechanism Variables

As analyzed above, AI development primarily influences regional pollution emissions through technological innovation and energy efficiency. Therefore, 2 mechanism variables were identified:

Green Technology Innovation (GT). The number of green invention patent applications per 1,000 people in each province is used as a proxy for green technology innovation levels [13].

Energy Efficiency (Effi). Energy efficiency is measured as the ratio of GDP to total energy consumption in each province [8].

Control Variables

To enhance the robustness of the regression results and mitigate estimation bias caused by omitted variables, the following control variables are included based on existing research: (1) Economic Development (Pgdp), measured by the logarithm of GDP per capita of each province; (2) Openness to the outside (Open), measured by the ratio of actual foreign capital utilization to GDP; (3) Urbanization level (Urban), measured by the proportion of urban population in the total population of each province; (4) Government Intervention (Gov), measured by the ratio of local fiscal general budget expenditure to GDP; (5) Environmental Regulation (ER), measured by the ratio of industrial pollution control investment to industrial added value in each province; and (6) Social Consumption Level (Sale), measured as the percentage of GDP in retail sales of consumer goods.

Variable definitions and descriptive statistics are shown in Table 2. The results indicate significant variations in AI development levels and regional pollution emissions, suggesting substantial potential for AI-driven pollution reduction across different regions in China. The descriptive statistics of other variables fall within normal fluctuation ranges, indicating no abnormalities in the dataset. Furthermore, the variance inflation factor (VIF) values for all variables range from 1.09 to 5.24, remaining below the critical threshold of 10, thus confirming the absence of severe multicollinearity in the subsequent empirical analysis.

Regression Model Design

(1) To examine the relationship between AI development and regional pollution emissions, this study constructs the following econometric model:

$$Poll_{it} = \alpha_0 + \alpha_1 AI_{it}^2 + \alpha_2 AI_{it} + \alpha_3 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{7}$$

where i represents the province, t represents the year; $Poll_{it}$ denotes the level of pollution emissions; AI_{it}^2

Table 2. Variable definitions and descriptive statistics.

Variables	Symbol	Measurement	Obs.	Mean	Std.	Min.	Max.
Polluting Emissions	Poll	Comprehensive evaluation indicators	360	37.587	37.859	0.110	182.918
Artificial Intelligence	AI	Comprehensive evaluation indicators	360	11.582	13.239	0.361	84.411
Green Technology Innovation	GT	Patent applications for green inventions per 1,000 people	360	7.823	13.364	0.211	109.634
Energy Efficiency	Effi	GDP/Energy consumption	360	17.455	9.283	4.093	60.231
Economic development	Pgdp	GDP per capita	360	5.855	3.059	1.591	19.021
Openness to the outside	Open	Actual utilization of foreign capital/GDP	360	0.321	3.479	0.000	41.905
Urbanization	Urban	Urban population/Total population	360	0.601	0.121	0.350	0.896
Government intervention	Gov	Local general budget expenditures/GDP	360	0.491	0.188	0.151	0.931
Environmental regulation	ER	Investment in industrial pollution control/Industrial value added	360	31.719	34.490	0.615	309.838
Social consumption	Sale	Retail sales of consumer goods/GDP	360	0.392	0.0655	0.180	0.610

indicates the squared term of AI development level; AI_{it} denotes the level of AI development; X_{it} refers to the set of control variables; μ_i denotes the province fixed effects, γ_t represents the time fixed effects, and ε_{it} is the random error of the model.

(2) To further investigate the transmission effect of the green technology innovation mechanism, this study expands Eq. (7) and constructs the following mediating effect model:

$$GT_{it} = \beta_0 + \beta_1 AI_{it}^2 + \beta_2 AI_{it} + \beta_3 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{8}$$

$$Poll_{it} = \varphi_0 + \varphi_1 AI_{it}^2 + \varphi_2 AI_{it} + \varphi_3 GT_{it} + \varphi_4 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{9}$$

where GT_{it} denotes the level of green technology innovation, and the other variables remain consistent with Eq. (7).

