3. AI Development and Air Pollution: Evidence from China[1]

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Abstract

The impact of corporate activities on air pollution is a crucial aspect of ESG evaluation. In the digital era, where firms increasingly adopt artificial intelligence (AI) technology to drive production transformation, a nuanced understanding of the relationship between AI and air pollution is essential for accurately assessing corporate ESG performance. This study uses panel data from 256 Chinese cities between 2003 and 2020 to examine the impact of AI development on air pollution. We find that AI development, measured by AI patents, increases $PM_{2.5}$ emissions. This conclusion remains robust across a series of tests, including alternative measurements of the independent variable, exclusion of policy interference, removal of special samples, and addressing endogeneity concerns with instrumental variables. Heterogeneity analysis reveals that utility model AI patents primarily drive the increase in air pollution, with the impact of AI development on air pollution levels being more pronounced in small cities, non-core cities, and cities with weaker air pollution control efforts. Regarding underlying mechanisms, AI development exacerbates air pollution through increased energy consumption and expanded industrial output. Our study underscores the necessity of including AI-driven air pollution externalities in assessing corporate ESG performance.

Keywords: *Artificial Intelligence, Air Pollution, Energy Consumption, Industrial Output, ESG*

JEL Classification: *M14, O33, Q53*

1. Introduction

How to manage the environmental impacts of business operations is an important aspect of ESG (Environmental, Social, Governance) performance (Porter and Van der Linde, 1995; Kolk and Van Tulder, 2010; Fahimnia, Sarkis and Davarzani, 2015). How firms use resources and energy, as well as their emissions management, is closely related to environmental quality (Stavins, 2003;

[1] *This work is supported by the National Social Science Fund of China (23&ZD084), the National Natural Science Foundation of China (72403078) and Natural Science Foundation of Hunan Province of China (2025JJ60443).*

Paper from the special issue "Artificial Intelligence for Enhanced ESG Integration in Economic Forecasting", Guest Editors: Chi-Wei SU and Malin SONG.

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Guest, 2010; Fahimnia, Sarkis and Davarzani, 2015). Air pollution, as a typical representative of environmental pollution, has significant negative externalities at the individual, enterprise, and macroeconomic levels. According to the Global Burden of Disease Report (Murray et al., 2020), around 6.67 million deaths globally were attributed to air pollution in 2019. It is estimated that by 2060, air pollution will result in an annual economic burden of $2.6 trillion, representing around 1% of the global GDP (Lanzi and Rob Dellink, 2019). Studies have confirmed that air pollution harms individuals' medical expenditures, health conditions, mortality, employment, and labor productivity (Chay and Greenstone, 2003; Graff Zivin and Neidell, 2012; Deryugina et al., 2019; Qin et al., 2024). For enterprises, air pollution can have significant negative impacts on human capital, production efficiency, and corporate performance (He, Liu and Salvo, 2019; Zhang et al., 2019; Xue, Zhang and Zhao, 2021). These negative effects pose challenges to macroeconomic development, such as regional inequality, poverty, and economic policy uncertainty (Greenstone et al., 2021; Heblich, Trew and Zylberberg, 2021; Su et al., 2024b). Understanding the causes of air pollution and implementing effective controls are a crucial part of improving ESG performance and sustainable business capabilities (Zhao et al., 2024).

As a representative technology of the digital economy era, AI has greatly driven social and economic transformation (Agrawal, Gans and Goldfarb, 2019). Existing research focuses on the impacts of AI on employment, economic growth, corporate development, and so on (Agrawal, Gans and Goldfarb, 2019; Ruiz-Real et al., 2021), but overlooks its effects on air pollution. The relationship between technological advancement and environmental pollution is theoretically ambiguous. On the one hand, technological progress helps optimize production methods and reduce energy consumption per unit, thereby lowering environmental pollution (Newell, Jaffe and Stavins, 2010; Acemoglu et al., 2012). On the other hand, technological development can also increase energy consumption and promote the expansion of production scales, which are often direct causes of rising environmental pollution (Dinda, 2004). The United Nations Environment Programme (UNEP) expresses concern about the environmental impact of AI, suggesting that AI could have significant negative effects on the environment through the construction of data centers, the generation of electronic waste, and the energy consumption required for power generation[5] . Understanding the relationship between AI and air pollution is not only beneficial for helping businesses enhance their ESG performance in the digital economy era, but also an important aspect of understanding the socio-economic benefits of AI. However, research on the relationship between AI development and air pollution still remains scant.

This paper empirically investigates the impact of AI development on air pollution for the first time. We identify AI patents in the Chinese patent database based on the "Key Digital Technology Patent Classification System (2023)" released by the China National Intellectual Property Administration, and then annually aggregate these AI patents at the city level to measure AI development of the cities. Using panel data from 256 Chinese cities from 2003 to 2020, we employ a two-way fixed effects model to explore the relationship between AI development and air pollution. We find that AI development increases $PM_{2.5}$ emissions at the city level. This conclusion remains valid when the dependent variable is replaced with PM_{10}, NO_2, and the Air Quality Index (*AQI*). Our finding is robust to alternative measurements of the independent variable, exclusion of policy interference, removal of special samples, addressing endogeneity concerns with instrumental variables, and other checks. The results exhibit heterogeneity across different types of patents and cities. Specifically, utility model AI patents have a more significant impact on air pollution; the effect of AI on air pollution is more pronounced in small cities, non-core cities, and cities with weaker air pollution control efforts. We also explore the mechanisms through which AI

[5] *United Nations Environment Programme, 2024. Artificial Intelligence (AI) end-to-end: The Environmental Impact of the Full AI Lifecycle Needs to be Comprehensively Assessed - Issue Note. Available at: https://wedocs.unep.org/20.500.11822/46288.*

development affects air pollution. Our findings indicate that it is mainly due to increased energy consumption and expanded industrial output.

