Study on the Effect of Artificial Intelligence Development on Urban Air Pollution: Evidence from 226cities of China

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Abstract. Investigating the impact of AI development on urban air pollution holds practical significance for better leveraging AI's role in air pollution governance. Using panel data of 226 Chinese cities from 2010 to 2023, we first employ the entropy weight-TOPSIS method to evaluate AI advancement, then apply fixed effects and spatial Durbin models for analysis. Key findings: First, China's AI development shows an upward trend but marked regional disparities. Specifically, the eastern region outperforms the central region, while the central region surpasses both the western and northeastern regions. Second, AI development significantly inhibits urban air pollution, with heterogeneous effects: negative and significant in northeastern and resource-based cities, insignificant in others. Third, AI development and urban air pollution exhibit significant spatial correlation; AI advancement negatively impacts local air pollution and generates negative spillover effects on neighboring regions.Based on these findings, four policy recommendations are proposed to optimize AI's role in air pollution governance.

Keywords: China; City; Artificial Intelligence Development; Air Pollution.

1. Introduction

Against the dual backdrop of accelerated global urbanization and severe ecological damage, urban air pollution has become a critical bottleneck restricting sustainable development. For China, as the national economy has grown rapidly since the beginning of the 21st century, air pollution has become one of the country's increasingly prominent environmental issues. Relevant government agencies and studies indicate that air pollution causes an annual economic loss of approximately 20 billion yuan in China, accounting for about 3.8% of GDP. Beyond economic impacts, research shows that prolonged exposure to polluted air elevates the likelihood of developing lung cancer by 15 percent, with medical expenses for respiratory illnesses making up more than 12% of overall health spending. Additionally, data reveals that air pollution is linked to 161.1 deaths per 100,000 individuals [1]. These findings collectively demonstrate that urban air pollution poses significant threats to public health, socioeconomic stability, and ecological balance. As a result, China has long been dedicated to urban air pollution control efforts aimed at enhancing urban air quality. Yet, urban air pollution management in China has long encountered obstacles including the arduous task of transforming and upgrading traditional industrial operations, the relatively underdeveloped systems for monitoring urban air pollution parameters, and the inefficient collaboration among various parties involved in governance. Against this backdrop, significant advancements in next-gen AI technologies have paved the way for new applications. Equipped with robust capabilities in gathering, analyzing data, and conducting predictive simulations, AI systems are now establishing innovative frameworks and infusing fresh energy into urban air pollution management. This technological advancement, however, is not without potential environmental implications. The growth of AI's own industrial ecosystem, for instance, entails substantial energy usage in its infrastructure setup and operational procedures, which in turn leads to an increase in carbon emissions and other pollutants. Specifically, the building and daily operation of AI-related infrastructure demand substantial energy input, which in turn leads to higher carbon footprints and the release of more pollutants into the environment. Therefore, the advancement of artificial intelligence also poses adverse effects on managing urban air pollution, necessitating that all parties including government, businesses, and the public take proactive measures to address this issue. Given this, a systematic exploration into how AI advancement influences urban air pollution is not only theoretically significant but also practically valuable for establishing an effective framework that drives the transition toward a more sustainable urban environment through technological innovation and environmental protection. This research will explore how advancements in artificial intelligence affect urban air pollution, a topic that holds great practical value in facilitating a more systematic and scientific grasp of AI's role in addressing environmental degradation.

2. Literature Review

As one of the issues that cause severe harm to human, addressing urban air pollution is of great practical significance for improving human health. Regarding urban air pollution control, extant research predominantly centers on three dimensions: the causes of air pollution, its specific impacts, and corresponding response measures.

First, regarding the causes of air pollution, existing studies indicate that such causes mainly fall into natural and anthropogenic.In terms of natural causes, factors contributing to air pollution primarily include natural wildfires and climate change. Scholars such as Mark argue that natural wildfires emit substantial fine particulate matter, thereby contributing to air pollution [2]. Additionally, other academics have investigated how climate change influences urban air quality, pointing out that climate change disrupts various atmospheric conditions, thereby impairing the dilution and diffusion of air pollutants [3] and exacerbating air pollution. In terms of anthropogenic causes, as experts commonly acknowledge that the process of urban development contributes to the escalation of urban air pollution issues [4], primarily through two channels: human activities and urban construction. Regarding human activities, with the accelerated development of urbanization, urban density has increased, and populations and industries have concentrated in cities. This has led to a continuous rise in the consumption of fossil fuels, which in turn has increased the emission of air pollutants and aggravated urban air pollution [5][6]. Regarding urban construction, the in-depth development of urbanization has formed the heat island effect, making it difficult for air pollutants to diffuse and exacerbating urban air pollution [7][8]. Second, regarding the impacts of air pollution, existing studies mainly elaborate on its adverse effects from two perspectives.The first is the perspective of human health. Numerous researchers acknowledge that air pollution ranks among the primary contributors to a range of illnesses [9]. Air pollution can cause short-term effects on the human body, including wheezing, and bronchitis. Long-term exposure to polluted air is harmful to the human nervous, reproductive, and respiratory systems, and may even lead to cancer [10], which is detrimental to human health.The second is the perspective of economic development. Scholars like Philip maintain that air pollution incurs substantial economic losses, while undermining social work efficiency and thereby impeding economic development [11][12]. Finally, regarding urban air pollution control, existing studies are mainly divided into two aspects: macro policy design and micro tool application.In terms of macro policy design, scholars such as Liu [13] have pointed out the important role of policy orientation in urban air pollution control. The government can improve urban air quality by promoting the development of infrastructure such as urban green spaces and parks [14].In terms of micro tool application, in today’s society, cities have increasingly integrated AI technologies—such as intelligent large models and real-time monitoring systems—into air pollution control processes [15][16]. This not only advances the smart governance of air pollution but also promotes the development of smart cities.