(3) To investigate the transmission effect of the energy efficiency mechanism, this study expands Eq. (7) and constructs the following mediating effect model:

$$Effi_{it} = \beta_0 + \beta_1 AI_{it}^2 + \beta_2 AI_{it} + \beta_3 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{10}$$

$$Poll_{it} = \varphi_0 + \varphi_1 AI_{it}^2 + \varphi_2 AI_{it} + \varphi_3 Effi_{it} + \varphi_4 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{11}$$

where $Effi_{it}$ represents the energy efficiency, and the other variables remain consistent with Eq. (7).

Results and Discussion

Benchmark Regression Results

Columns (1) and (2) of Table 3 present the benchmark regression results for AI-induced pollution emissions, both before and after the inclusion of control variables[3]. As shown in column (2), the quadratic coefficient (AI^2) and the primary coefficient (AI) of artificial intelligence are 0.026 and -3.826, respectively, both of which pass the 1% significance test. These findings suggest a significant U-shaped relationship between AI development and regional pollution emissions. Specifically, when AI development remains below the threshold value of 73.577, it significantly suppresses regional pollution emissions. However, once AI development surpasses this threshold, it exacerbates pollution emissions. Thus, hypothesis 1 is validated. To enhance robustness, a U-test was conducted. The results indicate that the extreme points lie within the data interval, with opposite monotonicity on both sides, confirming the existence of a significant U-shaped relationship. However, it is noteworthy that in 2022, the 75th percentile of AI development levels across Chinese provinces stood at 19.981, substantially lower than the threshold of 73.577. This suggests that AI development in most regions remains well below the inflection point of the U-curve, indicating considerable potential for further reductions in regional pollution emissions through AI advancement.

Mechanism Test Results

Column (1) of Table 4 reports the impact of AI development on regional green technology innovation. As shown in column (1), the quadratic coefficient (AI^2)

[3] For space reasons, the results of the correlation coefficient are not displayed in the text and are kept for reference.

Table 3. Benchmark regression results.

	(1)	(2)
Variables	Poll	Poll
AI^2	0.012**	0.026***
	(0.005)	(0.006)
AI	-1.484**	-3.826***
	(0.649)	(0.703)
Pgdp	-	3.759*
	-	(2.064)
Open	-	0.696***
	-	(0.182)
Urban	-	-499.140***
	-	(73.904)
Gov	-	-22.248
	-	(32.486)
ER	-	-0.026
	-	(0.033)
Sale	-	140.539***
	-	(27.785)
Constant	51.190***	308.510***
	(5.993)	(48.432)
Province FE	Yes	Yes
Time FE	Yes	Yes
N	360	360
R^2	0.027	0.341

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses. The same below.

and the primary coefficient (AI) of artificial intelligence are -0.003 and 0.400, respectively, both of which pass the 1% significance test. These findings suggest a significant inverted U-shaped relationship between AI development and green technology innovation. Based on this, column (2) further examines the mediating effect of green technology innovation on the relationship between AI development and regional pollution emissions. The coefficients of AI^2 and GT are both significantly positive, confirming that green technology innovation serves as a partial mediator, thereby validating hypothesis 2. Specifically, when AI development remains below a certain threshold, it promotes green technology innovation and reduces pollution emissions. However, once AI development exceeds the threshold, it hinders green technology innovation and, in turn, exacerbates pollution emissions. Column (3) presents the impact of AI development on energy efficiency. As shown in column (3), the quadratic coefficient (AI^2) and the primary coefficient (AI) of artificial intelligence are -0.001 and 0.187, respectively, and pass the 10% and 5% significance tests, respectively. These findings suggest a significant inverted U-shaped relationship between AI development and energy efficiency. Based on these results, column (4) further analyzes the mediating effect of energy efficiency in the AI-pollution relationship. The coefficients of AI^2 and Effi are both significantly positive, demonstrating that energy efficiency serves as a partial mediator, thereby validating hypothesis 3. Specifically, when AI development remains below a certain threshold, it improves energy efficiency and helps reduce pollution emissions. However, when AI development exceeds the threshold, it reduces energy efficiency, which in turn increases pollution emissions.