This study contributes to the literature in several ways. First, it enriches the literature on the economic impacts of AI development. While a body of studies have focused on the positive economic effects of AI, such as enhancing production efficiency, driving innovation, and improving customer experience (Agrawal, Gans and Goldfarb, 2019; Ruiz-Real et al., 2021), less attention has been paid to its negative impacts, primarily concerning its effects on employment. This paper documents another negative effect of AI: increasing air pollution levels. This insight can help firms utilizing AI technologies adjust their ESG strategies and foster a more comprehensive understanding of the socio-economic impacts of AI.

Second, this paper enriches the literature on the relationship between technological progress and environmental pollution. Although technological progress aids in enhancing production efficiency, its relationship with the environment remains inconclusive, posing challenges for corporate ESG management. On the one hand, technological advancements can reduce pollution by promoting production efficiency; on the other hand, they can increase pollution by expanding production scale, reflecting the double-edged characteristic of technological progress (Grossman and Krueger, 1995; Clark, 2007; Aghion et al., 2016). By focusing on the relationship between AI, a novel technology in the digital era, and air pollution, this paper provides new empirical evidence for the ongoing debate.

Third, this study contributes to research on the causes of air pollution. Tackling air pollution is a critical issue in the digital era. Incorporating the impact of corporate activities on air pollution into the ESG evaluation framework is also imperative. Existing studies primarily focus on the role of digital technologies in pollution control (Wan and Shi, 2022; Yang et al., 2024). However, there is little direct evidence on the effects of non-environmental digital technologies on pollution. This paper attempts to fill this void by analyzing the impact of AI development on air pollution at the city level, thus providing further ESG management insights for companies that extensively use AI technology.

2. Literature Review

2.1 Technological Progress and Environmental Pollution

Technological progress plays a pivotal role in shaping firms' ESG performance (Eccles, Ioannou and Serafeim, 2014). However, the impact of a firm's adoption of new technologies on the environment is not always straightforward. On the one hand, technological innovation often facilitates pollution control through improved detection, management, and production processes. The "Porter Hypothesis" suggests that environmental regulations can stimulate technological innovation, which improves both economic and environmental outcomes (Porter and Linde, 1995). And economic policies can also play a role in promoting technological innovation to some extent (Su et al., 2024a). A body of studies confirm that cleaner production technologies and the development of the digital economy can significantly reduce firms' pollution levels, as seen in sectors like manufacturing and energy (Aghion et al., 2016; Huo et al., 2022; Wan and Shi, 2022; Yang et al., 2024). Moreover, technology-driven environmental monitoring and data collection systems allow firms to better assess and respond to pollution challenges. Enhanced detection technologies, such as real-time emissions monitoring, enable firms to comply with stricter regulations and reduce their environmental footprint (Yang et al., 2024). Through such mechanisms, technological innovation can lower the cost of pollution control and encourage more sustainable business practices, aligning firms' operational strategies with ESG objectives (Ambec and Lanoie, 2008).

However, technology can also increase environmental harm. As firms expand operations due to productivity gains from new technologies, pollution may rise, particularly in industries lacking stringent environmental regulations (Copeland and Taylor, 2004). For example, the industrialization of emerging economies demonstrates how technological progress can drive economic growth while simultaneously increasing emissions (Grossman and Krueger, 1995; Clark, 2007). Furthermore, the Jevons paradox posits that increased efficiency in resource use, driven by technological improvements, can lead to higher overall resource consumption rather than reductions (Alcott, 2005). Moreover, heightened competition fueled by technological advances can exacerbate these effects. Firms, in their pursuit of competitive advantage, may prioritize short-term gains in productivity at the expense of environmental sustainability, leading to an aggregate increase in emissions (Antweiler, Copeland and Taylor, 2001).

In summary, while technological progress holds the potential to reduce environmental pollution by improving the efficiency of production processes and enhancing firms' ability to monitor their environmental impact, it also introduces risks. The expansion of production capacity and the intensification of market competition can counterbalance these gains, potentially leading to higher pollution levels (Ambec and Lanoie, 2008; Kolk and Van Tulder, 2010; Acemoglu et al., 2012). The net environmental impact of technological advancements, therefore, depends on a variety of factors, including the scale of production, regulatory frameworks, and firms' strategic responses to technological changes. In the era of the digital economy, the emergence of many digital technologies has brought unprecedented innovations to corporate production methods and pollution control approaches, further complicating the relationship between technological progress and environmental pollution. Therefore, stronger and robust empirical evidence is needed to examine this relationship.