As AI technology advances, it is being increasingly integrated into air pollution governance practices. Studies have shown that technological progress brought by AI has created a new paradigm for reducing urban pollution [17]. Regarding the impact of artificial intelligence (AI) on urban air pollution, most existing academic studies focus on how specific intelligent models and algorithms facilitate the governance of urban air pollution. numerous scholars have researched the application of air pollution prediction models. For instance, Neo argued that AI-enabled systems assist governments in air pollution prediction and low-carbon city goal attainment assessment [18]. In addition, relevant studies have also involved the application of intelligent technologies such as AI monitoring models in urban air pollution control. Scholars such as Bainomugisha introduced an air quality monitor and digital tools engineered on the basis of IoT technology in their research, offering air quality information and interpretive explanations[19] that are of notable significance to urban air pollution control efforts. Although AI development offers substantial opportunities for urban air governance, its energy-intensive nature necessitates extensive electricity and other resources, potentially exerting adverse ecological impacts. Consequently, scholars have explored AI's negative implications for urban air pollution through lenses such as energy consumption and power generation structures [20].

Despite extensive exploration of AI's applications in mitigating air pollution, the sector's rapid expansion may inadvertently exacerbate environmental degradation. Thus, investigating AI development's impact on urban air pollution is pivotal for comprehensively understanding its dual influence on urban environmental quality. This study examines AI advancement's direct effects on urban air pollution, employs spatial econometric methodologies to dissect its spillover effects on adjacent cities and regions, and formulates targeted recommendations based on derived findings.

3. Research Design

3.1. Research Methods

3.1.1. Entropy Weight-TOPSIS Method

This study employs the entropy weight-TOPSIS method to quantify AI development levels, first using the entropy weight method to calibrate weights for each AI evaluation indicator. Subsequently, the TOPSIS method is utilized to establish the rankings of individual sample cities[21]. Drawing upon the calculation approach proposed by Ma Xiangfei et al.[22], this study conducts a quantitative assessment of the AI development levels across the sample cities. The calculation procedure is outlined as follows:

Step 1: Construct an evaluation matrix.

$$Y=\begin{bmatrix} y_{11} & \cdots & y_{m1} \\ \vdots & y_{ij} & \vdots \\ y_{1n} & \cdots & y_{mn} \end{bmatrix} (i=1,2,\cdots m;\ \ j=1,2,\cdots,n) \tag{1}$$

Step 2: Implement standardized treatment of the data.

$$\text{positive indicator:} z_{ij}=\frac{y_{ij}-\min(y_{1j},\cdots,y_{mj})}{\max(y_{1j},\cdots,y_{mj})-\min(y_{1j},\cdots,y_{mj})} \tag{2}$$

$$\text{negative indicator:} z_{ij}=\frac{\max(y_{1j},\cdots,y_{mj})-y_{ij}}{\max(y_{1j},\cdots,y_{mj})-\min(y_{1j},\cdots,y_{mj})} \tag{3}$$

In formula (2) and formula(3), z_{ij} represents the standardized indicator value, y_{ij} represents the original indicator value, $max\left(y_{mj}\right)$ represents the maximum value among the sample values, and $min\left(y_{mj}\right)$ represents the minimum value among the sample values.

Step 3: Calculate the information entropy.

$$E_i=\left[-\frac{1}{\ln(n)}\right]\sum_{j=1}^{n}\left[\frac{z_{ij}}{\sum_{j=1}^{n} z_{ij}}\times\ln\left(\frac{z_{ij}}{\sum_{j=1}^{n} z_{ij}}\right)\right] \tag{4}$$

Step 4: Calibrate the weighting coefficients of indicators.

$$w_i=\frac{1-E_i}{\sum_{i=1}^{m}(1-E_i)} \tag{5}$$

Step 5: Formulate the weighted standardized decision matrix *W*.

$$W=w_i\times z_{ij}\ \ (i=1,2,\cdots m;\ \ j=1,2,\cdots,n) \tag{6}$$

Step 6: Determine the positive ideal solution W^+ and the negative ideal solution W^-, and calculate the Euclidean distances G^+ and G^- to the ideal solutions.

$$W^{+}=[w_1^{+},w_2^{+},\cdots,w_m^{+}],\ \ w_i^{+}=\max_{j=1}^{n}\{W_{ij}\} \tag{7}$$

$$W^{-}=[w_1^{-},w_2^{-},\cdots,w_m^{-}],\ \ w_i^{-}=\min_{j=1}^{n}\{W_{ij}\} \tag{8}$$

$$G^{+}=\sqrt{\sum_{i=1}^{m}(W\text{-}W^{+})^2} \tag{9}$$

$$G^{-}=\sqrt{\sum_{i=1}^{m}(W\text{-}W^{-})^2} \tag{10}$$

Step 7: Calculate the relative closeness *P*.