Robustness Tests

To further verify the robustness of the regression results, we conduct robustness tests by replacing variables, adding control variables, and applying lagging. (1) Columns (1) to (3) of Table 5 present the regression results of substituting regional pollution emissions with "total industrial sulfur dioxide emissions" (SO_2) [8], replacing AI development levels with the number of AI enterprises in each province (AIF), and simultaneously applying both substitutions; (2) column (4) of Table 5 reports the regression results after incorporating industrial structure (Ind1) and industrialization level (Ind2) as control variables; (3) columns (5) and (6) of Table 5 display the regression results with the explanatory variable lagged by one and two periods, respectively. The direction and significance of the estimated coefficients across all these regressions align with the benchmark results, confirming the robustness of the U-shaped relationship between AI development and regional pollution emissions.

Endogenous Treatment

To address potential endogeneity issues stemming from sample selection bias and omitted variables, instrumental variable methods and high-dimensional fixed effects models are applied for endogeneity testing. In terms of instrumental variable selection, drawing on the research approach of Nunn and Qian [32], we select the product of a historical constant variable and a time-varying variable to represent the time-varying nature of the instrumental variable. Since the development of AI relies on the internet and has a certain degree of spillover effect. Hangzhou has been at the forefront of internet development and is a representative city in China's internet development. Therefore, the distance between provincial capital cities and Hangzhou is closely related to regional AI development. Following the approach of Sun et al. [33], this study uses the inverse of the spherical distance between provincial capital cities and Hangzhou as the instrumental variable to meet the correlation requirements. Additionally, considering that

Table 4. Mechanism test results.

	(1)	(2)	(3)	(4)
Variables	GT	Poll	Effi	Poll
AI^2	-0.003***	0.028***	-0.001*	0.029***
	(0.001)	(0.006)	(0.001)	(0.006)
AI	0.400***	-4.205***	0.187**	-4.270***
	(0.085)	(0.705)	(0.081)	(0.780)
GT	-	0.948***	-	-
	-	(0.236)	-	-
Effi	-	-	-	2.372***
	-	-	-	(0.788)
Pgdp	2.418***	1.467	1.630***	-0.107
	(0.490)	(2.127)	(0.197)	(2.241)
Open	0.773***	-0.036	0.203***	0.216
	(0.145)	(0.208)	(0.025)	(0.213)
Urban	-112.386***	-392.596***	-1.219	-496.250***
	(16.295)	(76.432)	(7.217)	(70.577)
Gov	4.117	-26.151	-6.472**	-6.896
	(5.615)	(31.014)	(2.805)	(31.762)
ER	-0.003	-0.023	0.011***	-0.051
	(0.005)	(0.032)	(0.004)	(0.035)
Sale	8.300***	132.670***	10.506***	115.616***
	(3.140)	(26.380)	(2.492)	(25.573)
Constant	51.971***	259.240***	5.522	295.412***
	(9.757)	(48.311)	(4.753)	(46.628)
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	360	360	360	360
R^2	0.816	0.359	0.706	0.373

distance variables as cross-sectional data do not exhibit temporal trends, this paper constructs an interaction term between the inverse of the spherical distance between provincial capital cities and Hangzhou and the previous year's national internet access port count as the instrumental variable (IV). In this interaction term, the former is a historical geographical variable, and the national internet access port count cannot directly influence individual provinces' pollution behavior, thus addressing endogeneity. Columns (1) to (2) of Table 6 report the instrumental variable regression results. The first-stage regression results in column (1) reveal that the instrumental variables exhibit significantly positive coefficients at the 1% level. The regression results for the second stage are shown in column (2). The Kleibergen-Paap rk LM statistic is 13.598 (p-value = 0.0002), rejecting the null hypothesis of insufficient instrument identification; the Cragg-Donald Wald F-value is 12.000, which is greater than the critical value (7.03) for the Stock-Yogo instrumental variable identification test at the 10% significance level, rejecting the null hypothesis of weak instrumental variables. According to the analysis of the regression results, the U-shaped relationship between AI development and regional pollution emissions still exists, confirming that the benchmark regression results remain robust after considering endogeneity issues. In addition, a high-dimensional fixed effects model is applied to control for the impact of higher-dimensional differences to alleviate the endogeneity problem caused by omitted variables. Specifically, "province×time" fixed effects are introduced in Eq. (7). The regression results, displayed in column (3) of Table 6, show that the