2.2 AI development and air pollution

The causes of air pollution are not only related to physical and chemical factors but are also closely linked to human political and economic activities (Xu and Lin, 2016). Relevant studies have found that meteorological elements such as wind speed and direction (Fang, Wang and Xu, 2016), air temperature and pressure (Tunno et al., 2016), as well as environmental factors like altitude, terrain, and vegetation coverage, all have significant impacts on air pollution (Hao and Liu, 2016). Liu et al. (2020) even contend that natural factors dominate over any socioeconomic factors. From the perspective of human activities, industrial emissions from the combustion of fossil fuels, population density, traffic intensity, and agricultural activities also play important roles in air pollution (Duranton and Turner, 2011; Graff Zivin and Neidell, 2012; Wang et al., 2017a; Chen, Oliva and Zhang, 2022). Cheng, Li and Liu (2017) found that a high-proportion of secondary industry, a coal-dominated energy structure and increasing traffic intensity all exacerbate air pollution.

AI, as a defining technology of the digital era, significantly transforms various economic sectors. AI's positive contributions have been particularly noted in sectors like healthcare, manufacturing, and logistics, where automation and machine learning algorithms have led to greater efficiency and lower operational costs (Agrawal, Gans and Goldfarb, 2022). Moreover, AI has shown the potential to drive innovation by unlocking new business models and facilitating more personalized services, which in turn fosters economic growth (Cockburn, Henderson and Stern, 2018). However, the literature also underlines AI's negative externalities, most notably its impact on employment (West, 2018). Acemoglu et al. (2022) use establishment-level data on the near universe of online vacancies in the US and find that those AI-exposed establishments reduce hiring in non-AI positions. Mindell and Reynolds (2023) highlight that automation technologies, including AI, have contributed to job polarization, reducing employment in routine-based occupations while increasing demand for high-skilled workers. Furthermore, the development of AI technology will increase the sources of air pollution. AI development imposes higher demands on digital infrastructure (Peng, 2013), which in turn increases energy consumption (Wang and Ding, 2023), thereby intensifying air pollution.

In addition to its economic and employment effects, some research start exploring AI's potential in addressing environmental issues, particularly air pollution. These studies emphasize AI's role in improving pollution forecasting and monitoring. For instance, AI-driven models have been developed to predict pollution levels based on real-time data, enabling more accurate and timely interventions (Masood and Ahmad, 2021; Sarkar et al., 2022). These predictive tools help policymakers and businesses anticipate pollution spikes and take preventive measures, reducing harmful emissions (Masood and Ahmad, 2021). And the AI service trade can significantly enhance urban energy efficiency (Huo et al., 2024). However, there is limited understanding of how AI technologies not directly aimed at pollution control—such as those used in e-commerce, finance, or transportation—affect air quality. For instance, AI-driven increases in industrial activity or logistics optimization could potentially lead to increased energy consumption and emissions, raising concerns about the unintended environmental impacts of widespread AI adoption (Peter, 2022).

In conclusion, while there is robust evidence that AI can play a critical role in improving pollution monitoring and forecasting, the environmental consequences of other AI applications are less clear. These less-studied areas highlight a gap in the literature, where AI's broader environmental footprint remains underexplored. Further research is necessary to assess how AI technologies, most of which are not specifically targeted at environmental outcomes, affect air pollution. Accurately understanding this relationship is essential for companies to enhance their ESG performance in the digital era.

3. Data and Variables

3.1 Data

This study measures city-level AI development using patent data. The patent data is sourced from the China National Intellectual Property Administration, which has published detailed application information for all patents since 1985, including application publication numbers, publication dates, applicants, summaries, and so on. The data on AI companies comes from the Tianyancha database, which contains information on over 1180 million registered companies in China, including company names, founding dates, registered capital, business scopes, and so on. Data on pollutants such as $PM_{2.5}$, PM_{10}, and NO_2 is sourced from the ChinaHighAirPollutants (CHAP) database (Wei et al., 2023), which provides several long-term, full-coverage, high-resolution, and high-quality datasets of ground-level air pollutants in China. Nighttime light data is obtained from the Harvard Dataverse (Wu et al., 2021), which offers an enhanced time-series dataset similar to DMSP-OLS (1992-2023) by integrating DMSP-OLS and SNPP-VIIRS data. Weather data, such as precipitation, sunlight hours, and humidity, is sourced from the Global Surface Summary of the Day (GSOD), derived from the Integrated Surface Hourly (ISH) dataset, which provides meteorological data from over 9,000 stations since 1973. Data on control variables, such as population and industrial structure, is obtained from the National Bureau of Statistics' city statistical yearbook. Electricity consumption data comes from Chen et al. (2022), providing global electricity consumption raster data at a 1km x 1km resolution from 1992 to 2019. AQI data is sourced from the China National Environmental Monitoring Center, which provides real-time air quality data from over 2,000 monitoring stations since 2014. For weather or environmental observation station data, we first interpolate the station data into gridded data using the Inverse Distance Weighting (IDW) method, and then calculate the averages or sums to obtain variables at the city-year level. We ultimately construct a panel dataset of 256 Chinese cities spanning from 2003 to 2020.

3. 2 Measurement of variables

The independent variable in this study is the city-level AI development. We measure this variable by the total number of annual AI patent applications in each city (*AIpatent*). AI patents are selected based on the "Key Digital Technology Patent Classification System (2023)" released by the China National Intellectual Property Administration. In the robustness analysis, we use the number of AI enterprises in each city (*AIenterprise*) from the Tianyancha database as a proxy variable for AI development. A firm is identified as an AI firm if its business scope includes keywords related to AI, such as chips, image recognition, computer vision, voice recognition, and sensors.