$$P=\frac{G^{-}}{G^{+}+G^{-}}\,(0<P<1) \tag{11}$$

3.1.2. Specification of the Benchmark Regression Model

This research deploys a benchmark regression framework to verify AI development's influence on urban air pollution, with the model specified below:

$$UAP_{i,t}=\alpha_0+\beta AI_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \tag{12}$$

In formula (12), $UAP_{i,t}$ represents urban air pollution intensity; $AI_{i,t}$ represents AI's development level; $Controls_{i,t}$ signifies a vector of control variables; μ_i denotes the time-invariant individual fixed effect of city i; $\delta_t$denotes the time fixed effect; α_0 is the intercept term; β stands for the coefficient of the explanatory variable; γ denotes coefficients of control variables; and $\varepsilon_{i,t}$ represents the random error term.

3.1.3. Spatial Econometric Model

Cities are closely interconnected in terms of industrial clustering, technology sharing, talent mobility. Thus, AI advancement not only shapes local urban air pollution but also impinges on that of adjacent cities [23]. To empirically scrutinize this nexus, the study employs a Spatial Durbin Model to dissect AI advancement's spillover effects on adjacent cities' air pollution. The model specification is detailed below.

$$UAP_{i,t}=\alpha_0+\rho WUAP_{i,t}+\beta_1 WAI_{i,t}+\beta_2 AI_{i,t}+\gamma_1 WControls_{i,t}+\gamma_2 Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \tag{13}$$

In formula (13), β_1 denotes the coefficient for the spatial lag term of the explanatory variable, while γ_1 represents the coefficient for the spatial lag term of the control variables. ρ signifies the spatial autoregressive coefficient to be estimated, and W denotes the spatial weight matrix. The remaining variables are defined as in formula (12).

3.2. Variable Selection

3.2.1. Response Variable

In this research, the variable being analyzed is urban air pollution (UAP). As a key constituent of urban atmospheric contaminants, sulfur dioxide mainly comes from fossil fuel combustion, with a high proportion of anthropogenic emissions, which can directly reflect the degree of urban air pollution. Meanwhile, industrial sulfur dioxide emissions can cause significant harm. Firstly, the increase in sulfur dioxide content in the air can lead to acid rain and other phenomena, severely damaging ecosystems. Secondly, industrial sulfur dioxide emissions can irritate the respiratory system, trigger diseases such as asthma and bronchitis, and harm human health [24]. Thus, this study designates industrial sulfur dioxide emissions as the metric for quantifying urban air pollution levels [25].

3.2.2. Explanatory Variable

The explanatory variable in this paper is AI development. The development of AI is based on the support of internet infrastructure and the growth of intelligent industry entities, and relies on R&D investment from all sectors of society as well as advanced technological support. Therefore, this paper comprehensively constructs a measurement index system for AI development level from four dimensions: basic support, R&D investment, industrial entities, and technological penetration (Table 1), with specific explanations as follows: Firstly, the development of AI is inseparable from the support of internet broadband access. Thus, in terms of basic support, the number of internet broadband subscribers is selected as an indicator for measurement [26][27]. Secondly, regarding R&D investment: first, the development of AI depends on enterprises' understanding, investment, and attention to AI; second, government financial support for science and technology is also an indispensable part; meanwhile, AI development relies on research and inventions by relevant technical personnel. Based on this, four indicators are selected to measure R&D investment: the quantity of AI industry researchers, internal R&D outlays of major industrial firms, government funding for scientific activities, and the count of domestically granted patents for inventions [26][28]. Thirdly, in terms of industrial entities, the development of AI depends to a certain extent on the existence of AI-related enterprises. Thus, this paper selects the quantity of AI-related firms as an indicator to assess industrial entities [22]. Fourthly, concerning technological penetration: science and technology provide theoretical support for AI development, but theories need to be applied in practical enterprise operations to better promote AI development. In view of this, this paper selects robot installation density and the adoption degree of AI by listed firms to measure technological penetration [29][30].

Table 1. Measurement Index System of Urban Air Pollution and AI Development.

First-level indicators	Second-level indicators	Third-level indicators(Unit)
Urban air pollution	Waste gas emissions	Industrial sulfur dioxide emissions (ton)
AI development	Basic support	Number of internet broadband subscribers (thousand households)
	R&D investment	Quantity of AI industry researchers (person)
		Internal R&D outlays of major industrial firms (trillion yuan)
		Government funding for scientific activities (ten thousand yuan)
		Count of domestically granted patents for inventions (piece)
	Industrial entities	Quantity of AI-related firms (piece)
	Technological penetration	Robot installation density (%)
		Adoption level of artificial intelligence by listed firms (yuan)

3.2.3. Control Variables

This study selects the following control variables: First, industrial structure (IS) exerts a salient impact on urban air pollution [26]. Secondary industry discharges substantial air pollutants, with inadequate abatement rendering it a primary pollution source. Accordingly, the share of secondary industry's added value in GDP serves as its proxy. Second, foreign trade level (TB) is identified to influence urban air pollution; the trade balance gauges this dimension. Third, energy consumption (YEC) bears a significant association with urban air pollution intensity [31], with annual electricity consumption as its measurement proxy. Fourth, economic development level (GDP) is closely intertwined with pollution severity [29], operationalized via per capita GDP [32]. Finally, urban development level (UR) indirectly reflects facets like industrial composition and development status; the urbanization rate thus proxies this variable [29].