Table 5. Robustness test results.

	Replacing variables			Adding control variables	Lagging one	Lagging two
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SO_2	Poll	SO_2	Poll	Poll	Poll
AI^2	0.024***	-	-	0.024***	0.029***	0.035***
	(0.005)	-	-	(0.006)	(0.007)	(0.009)
AI	-3.621***	-	-	-3.571***	-4.096***	-4.466***
	(0.609)	-	-	(0.702)	(0.804)	(1.022)
AIF^2	-	0.454***	0.427***	-	-	-
	-	(0.143)	(0.127)	-	-	-
AIF	-	-10.289***	-9.835***	-	-	-
	-	(2.622)	(2.290)	-	-	-
Constant	277.511***	358.350***	324.668***	193.311***	310.427***	255.135***
	(43.529)	(51.151)	(46.684)	(65.871)	(48.455)	(53.151)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	330	300
R^2	0.364	0.279	0.293	0.362	0.372	0.333

Table 6. Endogeneity test results.

	2SLS		High-dimensional fixed effects
	(1)	(2)	(3)
Variables	AI	Poll	Poll
IV	1.019***	-	-
	(0.197)	-	-
AI^2	-	0.025*	0.015***
	-	(0.013)	(0.006)
AI	-	-5.171***	-2.746***
	-	(1.493)	(0.709)
Constant	12.583	401.945***	-6644.236***
	(17.667)	(84.481)	(1039.401)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Province×Time FE	-	-	Yes
Kleibergen - Paap rk LM statistic	-	13.598	-
Cragg-Donald Wald F statistic	-	12.000	-
Stock-Yogo weak ID test critical values: 10% maximal IV size	-	7.03	-
N	360	360	360
R^2	0.926	0.856	0.433

coefficients and significance levels of AI development level remain consistent with the benchmark results, further supporting their robustness.

Heterogeneity Analysis

Heterogeneity of Regional

The “Hu Huanyong Line” serves as a significant demarcation that highlights the spatial distribution of China’s socioeconomic development. Considering the substantial impact of economic development disparities on the relationship between AI development and pollution emissions, this paper examines the heterogeneous impact of AI development on regional pollution emissions across the “Hu Huanyong Line”, with regression results presented in columns (1) and (2) of Table 7. The results indicate a significant U-shaped relationship between AI development and regional pollution emissions in the southeast of the “Hu Huanyong Line”, while an inverted U-shaped relationship is evident in the northwest region. This phenomenon may be attributed to the northwest region, which mainly consists of Xinjiang, Ningxia, Qinghai, Inner Mongolia, and other western provinces with relatively low economic development, insufficient AI infrastructure, and lagging green technology innovation and energy efficiency. Consequently, large-scale infrastructure investments in the initial stages of AI development lead to an increase in pollution emissions. As AI development matures and its applications expand, the “pollution reduction effect” driven by green technology innovation and improved energy efficiency gradually emerges, resulting in reduced pollution emissions.

Heterogeneity of Marketization Level

The level of marketization directly reflects the institutional environment and provides a comprehensive indicator of the completeness of each region’s economic system. Considering the considerable influence of institutional environment disparities on the relationship between AI development and pollution emissions, this study investigates the heterogeneous impact of marketization level [34]. Regions are divided into high and low marketization groups based on whether their marketization index is above or below the median. The corresponding regression results are presented in columns (3) and (4) of Table 7. The results indicate a significant U-shaped relationship between AI development level and pollution emissions across both high and low marketization regions. The difference in test results reveals that the relationship between AI development level and pollution emissions is steeper in regions with lower marketization levels, suggesting that AI development in regions with lower marketization has a greater marginal effect on pollution emissions.