The dependent variable in this study is air pollution. We measure this variable using the annual $PM_{2.5}$ emissions in each city ($PM_{2.5}$). The original data comes from 1km x 1km raster data in the CHAP database, which is processed at the city level based on administrative boundaries. In the robustness analysis, we use PM_{10}, NO_2, and the Air Quality Index (*AQI*) as the dependent variables.

To reduce omitted variable bias, we control for regional, industrial, and weather-related covariates in the regression (Shen and Zhang, 2024). The regional covariates include *Nightlight*, *Population*, and *Govern_interv*. *Nightlight* is the average nightlight intensity, controlling for economic development. Given the strong correlation between nightlight intensity and traditional indicators such as GDP per capita, it has become a commonly used proxy variable for assessing local economic levels (Chor and Li, 2024). Zhong and Jiang (2021) reveal that socioeconomic factors can explain over 40% of the variance in $PM_{2.5}$ emissions. *Population* indicates the registered population. A larger population size implies greater urban transport demand, which in turn significantly impacts actual air pollution emissions (Duranton and Turner, 2011). *Govern_interv* denotes government intervention, which is measured by the ratio of general fiscal expenditures to regional GDP (Shen and Zhang, 2024). It reflects the extent of government management and regulation of economic activities, including the intensity of environmental policy implementation. The industrial covariates include *Firstind_ratio* and *Secondind_ratio*. These are represented by the proportion of value added by the primary industry and the secondary industry in GDP, respectively, to reflect the industrial structure. The proportion of the secondary industry is usually associated with industrial emissions, which are a major source of air pollution. For weather-related data, we collect *Temperature*, *Humidity*, *Air_pressure*, *Sunlight_hours*, and *Precipitation* to control for local climate conditions (Chang et al., 2019). According to Zivin and Neidell (2018), potential confounding caused by weather conditions may introduce bias in the results, as the aforementioned meteorological factors directly affect the formation, dispersion, and deposition of air pollutants. For temperature, relative humidity, and air pressure, we calculate the annual mean. For precipitation and sunshine hours, we calculate the total annual precipitation and total annual sunshine hours. In the empirical analysis, we apply a logarithmic transformation to non-negative variables. Appendix A reports the descriptive statistics.

4. Identification

This study aims to explore the impact of AI development on air pollution using city-level panel data. The identification model is as follows:

$$Airpollution_{it} = \alpha + \beta AI_{it} + \sum X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \qquad (1)$$

Where *i* represents the city and *t* represents the year. $Airpollution_{it}$ denotes air pollution, measured by $PM_{2.5}$ emission in the baseline regression, and PM_{10}, NO_2, and AQI are used as substitutes in the robustness analysis. AI_{it} indicates the level of AI development in the city, represented by the number of AI patent applications (*AIpatent*) in the baseline regression, and by the number of AI enterprises (*AIenterprise*) in the robustness analysis. X_{it} represents control variables, including *Nightlight*, *Population*, *Govern_interv*, *Firstind_ratio*, *Secondind_ratio*, *Temperature*, *Humidity*, *Air_pressure*, *Sunlight_hours*, and *Precipitation*. γ_i captures city fixed effects to control for the impact of time-invariant city characteristics on pollution. δ_t indicates year-fixed effects to account for uniform shocks that change over time affecting pollution. ε_{it} denotes the random error term. β is the coefficient of interest, which captures the elasticity of air pollution for AI development

5. Results

5.1 Baseline results

Table 1 reports the results of the baseline regression. Columns (1) to (3) sequentially add regional control variables, industrial control variables, and weather-related control variables.

Table 1. Baseline regression results

Variable	(1)	(2)	(3)
	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
AIpatent	0.0025**	0.0033***	0.0036***
	(0.0013)	(0.0012)	(0.0012)
Nightlight	-0.0387***	-0.0368***	-0.0361***
	(0.0024)	(0.0025)	(0.0025)
Population	-0.0466***	-0.0269	-0.0281*
	(0.0176)	(0.0164)	(0.0166)
Govern_interv	0.0495**	0.0273	0.0191
	(0.0207)	(0.0207)	(0.0195)
Firstind_ratio		0.0651***	0.0631***
		(0.0061)	(0.0061)
Secondind_ratio		0.0392***	0.0407***
		(0.0099)	(0.0099)
Temperature			-0.0005
			(0.0036)
Humidity			-0.0523
			(0.0351)
Air_pressure			1.1864***
			(0.4363)
Sunlight_hours			0.0765***
			(0.0145)
Precipitation			-0.0608***
			(0.0075)
Constant	4.0443***	3.6301***	-4.4547
	(0.1045)	(0.1117)	(2.9826)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4869	4869	4869
Adj. R^2	0.9749	0.9758	0.9770

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

The results show that the coefficients of AIpatent are significantly positive at least at the 5% level across all models. According to column (3), the development of AI contributes to worsening air pollution. Specifically, a 1% increase in AI patents leads to a 0.0036% increase in PM2.5 pollution emissions. The findings indicate that AI development has a significant negative impact on environmental quality, highlighting the double-edged nature of technological progress. This suggests that, while AI boosts production efficiency and economic growth in the digital era, it likely does so at the expense of worsening environmental pollution.