3.3. Data Sources

In light of data comprehensiveness, this study utilizes panel data from 226 Chinese cities spanning 2010–2023. Primary data sources include the National Bureau of Statistics, China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Science and Technology Statistical Yearbook, China Industrial Statistical Yearbook, and provincial statistical yearbooks. Missing values in the raw data are imputed via interpolation.

4. Empirical Analysis

4.1. Measurement Results of Artificial Intelligence Development

For China's AI status assessment, this study deploys entropy weight-TOPSIS to evaluate 226 municipal entities from 2010 to 2023. These selected cities are geographically divided into four major regions: Eastern, Northeast, Central, and Western China, following the most recent regional classification guidelines issued by China's National Bureau of Statistics. The outcomes of the comprehensive evaluation are illustrated in Table 2 and Figure 1.

Table 2. Comprehensive Measurement Results of AI Development.

Year	China	Eastern region	Northeast region	Central region	Western region
2010	0.016	0.028	0.012	0.011	0.010
2011	0.017	0.030	0.012	0.012	0.011
2012	0.017	0.030	0.011	0.012	0.010
2013	0.021	0.037	0.013	0.014	0.012
2014	0.025	0.043	0.017	0.019	0.016
2015	0.028	0.047	0.019	0.021	0.019
2016	0.034	0.054	0.023	0.026	0.023
2017	0.047	0.070	0.034	0.038	0.034
2018	0.047	0.072	0.034	0.039	0.034
2019	0.048	0.071	0.045	0.038	0.033
2020	0.045	0.069	0.036	0.035	0.031
2021	0.044	0.072	0.026	0.034	0.030
2022	0.045	0.075	0.025	0.034	0.031
2023	0.055	0.092	0.038	0.036	0.039

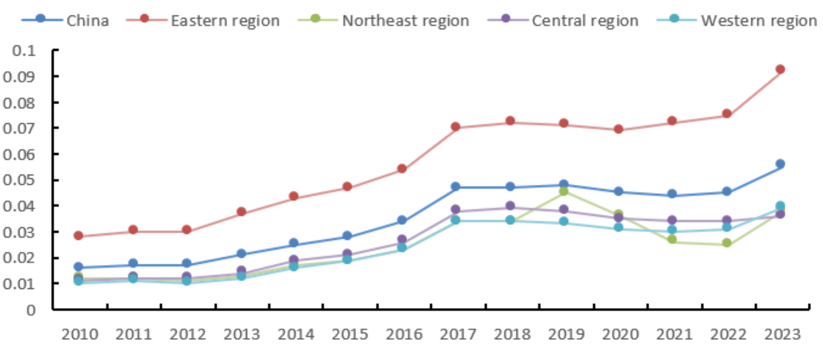

Fig 1. Measurement Results of AI Development.

On a national scale, progress in the field of artificial intelligence has been on the rise, with its development index increasing from 0.016 to 0.055. Before 2017, to enhance technological capabilities, the Chinese government strongly supported the development of emerging industries such as AI, leading to a significant overall rise in China's AI development level. After 2017, changes occurred in the financing environment: investors' enthusiasm for the AI sector declined, which caused a slight drop in the AI development level. Particularly between 2020 and 2021, affected by the COVID-19 pandemic that broke out in 2020, China's AI industrial and supply chains were disrupted, capital investment decreased, and talent exchange and mobility weakened—all of which contributed to a further decline in the AI development level. Since 2021, the AI industry has started to recover, and China's AI development level has improved again.

Regarding the AI development level across the four major regions, although it generally shows an upward trend, there are significant regional disparities: the eastern region outperforms the central region, while the central region surpasses both the western and northeastern regions. The eastern region has the highest AI development level, significantly exceeding the national average. This is attributed to the concentration of developed cities in the east, which possess distinct advantages in talent attraction, innovation collaboration, policy support, and capital supply—providing fertile ground for AI development and application. Moreover, the region has formed a relatively complete industrial chain, further propelling the rapid development of AI. The northeastern region has suffered from severe talent outflow and initially failed to provide a favorable platform for AI development. However, with the deepening implementation of the Northeast Revitalization Plan, its AI development level has improved, increasing by more than 200% over the 13-year period. The central region initially had a low AI development level due to its relatively underdeveloped economy, over-reliance on traditional energy for economic growth, severe talent drain, and poor industrial development environment. In later stages, however, the implementation of strategies such as the Rise of Central China Strategy, and paired assistance programs to develop emerging technology industries has elevated its AI development level. The western region, characterized by a sparse population and relatively backward economy, had a weak foundation for AI development, resulting in a low initial AI development level. In recent years, however, the relocation of computing power equipment by the AI industry to the western region has boosted the development of its AI sector, driving an improvement in its AI development level.