Conclusions

Using panel data from 30 provinces in China from 2011 to 2022, this paper constructs an evaluation index system to assess regional AI development. It empirically

Table 7. Results of heterogeneity analysis.

	Southeast	Northwest	High	Low
	(1)	(2)	(3)	(4)
Variables	Poll	Poll	Poll	Poll
AI^2	0.021***	-4.192***	0.023***	0.335***
	(0.006)	(0.932)	(0.007)	(0.122)
AI	-3.296***	8.657	-3.500***	-12.839***
	(0.769)	(7.157)	(0.894)	(3.264)
Constant	319.522***	-198.687	172.325**	351.112***
	(51.156)	(222.504)	(82.736)	(59.768)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	300	60	178	179
R^2	0.403	0.826	0.505	0.316
Differences and significance of coefficients between groups	4.213***		0.312***	

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses; p-values for tests of coefficient group differences were calculated using Fisher’s Combined Test (1000 samples).

examines its nonlinear impact on regional pollution emissions. The main research conclusions are outlined below.

First, there is a significant U-shaped relationship between the development of artificial intelligence and regional pollution emissions. After a series of robustness tests, this conclusion remains valid. It is worth noting that most regions in China exhibit AI development levels far below the inflection point (73.577) of the U-curve, suggesting considerable potential for AI to mitigate regional pollution emissions.

Second, mechanism test results indicate that AI development has an inverted U-shaped association with green technology innovation, as well as with energy efficiency. Furthermore, AI development can influence regional pollution emissions through the mediating effects of green technology innovation and energy efficiency.

Third, the heterogeneity analysis reveals that the U-shaped relationship between AI development and regional pollution emissions is only significant in the southeast area of the "Hu Huanyong Line". In the northwest area of the "Hu Huanyong Line", however, an inverted U-shaped relationship is observed. We believe this reversal may be attributed to the initial phase of AI development, where large-scale infrastructure investments led to increased pollution emissions. Additionally, compared to regions with higher levels of marketization, the U-shaped relationship between AI development and regional pollution emissions with lower levels of marketization is steeper, indicating that the marginal effect of AI on pollution emissions is stronger.

Policy Implications

Based on the findings, this paper proposes the following policy recommendations:

First, promote coordinated regional development and strengthen pollution control in high-emission areas. Western regions are advised to capitalize on development opportunities presented by the national "East Data, West Computing" project and various AI policies by hosting AI resources, such as computing services from the eastern region, leveraging AI development to stimulate industrial intelligence and intelligent industries, and fostering regional coordination and cooperation of artificial intelligence between regions.

Second, accelerate the development of AI infrastructure and maximize its pollution-reduction potential before reaching the inflection point. In high-pollution regions, policy enhancements are recommended to advance AI adoption, reduce regional pollution emissions, and promote high-quality economic growth. For regions where AI development has surpassed the inflection point, maintaining vigilance against potential adverse effects (e.g., "green technology gap" and "energy demand growth") is warranted, with targeted mitigation policies implemented accordingly.

Third, implement region-specific "AI+" emission reduction strategies. Southeast regions with advanced AI capabilities are encouraged to fully harness AI's positive role in pollution reduction, utilizing intelligent technologies for industrial optimization. Northwest regions are advised to prioritize policy interventions to mitigate emissions during accelerated intelligent infrastructure deployment, expediting progress toward the "pollution reduction" inflection point. Furthermore, all regions are advised to pursue expedited enhancement of institutional environments – particularly in areas with low marketization – to maximize AI's marginal emission-reduction effects before the inflection point, while actively leveraging AI for energy conservation and emission reduction to advance regional green economic development.

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Conflict of Interest

The authors declare no conflict of interest.

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