5.2 Robustness checks

5.2.1 Replacing the dependent variable

In the baseline regression, we primarily examine the impact of AI development on $PM_{2.5}$. To investigate whether AI development similarly affects other pollutants, we replace the dependent variable with PM_{10} and NO_2, as shown in Table 2. We observe that AI also increases PM_{10} and NO_2 emissions. More broadly, we replace the dependent variable with the Air Quality Index (*AQI*) as a comprehensive measure of air pollution. The results, shown in column (3), indicate that AI development raises overall air pollution levels. These results indicate that the impact of AI on air pollution is robust, and the baseline regression findings are not driven solely by the specificity of $PM_{2.5}$.

Table 2. Robustness test results with replacing the dependent variable

Variable	(1)	(2)	(3)
	PM_{10}	NO_2	AQI
AIpatent	0.0020*	0.0069***	0.0085**
	(0.0011)	(0.0019)	(0.0040)
Constant	-0.8881	-8.5365**	-2.5559
	(2.5898)	(3.4535)	(4.1347)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4869	3664	2030
Adj. R^2	0.9811	0.9628	0.9549

*Notes: Limited by data availability, NO_2 data starts from 2008, and AQI data starts from 2014. The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

5.2.2 Replacing the independent variable

To ensure that our findings are not influenced by a specific classification standard of AI patents, we consider another aggregation method to measure the independent variable. Unlike the baseline regression, which uses patent data based on primary classification numbers, we substitute the independent variable with patent data aggregated by full classification numbers (*AIpatent_divide*). According to the “Key Digital Technology Patent Classification System (2023)”, the primary classification approach focuses on the main use of the patent, whereas the full classification numbers encompass all potential technical branches involved in the patent. This means that primary classification tends to represent the core innovation direction of the technology, while the full classification better reflects cross-disciplinary applications of the patent. Column (1) of Table 3 shows that the coefficient of *AIpatent_divide* on $PM_{2.5}$ is 0.0035, similar to the coefficient of *AIpatent* in the baseline regression, and is statistically significant at the 1% level.

Table 3. Robustness test results with replacing the independent variable

Variable	(1)	(2)
	$PM_{2.5}$	$PM_{2.5}$
AIpatent_divide	0.0035***	
	(0.0012)	
AIenterprise		0.0113***
		(0.0030)
Constant	-4.0414	-4.3634*
	(2.9443)	(2.5997)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	4955	5117
Adj. R^2	0.9767	0.9764

To avoid relying solely on patent data as the only measurement indicator, we select the number of AI companies (*AIenterprise*) as an alternative proxy for AI development. Compared to patent counts, the number of AI companies more directly reflects actual AI market presence, providing a supplementary perspective for analysis. Column (2) of Table 3 shows that *AIenterprise* is also strongly positive at the 1% level. The results indicate that the baseline regression findings remain robust even after replacing the measurements for the independent variable.

5.2.3 Other robustness checks

To enhance the validity of the conclusions, we also conducted the following robustness tests. First, given the potential regional systematic differences and the interference of provincial common factors, we further include region-year fixed effects and province-year fixed effects (see Appendix B1). Second, the clustering level in the baseline regression model is redefined at the provincial level. We find that the choice of standard errors does not affect the conclusions of this study (see Appendix B2). Third, considering the possible differential impacts due to special samples, we exclude certain samples for robust estimation (see Appendix B3). Fourth, adjusting the sample period as a robustness check helps eliminate the influence of external shocks or policy interventions in specific years on the estimated results (see Appendix B4). Fifth, we include four environment-related policies and two AI-related policies as control variables in the model to mitigate endogeneity (see Appendix B5).

5.3 Endogeneity analysis

The impact of AI applications on air pollution may present endogeneity issues. First, cities with higher levels of air pollution often have relatively insufficient infrastructure and environmental management capabilities. These cities may rely more on technological advancements like AI to optimize resource management, monitor pollution, and enhance the efficiency of environmental governance(Granell et al., 2016; Toetzke, Probst and Feuerriegel, 2023). Consequently, there may exist a reverse causality between air pollution levels and AI development. Second, there are likely omitted variables that simultaneously influence the level of AI application and air pollution. To address these issues, this study uses the instrumental variable (IV) approach to eliminate bias arising from endogeneity. Specifically, the two-stage least squares (2SLS) method is employed to examine the causal relationship between AI application and air pollution.

Following the approach of Fisman and Svensson (2007), we use the average AI patent applications from other cities in the same province, excluding the focal city, as an instrumental variable (*other_city_mean_AI*). First, cities within the same province, due to their geographical proximity and administrative division, often share similarities in terms of policy environment, economic development levels, and technological infrastructure. This integration makes the trends and stages of AI development in cities within the same province typically more consistent. As a result, the AI development level of other cities in the province can serve as an effective indicator influencing the AI development of the target city. Additionally, there may be spillover effects of technology and knowledge between cities within the province, especially in high-tech fields such as AI, where these effects are more pronounced (Tang, Qiu and Dou, 2022). Therefore, the level of AI application in cities within the same province satisfies the relevance requirements for the instrumental variable. Second, after excluding the target city, the average number of AI patent applications in other cities within the province may be less influenced by factors from the target city. The average level of AI applications in other cities in the same province, after excluding the focal city, exerts minimal influence on AI development in that particular city. Hence, this instrumental variable meets the two critical conditions of relevance and exogeneity. The results of the instrumental variable are presented in Table 4.