4.2. Analysis of the Impact of Artificial Intelligence Development on Urban Air

4.2.1 Benchmark Regression Results

Utilizing AI progress assessment data, this study employs a fixed-effects model to examine AI advancement's direct impact on urban air quality. Regression results are presented in Table 3.

Table 3. Benchmark Regression Results.

Variable	*UAP*	
	(1)	(2)
AI	-2.577***	-0.787
IS		0.01***
TB		-0.003
YEC		-0.000***
GDP		-0.050***
UR		-0.135
City effect	yes	yes
Time effect	yes	yes
_cons	9.512***	10.179***
N	3164	3164
adj. R-sq	0.788	0.790

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

In Table 3, when controlling for city fixed effects and spatial effects but excluding control variables like industrial structure and energy consumption, the regression coefficient measuring the influence of AI advancement on urban air pollution stands at -2.577, which is significantly negative. This result indicates that AI advancement imposes a distinct inhibitory effect on urban air pollution. With city fixed effects, spatial effects, and control variables incorporated, the regression coefficient stands at -0.787 but lacks statistical significance.

Regarding control variables, Table 3 reveals industrial structure exerts a significantly positive impact on urban air pollution. Historically reliant on secondary industry, China’s economic growth saw sulfur dioxide and other pollutants from this sector triggering severe air pollution. Despite recent urban transformation, most cities remain secondary industry-dominated, impeding pollution control. Energy consumption and economic development level show significantly negative impacts, underscoring their pivotal role in hindering air quality improvement. Traditional fossil energy has long dominated the energy mix; reduced use curtails emissions and alleviates pollution. Early Chinese urban development centered on industrial raw material, leading to relatively acute air pollution. In recent years, guided by national macro-policies and economic transformation, emerging industries have gradually become the backbone of national economic growth, effectively reducing urban air pollution. Other control variables exert no statistically significant impact.

4.2.2 Robustness Analysis

For enhanced result credibility and consistency, two robustness checks are conducted: initially, by removing extreme values from certain samples; subsequently, by excluding central municipalities.

Table 4. Robustness Test Results.

Robustness test	Excluding extreme values of some samples	Excluding municipalities directly under the Central Government
	(1)	(2)
AI	-0.787	-1.132
Control variable	yes	yes
City effect	yes	yes
Time effect	yes	yes
_cons	10.179***	10.849***
N	3164	3,108
adj. R-sq	0.790	0.787

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

Initially, the sample city data were subjected to 1% winsorization at both tails, followed by regression analysis. As shown in Table 4, the coefficient for AI development's impact on urban air pollution is -0.787, which is statistically insignificant.Subsequently, the four municipalities directly under the central government (Beijing, Tianjin, Shanghai, Chongqing) were excluded from the sample prior to regression. The results, presented in Table 4, indicate a regression coefficient of -1.132 for AI development's effect on urban air pollution, which is also not statistically significant.

4.2.3. Heterogeneity Analysis

Cities exhibit substantial heterogeneity in geography, urban orientation, infrastructure, and resource endowments. Such disparities lead to variations in both AI development levels and the heterogeneous impacts of AI on urban air pollution across cities. Consequently, this paper conducts a heterogeneity analysis by categorizing the 226 sample cities along three dimensions. In the dimension of regional division, cities are grouped into the eastern region (ER), northeastern region (NR), central region (CR), and western region (WR).In the dimension of administrative level, cities are classified into municipalities directly under the central government (MDCG), sub-provincial cities (SPC), non-sub-provincial provincial capitals (NSPC), and ordinary prefecture-level cities (OPC). In the dimension of resource endowment, cities are divided into resource-based cities (RBC) and non-resource-based cities (NRBC).Specific findings are presented in Table 5.

Table 5. Heterogeneity Analysis.

Variables	Regional division				Administrative level				Resource endowment	
	Cities in ER	Cities in NR	Cities in CR	Cities in WR	MDCG	SPC	NSPC	OPC	RBC	NRBC
AI	-0.070	-4.407*	-0.442	2.217	0.492	-1.048	3.868	0.211	-3.857*	-0.441
Control variable	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
City effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
_cons	12.356***	10.579***	10.102***	9.922***	-2.271	10.527***	11.060***	11.5411***	11.577***	11.449***
N	1008	350	952	854	56	196	182	2730	1,330	1,834
adj. R-sq	0.840	0.862	0.800	0.794	0.980	0.879	0.688	0.787	0.807	0.779

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

First, regarding regions, AI advancement exerts no primary influence on eastern cities' air pollution—stemming from severe pollution via dense industrial/population agglomeration and misalignment between AI orientation and pollution control. Northeastern cities see a significantly negative impact at the 10% statistical threshold, as local AI targets traditional industrial intelligent upgrading to undergird pollution control. Central cities show no statistically meaningful correlation: with numerous resource-based cities, AI remains nascent and lacks sufficient driving force for tangible effects. Western cities face a positive AI impact on pollution—relying on eastern computing power center transfers that boost AI yet introduce novel pollution, with no effective abatement measures.

Second, regarding administrative rank, AI development exerts no significant impact on air pollution in municipalities directly under the Central Government, non-sub-provincial capitals, or ordinary prefecture-level cities. Municipalities boast distinct functional orientations—Shanghai, for example, allocates most AI computing infrastructure to western districts, alleviating local environmental implications. Non-sub-provincial capitals see muted AI-induced pollution effects, shaped by policy frameworks and urban functional positioning. Constrained by scarce financial and human capital, ordinary prefecture-level cities have underdeveloped AI ecosystems, leading to insignificant impacts. For sub-provincial cities, AI development yields a negative pollution coefficient but lacks statistical significance; despite high population and industrial agglomeration, AI advancement has not delivered tangible air pollution inhibition.

Third, regarding resource endowment, AI development significantly reduces air pollution in resource-based cities at the 10% statistical level. Historically reliant on non-renewable energy, these cities face severe air pollution. Amid the rising focus on green development, they are transitioning their growth models, with AI playing a clear inhibitory role in curbing air pollution. In contrast, most non-resource-based cities depend on sectors like tourism and services, resulting in inherently low air pollution levels. Thus, AI expansion exerts no notable impact on their air quality.

4.3. Spatial Spillover Effects

4.3.1. Global Spatial Correlation Test

With continuous economic development, the connections among cities regarding talent, resources, and other factors have become increasingly close, and the synergy of AI industries and layouts across different cities has also become more intensive and frequent.Against this backdrop, this study employs STATA18 software to compute the global Moran's I statistic for both AI development metrics and urban air quality indicators, with the primary objective of exploring their inherent global spatial autocorrelation patterns. The results are presented in Table 6.

Table 6. Global Moran's I Index of AI Development Level and Urban Air Pollution Degree.

Year	AI development	Urban air pollution degree
2010	0.144***	0.540***
2011	0.165***	0.155***
2012	0.195***	0.135***
2013	0.257***	0.151***
2014	0.279***	0.179***
2015	0.327***	0.148***
2016	0.324***	0.224***
2017	0.330***	0.169***
2018	0.265***	0.170***
2019	0.184***	0.171***
2020	0.207***	0.189***
2021	0.187***	0.163***
2022	0.153***	0.182***
2023	0.106**	0.120***

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

Table 6 reveals that the global Moran's I indices for both AI advancement and urban air pollution are positive. Specifically, the former is significant at the 5% level, while the latter is significant at the 1% level. This points to a statistically meaningful positive spatial association between inter-city AI development and air pollution, indicating the presence of spatial dependence. Consequently, the spatial Durbin model is employed for subsequent analysis.

4.3.2. Local Spatial Correlation Test

The global spatial correlation test delineates the overarching spatial interdependence trend. Yet, amid potential spatial correlation heterogeneities within the research scope—especially for expansive areas—global spatial autocorrelation metrics fail to encapsulate local geographical unit dependencies [33]. To further dissect the local spatial correlation between AI development and urban air pollution across Chinese cities, this study employs STATA18 to generate 2010 and 2023 local Moran scatter plots for AI development and urban air pollution levels. Specific results are presented in Figure 2.