Column (1) of Table 4 shows the results of the first stage, where the instrumental variable's coefficient on *AIpatent* is 0.4083, and it is significant at the 1% level, thereby meeting the relevance condition of the instrumental variable. The LM statistic for the underidentification test is 131.807. It rejects the null hypothesis at the 1% level, indicating that the instrumental variable is identifiable. The Kleibergen-Paap rk Wald F statistic is 133.840, significantly higher than the 10% critical value of 16.38, which rules out concerns about weak instruments. Column (2) of Table 4 shows the results of the second stage, where the coefficient of *AIpatent* on $PM_{2.5}$ is 0.0123, which is significant at the 1% level. This finding indicates that AI patents exacerbate air pollution remains valid even after addressing endogeneity.

Table 4. Endogeneity analysis results

Variable	(1)	(2)
	AIpatent	$PM_{2.5}$
other_city_mean_AI	0.4083***	
	(0.0353)	
AIpatent		0.0123**
		(0.0059)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	4797	4797
Adj. R^2	0.9207	0.1338
Kleibergen-Paap rk LM		131.807
Kleibergen-Paap rk Wald F statistic		133.840

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

5.4 Heterogeneity analysis

5.4.1 Heterogeneity across patent types

Existing studies indicate that innovative applications of AI and its concrete industrial applications have different impacts on the environment, particularly regarding carbon emissions (Gaur et al., 2023). To investigate the specific effects of different types of AI development on air pollution and to clarify the environmental mechanisms of innovative AI versus applied AI, we conduct a heterogeneity analysis based on patent types. In this study, AI patents are categorized into invention AI patents (*Innovation*) and utility AI patents (*Utility*), representing innovative AI and applied AI respectively[6]. The empirical results, shown in Table 5, reveal that the coefficient of *Utility* is significantly positive at the 1% level, while the coefficient of *Innovation* is not significant. This suggests that different types of AI applications have distinct impacts on air pollution.

We explain why utility patents have a significant impact on air pollution, whereas invention patents do not from two perspectives. First, invention patents typically represent earlier-stage, more innovative technologies, which may still be in the experimental phases and not yet widely applied in actual production (Gross et al., 2018). Consequently, their direct impact on air pollution is minimal. In contrast, utility model patents generally involve more mature technologies that can be immediately applied. As shown by Haustein and Neuwirth (1982), such technologies tend to be adopted more quickly in the early stages of the technology diffusion cycle, thereby having a tangible effect on energy consumption. Zhou and Liu (2023) also find that higher energy expenditures negatively impact ESG investments, highlighting the importance of energy factors in achieving ESG goals. Second, in terms of application pathways, utility patents focus more on using existing infrastructure to enhance production efficiency and scale. Under short-term economic motivations, this approach is more likely to increase energy consumption, thereby intensifying environmental pollution. Invention innovations mostly belong to “non-immediate substitutes”. They may require substantial investment in technologies and infrastructure, with benefits that are often in the long term (Grubler, Wilson and Nemet, 2016).

Table 5. Heterogeneity results across patent types

Variable	(1)	(2)
	$PM_{2.5}$	$PM_{2.5}$
Innovation	0.0016	
	(0.0011)	
Utility		0.0034***
		(0.0012)
Constant	-4.8189	-4.0713
	(3.0177)	(2.9187)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	4645	4832
Adj. R^2	0.9772	0.9771

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

5.4.2 Heterogeneity across cities with different characteristics

Existing literature suggests that the degree of AI application may be influenced and constrained by urban characteristics (Guo, Ma and Zhao, 2023; Wang and Ding, 2023). Therefore, we categorize the research sample based on urban characteristics, specifically city size and urban development level. First, regarding city size, we follow the “Notice on Adjusting the Standards for

[6] *One of the main sources of air pollution is the energy consumption, exhaust emissions, and resource usage during industrial manufacturing processes. Invention patents and utility patents are typically closely related to technological innovations and improvements in production processes. These improvements can directly impact pollution emissions and energy structures. In contrast, design patents primarily focus on innovations in product appearance and usually do not involve changes in production processes or technological advancements, so their impact on air pollution is minimal.*

City Size Classification" issued in 2014 and classify cities into two categories based on their resident population: large cities (with populations above one million) and medium-small cities (with populations of one million or below). The regression results are shown in Table 6. According to columns (1) and (2) of Table 6, the impact of AI applications on air pollution is significant in smaller cities but not significant in larger cities. Second, in terms of urban development level, we refer to the study by Yao et al. (2022) and use two criteria: whether the per capita output meets the World Bank's high-income standard and whether the administrative level is at or above the prefecture level. Cities are then classified as either central cities or peripheral cities. According to columns (3) and (4) of Table 6, the impact of AI applications on air pollution is significant in peripheral cities but not significant in central cities.