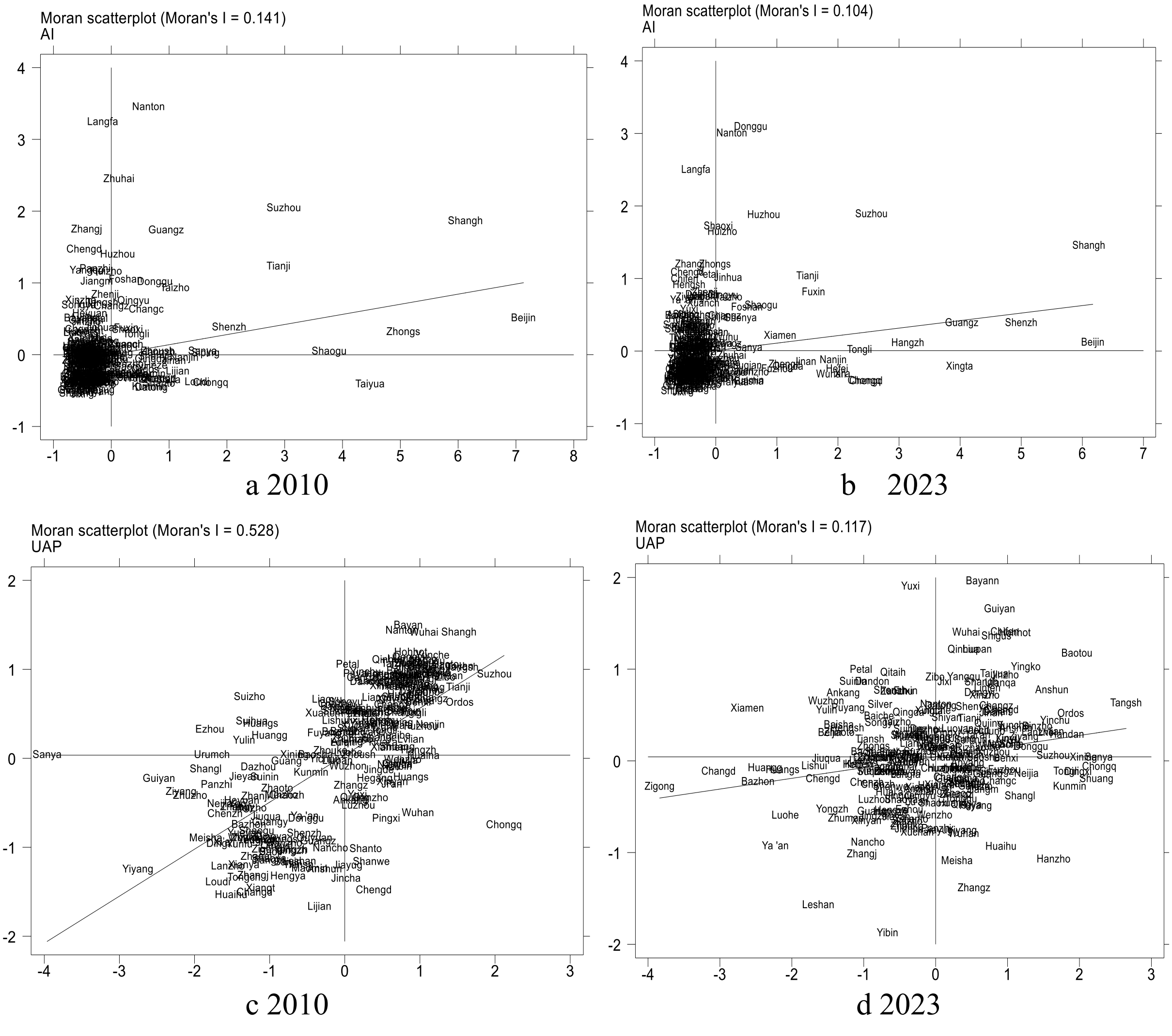

Fig 2. Local Moran Scatter Plots of AI Development and Urban Air Pollution in 2010 and 2023.

Figure 2 reveals that in both 2010 and 2023, most sample cities' AI development scatter points cluster in the third quadrant—indicating low-AI cities are surrounded by similarly underdeveloped neighbors. Some points lie at the boundary of the first and second quadrants, signifying their adjacent cities boast relatively high AI development. A handful of cities (e.g., Shanghai, Suzhou) reside in high-value zones, encircled by high-AI peers. Compared to 2010, AI development's Moran's I value dropped from 0.141 to 0.104 in 2023, reflecting weakened local spatial positive correlation. As more cities embrace the AI industry, divergences in development pace and direction, coupled with easing spatial constraints, have somewhat dispersed the original spatial agglomeration trend.

Figure2 shows that in 2010, sample cities' urban air pollution scatter points clustered in the first quadrant—signaling high-pollution cities were surrounded by similarly high-pollution neighbors. A subset of low-pollution cities also had low-pollution adjacent areas, reflecting distinct spatial correlation. Compared to 2010, urban air pollution's Moran's I value dropped from 0.528 to 0.117 in 2023, with city distributions growing more dispersed. This denotes a marked weakening of local spatial positive correlation for urban air pollution, as inter-city pollution spatial correlation is no longer as conspicuously agglomerated as in 2010.

4.3.3. Testing and Selection of Spatial Econometric Models

In spatial econometrics, three primary analytical frameworks stand out: the Spatial Durbin Model (SDM), Spatial Error Model (SEM), and Spatial Autoregressive Model (SAR) [34]. To identify the most suitable model for this research, a series of diagnostic tests—including Lagrange Multiplier Test, Likelihood Ratio Test, and Hausman Test—are employed to assess whether the SDM can be parsimoniously reduced to either the SEM or the SAR. The detailed outcomes of these diagnostic procedures are presented in Table 7.

Table 7. Model Test Results.

Test	Statistic	P-value
LM-lag	87.770	0.000***
Robust LM-lag	3.825	0.05**
LM-error	488.639	0.000***
Robust LM-error	404.694	0.000***
LR-SDM-SAR	87.86	0.000***
LR-SDM-SEM	397.35	0.000***
Hausman	50.61	0.000***

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

As exhibited in Table 7, the Lagrange Multiplier LM-lag, LM-error, and robust LM-error tests attain significance at the 1% statistical benchmark, whereas the robust LM-lag test proves significant at the 5% threshold. The LR test is significant at 1%, affirming that SDM cannot be constrained to the SAR or SEM. The Hausman test garners significance at the 1% level, warranting the rejection of the null hypothesis and the adoption of a fixed-effects specification. Consequently, this study ultimately resorts to the bidirectional fixed-effect Spatial Durbin Model to scrutinize AI development's implications for urban air pollution.

4.3.4. Spatial Econometric Results

In this study, a spatial Durbin model with bidirectional fixed effects is employed to dissect the impact of AI development on urban air pollution, with detailed results reported in Table 8. Nevertheless, spatial autocorrelation inherent in the nexus between AI advancement and urban air quality implies that the coefficients of explanatory variables in the spatial Durbin model are insufficient to fully encapsulate the influence of independent factors on the dependent variable. Consequently, calculating direct, indirect, and total effects becomes imperative to explicate the spatial spillover effects [35], with specific findings presented in Table 9.

Table 8. Regression Results of the Spatial Durbin Model.

Variables	Coefficient	Standard error	*Z*	*P*
AI	-1.306	0.576	-2.27	0.023**
IS	0.007	0.003	2.31	0.021**
TB	0.002	0.002	1.30	0.195
YEC	-0.001	0.001	-1.48	0.140
GDP	-0.023	0.014	-1.70	0.089*
UR	0.334	0.177	1.89	0.059*
Wx_AI	1.309	1.033	1.27	0.205
Wx_IS	0.020	0.005	4.29	0.000***
Wx_TB	-0.001	0.003	-0.43	0.668
Wx_YEC	-0.001	0.001	-5.56	0.000***
Wx_GDP	-0.052	0.018	-2.90	0.004***
Wx_UR	-0.624	0.244	-2.56	0.010***
Spatial rho	0.387	0.020	19.87	0.000***
sigma2_e	0.342	0.009	39.08	0.000***
Obs	3164	3164	3164	3164

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

Table 9. Direct Effects, Indirect Effects, and Total Effects of the Spatial Durbin Model.

Variables	Direct effect	Indirect effect	Total effect
AI	-7.134***	-9.654***	-16.788***
IS	0.024***	0.013***	0.037***
TB	0.001	-0.012***	-0.012***
YEC	0.001***	0.001***	0.001***
GDP	-0.035***	0.004	-0.031
UR	0.371**	0.518*	0.890**

Note: *, **, and ***indicate significance levels of 10%, 5%, and 1%, respectively.

Table 8 evinces that AI advancement's influence on urban air pollution bears spatial attributes. With a spatial autoregressive coefficient of 0.205 lacking statistical significance, the spatial spillover effect of AI development on urban air pollution proves weak. This may be attributed to two reasons: on the one hand, AI development mainly targets the specific needs and positioning of local areas, making it difficult to replicate and apply in surrounding cities; on the other hand, the communication among various cities in terms of AI industry development and urban air pollution control is insufficient. Additionally, the relative independence in policies also leads to a weak spatial spillover effect.

Direct effects quantify the influence of a city's AI advancement on its own air pollution. Table 9 attests to a statistically significant regression coefficient of -7.134, signifying that AI progress mitigates energy use and curbs air pollutant discharges locally. Regarding the control variables: Industrial structure, energy consumption, and urban development level all demonstrate significant positive effects on urban air pollution.Economic development level shows a significant negative effect on urban air pollution.The impact of foreign trade level is statistically insignificant.

Indirect effects measure the impact of a city's AI development level on air pollution in neighboring cities. Table 9 verifies a significant regression coefficient of -9.654. For control variables: industrial structure, energy consumption, and urban development level impart distinct positive spillover effects on adjacent cities' air pollution; foreign trade level confers a salient negative spillover effect on neighboring areas' air pollution; economic development level's impact is statistically insignificant.

Total effects epitomize the holistic ramifications of AI development on urban air pollution. Table 9 vindicates a consequential regression coefficient of -16.788, signifying a material negative association with urban air pollution. Broadly, AI advancement has undergirded enhancements in urban air quality.

5. Conclusion

Leveraging panel data from 226 Chinese cities spanning 2010–2023, this study first comprehensively gauges AI development levels, then scrutinizes AI's influence on urban air pollution. The findings are as follows: Firstly, China's AI development level has shown an overall upward trend. This trend indicates that, with the attention of government macro-policies, the increase in financial investment, and the support from all sectors of society for the development of the AI industry, AI has achieved steady development. Secondly, AI development has a notable suppressive impact on urban air pollution. However, this impact exhibits heterogeneity. Specifically, the impact is statistically significant at the 10% level for cities in Northeast China and resource-based cities, while it is not significant for other types of cities. Third, AI development's impact on urban air pollution demonstrates pronounced spatial correlation: it exerts a marked negative effect locally while yielding a distinct negative spillover on adjacent areas' air pollution.

Drawing on the research findings, this study proffers four recommendations: First, intensify backing for AI advancement. All societal sectors ought to amplify support for AI development, expedite the deployment of AI technologies in urban air pollution abatement, and undergo sustainable urban development. Second, drive the revamping of industrial structure. Guided by technological innovation, vigorously develop the digital economy and modern service sectors, advance green tech innovation, nurture high-tech industries spearheaded by high-end manufacturing, and upgrade the industrial structure toward high-value-added segments [36]. Third, enforce context-specific urban policies. For cities diverging in region, administrative rank, and resource-environmental endowments, tailored measures should be adopted per local realities. Northeast China's cities and resource-based ones ought to further unlock AI's air quality enhancement potential and sustain its pollution curbing role. Other city types should deeply integrate AI's future development with urban air pollution control, exploring localized industrial models of AI-pollution abatement integration to better amplify AI's inhibitory effect. Fourth, enhance inter-regional AI collaboration. Achieve resource sharing, and technological complementarity through the collaborative agglomeration of industries among different cities and regions. Promoting cooperation in AI-based pollution control among geographically adjacent and economically interconnected cities to jointly address urban air pollution.

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