Table 6. Heterogeneity results across cities with different characteristics

Variable	City size		City status	
	(1)	(2)	(3)	(4)
	Large	Small	Central	Peripheral
	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
AIpatent	0.0059	0.0036***	0.0046	0.0038***
	(0.0063)	(0.0012)	(0.0061)	(0.0012)
Constant	5.6845	-4.5397	-3.0538	-3.0464
	(12.9400)	(6.2817)	(14.1945)	(6.0879)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	629	4201	642	4188
Adj. R^2	0.9759	0.9772	0.9740	0.9775

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

The possible reasons are as follows. First, large and central cities typically have higher levels of economic development, along with more technical resources and policy support. These factors help them mitigate air pollution (Wang et al., 2017b; Luo et al., 2018). Second, smaller and peripheral cities tend to lag behind central cities in terms of technology adoption and infrastructure modernization. As a result, when these cities introduce AI technologies, they rely more heavily on existing energy sources (such as electricity) to boost industrial and service sectors, leading to increased energy consumption. Wang and Chen (2022) show that higher dependency on resources is associated with increased air pollution. Third, the level of government corruption in smaller and non-core cities may be higher (Lecuna, 2012). Ren et al. (2021) find that corruption leads to increased carbon emissions. Additionally, Ucar and Staer (2020) further note that high corruption rates can lower corporate ESG scores.

5.4.3 Heterogeneity across cities with different air pollution control efforts

Considering that different cities have significant differences in policy implementation and environmental governance, various policy contexts may influence the mechanism by which AI application affects air pollution. State-listed famous historical and cultural cities often receive higher attention and protection in terms of environmental governance and policy, due to their unique historical heritage and cultural value. Cities designated for atmospheric pollution prevention are those selected by the government to implement special pollution control measures. These cities receive additional policy support and financial resources from both national and local governments to mitigate air pollution. Therefore, a heterogeneity analysis is conducted on the research sample based on two policy factors: state-listed historical and cultural cities and the "Blue Sky Protection Campaign".

First, based on the list issued by the State Council, the research sample is divided into "State-Listed Famous Historical and Cultural Cities" and "Non-State-Listed Famous Historical and Cultural Cities". Columns (1) and (2) in Table 7 show that for the group of state-listed historical and cultural cities, the impact of *AIpatent* on $PM_{2.5}$ is not significant. In contrast, for the non-state-listed group, the coefficient of *AIpatent* on $PM_{2.5}$ is 0.0043 and is significant at the 1% level. This finding is consistent with expectations. While AI applications may lead to a certain increase in industrial activities and energy consumption, the strengthened policy regulations and environmental governance in these cities likely effectively counterbalance the negative environmental impacts brought by the expansion of AI.

Second, based on the "Three-Year Action Plan to Win the Blue Sky Protection Campaign" issued by the State Council in 2018[7], the research sample is divided into "Cities Designated for Atmospheric Pollution Prevention" and "Cities Not Designated for Atmospheric Pollution Prevention". Results shown in columns (3) and (4) of Table 7, indicate that AI applications increase air pollution in cities not designated for atmospheric pollution prevention, but this is not the case for cities designated. The reason is that, in cities designated for atmospheric pollution prevention, the strict implementation of policies leads to limited pollution levels. Furthermore, the government reduces pollution loads through resource concentration and comprehensive management measures in these cities. Lu et al. (2022) find that the Blue Sky Plan not only significantly reduces emissions of air pollutants but also stimulates ESG investments in steel companies, improving their ESG performance.

Table 7. Heterogeneity results across cities with different air pollution control efforts

Variable	State-list famous historical and cultural cities		Cities designated for atmospheric pollution prevention	
	(1)	(2)	(3)	(4)
	State-Listed	Non-State-Listed	Cities Designated	Cities Not Designated
	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
AIpatent	0.0010	0.0043***	0.0027	0.0033**
	(0.0024)	(0.0014)	(0.0019)	(0.0014)
Constant	-22.0041***	0.7951	2.0619	-4.0386
	(5.5170)	(3.1746)	(3.5424)	(3.3016)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1567	3302	1171	3698
Adj. R^2	0.9798	0.9758	0.9769	0.9692

[7] *The Chinese government has continuously issued policies regarding atmospheric pollution prevention to promote sustained improvements in air quality. In 2013, the "Notice on Implementing Special Emission Limits for Air Pollutants" was released, followed by the "Three-Year Action Plan to Win the Blue Sky Protection Campaign" in 2018, and the "Action Plan for Sustained Air Quality Improvement" in 2023. In this study, we specifically select the 2018 document as the basis for categorization. The State Council, 2018. The State Council's Notice on the Issuance of the Three-Year Action Plan to Win the Battle for a Blue Sky. Available at: https://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm.*

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

5.5 Mechanism analysis

5.5.1 Energy Consumption Channel

The application of artificial intelligence indirectly exacerbates air pollution by increasing energy consumption. The in-depth application of AI technology requires large-scale data processing and analytical capabilities, which significantly increases the demand for digital infrastructure (Peng, 2013). The operation of these digital infrastructures is highly dependent on electricity (Salahuddin and Alam, 2015). Consequently, as AI applications deepen, electricity consumption shows a clear upward trend, creating a greater energy burden. With the increasing demand for electricity, the impact of energy consumption on air pollution becomes even more prominent, especially in a country like China where the power industry mainly relies on coal-fired power generation (Wang and Ding, 2023). China's electricity production heavily depends on fossil fuels, particularly coal, which significantly increases the emission of pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter ($PM_{2.5}$) (Ren et al., 2021). Therefore, although artificial intelligence technology brings certain efficiency improvements, its electricity demand is also increasing. Cong et al. (2022) find that energy consumption has a significant negative value. This indicates that ESG investments by Chinese companies are positive, but there has not yet been progress in relevant green technologies at this stage. In summary, under the current energy structure, AI applications lead to increased emissions of air pollutants.

Based on the substantial electricity demand discussed above, according to Chen et al. (2022), this study uses electricity consumption data (*Electricity_consumption*), which has been log-transformed, as a proxy variable for the energy consumption channel. Column (1) in Table 8 examines the effect of AI applications on electricity consumption levels. As can be observed, at the 1% degree, the *AIpatent* coefficient is markedly positive, indicating that the development of AI indeed increases electricity consumption. This result is in line with the conclusions of Ma et al. (2025), Wang and Ding (2023), and Raheem et al. (2020), who reported that during the development of the digital economy, telecommunications software and information technology services consume significant amounts of electricity, further contributing to energy use and carbon emissions. Therefore, the application of artificial intelligence will exacerbate air pollution by increasing energy consumption, supporting our analysis.

Table 8. Mechanism analysis results

Variable	Energy Consumption Channel	Scale Expansion Channel	
	(1)	(2)	(3)
	Electricity_consumption	Value_added	Industrial_output
AIpatent	0.0036***	0.0112***	0.0128***
	(0.0009)	(0.0025)	(0.0045)
Constant	18.0196***	14.4085***	9.3106
	(1.8559)	(5.0534)	(18.7368)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4578	4869	3694
Adj. R^2	0.9986	0.9915	0.9828

*Notes: The robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

5.5.2 Scale Expansion Channel

In the study of the impact of artificial intelligence (AI) applications on air pollution, the scale expansion effect serves as an important mechanism channel. The development of AI technology not only brings technological efficiency improvements but also drives the expansion of production scale. This scale expansion leads to the energy rebound effect and increased pollution emissions (Li and Wang, 2022). For instance, in the early stages, the deep integration of the digital economy with the real economy, especially the industrial sector, promotes scale expansion and increased energy use, thereby resulting in higher emissions (Ma et al., 2025).

First, the widespread application of AI promotes enterprises to purchase new production facilities, enhance production technology levels, and expand production scale, which in turn leads to an energy rebound effect and increased air pollution emissions (Li and Wang, 2022). As China accelerates its industrialization process, the share of the secondary industry rises along with increased electricity consumption (Wang et al., 2017b; Yang, Wang and Ren, 2022). A larger scale of industrial production implies greater demand for raw materials, which also leads to more industrial pollutant emissions and increased pressure on the environment. Second, industrial scale expansion is also accompanied by more auxiliary production activities, such as logistics, transportation, and the expansion of raw material supply chains. These activities further increase energy consumption and undoubtedly contribute to greater emissions of pollutants (Shvakov and Petrova, 2020; Usman et al., 2021). Third, the development of the digital economy promotes the expansion of economic activities, which influences pollution emissions through scale effects (Zhou, Zhou and Wang, 2018).

In this study, we use the log-transformed values of the secondary industry value-added (*Value_added*) and total industrial output above the designated scale (*Industrial_output*) from the National Bureau of Statistics' City Statistical Yearbook as proxies for scale expansion. According to columns (2) and (3) of Table 8, the coefficients of *AIpatent* on *Value_added* and *Industrial_output* are 0.0112 and 0.0128, both significant at the 1% level. This finding verifies the aforementioned hypothesis that AI development indeed aggravates air pollution through the scale expansion effect.

6. Conclusions

This study focuses on the impact of artificial intelligence (AI) development on air pollution. Technological progress plays a key role in corporate ESG performance (Eccles, Ioannou and Serafeim, 2014). However, the relationship between AI development and environmental pollution is theoretically ambiguous(Wang and Ding, 2023; Yang et al., 2023; Ma et al., 2025). Using panel data from 256 Chinese cities between 2003 and 2020, this study examines the effect of AI applications on air pollution. Our findings indicate that a 1% increase in AI patents leads to a 0.36% rise in $PM_{2.5}$ emissions. A series of robustness checks and instrumental variable regressions confirm the results, including alternative measurements of key variables, inclusion of high-dimensional fixed effects, exclusion of policy-related interference, and removal of specific samples and periods. Heterogeneity analysis shows that utility model AI patents, rather than invention AI patents, primarily increase air pollution. The effect of AI on air pollution is more pronounced in smaller cities, non-core cities, and cities with weaker air pollution control. Mechanism analysis indicates that AI development contributes to air pollution through higher energy consumption and expanded industrial output. Our findings highlight the negative externalities of AI development, suggesting that the impact of AI on air pollution should be considered when evaluating the ESG performance of firms deploying AI at scale. Firms need to use AI responsibly, maximizing its role in environmental protection and improving the effectiveness of environmental governance. In particular, industrial and heavily polluting public firms that are insensitive to ESG should recognize that one effective way to reduce pollutant emissions is to better implement ESG practices.

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