Supplementary Note S1

The quantification process for air pollution transmission intensity between cities is as follows:

Step 1: Based on the daily average air quality index of 157 cities, the Pearson correlation coefficient between two cities is calculated (the calculation formula is provided in equation (1), which yields the air pollution transmission correlation between cities. To ensure the stability of the network's topological structure, this study adopts the method of Chen et al. [54]. treating the average value of the non-diagonal elements in the correlation coefficient matrix as the threshold θ. Only when the correlation coefficient between two cities exceeds the threshold θ, their connection is considered valid and included in the initial directed unweighted network. This allows for the next step: constructing the air pollution transmission intensity between cities.

$$R_{ij}^{(t_1,t_2)}=\frac{\Sigma\left[AQI_i(t)-\overline{AQI_i}\right]\left[AQI_j(t)-\overline{AQI_j}\right]}{\left[\sqrt{\Sigma_{i-1}^{n}\left(AQI_i(t)-\overline{AQI_i}\right)^2}\right]\left[\sqrt{\Sigma_{j-1}^{n}\left(AQI_j(t)-\overline{AQI_j}\right)^2}\right]}\ (t_1\le t_1) \quad (1)$$

Here, $R_{ij}^{(t_1,t_2)}$ represents the pollution transmission correlation between city *i* and city *j* during the period from t_1 to t_2, with values ranging from -1 to 1. The absolute value of $R_{ij}^{(t_1,t_2)}$ indicates the strength of the correlation between the two cities, where a larger absolute value implies a stronger correlation. $AQI_i(t)$ and $AQI_j(t)$ denote the AQI values of city *i* and city *j* at time *t*, respectively. $\overline{AQI_i}$ and $\overline{AQI_j}$represent the average AQI values of air pollutants in city i and city *j* during the period from t_1 to t_2.

Step 2: Based on the connections constructed in Step 1 regarding air pollution transmission intensity between cities, this study further quantifies the intensity of air pollution transmission between cities. The diffusion of air pollution transmission between cities is influenced by multiple factors, not only constrained by geographic distance but also impacted by meteorological conditions and variations in pollutant concentrations [55] .In terms of geographic factors, the geographical distance and relative altitude difference between cities significantly affect the speed and range of pollutant diffusion, thereby determining the intensity and duration of pollutant transmission between cities [56]. Additionally, meteorological factors such as temperature, wind speed, and wind direction are critical determinants of pollutant diffusion, as widely demonstrated in prior research [57]. For instance, higher temperatures may accelerate chemical reaction rates, promote pollutant formation, and enhance atmospheric convection, leading to the broader diffusion of pollutants. Furthermore, wind speed and wind direction determine the transmission paths of pollutants by altering atmospheric diffusion conditions.

Therefore, relying solely on the correlation coefficient as the weight of the connecting edges fails to fully capture the spatial relationships of pollutant transmission between cities. To more accurately reflect these spatial relationships and avoid model overfitting, this study integrates multiple factors—including geographic distance, meteorological conditions, and changes in pollutant concentrations—to quantify the weights of pollutant transmission edges between cities. Following the methodology of Chen et al. [54], the intensity of air pollution transmission between cities is calculated using the following formula:

$$W_{ij}(t)=\frac{10^{R_{ij}^{(t_1,t_2)}}*F_i(t)*cos\vartheta_{ij}(t)*a^{\Delta AQI_{ij}(t)}}{D_{ij}*b^{-\Delta H_{ij}}} \quad (a>1,\ b\geq 1) \tag{2}$$

In the above formula, W_{ij} represents the air pollution transmission intensity between city i and city j. Here, $R_{ij}^{(t_1,t_2)}$ denotes the pollution transmission correlation coefficient between cities i and j during the period from t_1 to t_2. $F_i(t)$ represents the wind speed in city i at time t, and $\vartheta_{ij}(t)$ is the angle between the direction from city i to city j and the wind direction in city i at time t. A directed edge from city i to city j can only be established if $\vartheta > 90$ degrees. $a^{\Delta AQI_{ij}(t)}$ represents the difference in AQI values between city i and city j at time t, while D_{ij} represents the geographical distance between the two cities, and ΔH_{ij} represents the altitude difference between the cities.

In the model, a and b are adjustable parameters. Following Hou et al. [58], the value of a is set to 0.01 to adjust the sensitivity of the model. To accurately capture the effect of altitude differences on air pollutant transmission, b is set to 1 + abs(H)/1000, where abs(H) represents the absolute value of the altitude difference between the two cities.

Supplementary Note S2

Table S1. Variable definitions.

Control variable	symbol	Variable definition
Level of economic development	*pgdp*	Measured by the natural logarithm of real per capita GDP, representing economic development, to construct a matrix of economic development disparities between cities.
Vegetation coverage	*VC*	The normalized vegetation index for the city was used to construct a matrix of vegetation coverage disparities between cities.
Carbon emission intensity	*CO2*	Replaced by the direct and indirect carbon emissions within and outside the city, used to construct a matrix of carbon emission disparities between cities.
Energy consumption	*EN*	Measured by the ratio of total energy consumption to GDP, used to measure the intensity of energy consumption and construct a matrix of energy consumption disparities between cities.
Environmental regulation	*ER*	The natural logarithm of the frequency of environment-related terms in government work reports is used as a measure of the intensity of environmental regulation and to construct a matrix of environmental regulation disparities between cities.
Public supervision	*PS*	Baidu search term frequency
Air circulation	*AIR*	The logarithm of the air circulation coefficient
City size	*size*	The logarithmic form of the urban population is introduced to capture city size.
Geographical distance	*D*	Geographic distance between two locations is measured by computing the great-circle distance from their latitude and longitude coordinates, adding one, and taking the natural logarithm.

Table S2. Descriptive statistics of core variables

Variable	Symbol	Obs	Mean	Std. dev.	Min	Max
Air pollution transmission intensity	*CP*	97,968	0.393	1.093	0.000	7.655
AI gap	*AI_Gap*	97,968	1.296	1.012	0.009	4.585
Carbon emission intensity	*CO2*	97,968	1.051	0.778	0.017	3.379
Public supervision	*PS*	97,968	0.989	0.737	0.016	3.231
Energy consumption	*EN*	97,968	0.892	0.645	0.015	2.716
Vegetation coverage	*VC*	97,968	0.054	0.060	0.001	0.301
Environmental regulation	*ER*	97,968	0.407	0.325	0.000	1.594
Air circulation	*AIR*	97,968	0.422	0.331	0.006	1.469
Economic development level	*pgdp*	97,968	0.553	0.401	0.009	1.671
City size	*size*	97,968	0.965	0.839	0.013	3.712
Geographical distance	*D*	97,968	6.724	0.686	4.602	7.941

Table S3. Robustness test results

	(1)	**(2)**	**(3)**	**(4)**
	Replacing the explanatory variable	**Excluding special samples**	**2015-2018**	**2019-2022**
Variable	***CP***	***CP***	***CP***	***CP***
AI_Gap1	0.0042***			
	(0.0010)			
AI_Gap		0.0057***	0.0015	0.0066***
		(0.0011)	(0.0012)	(0.0016)
CP×dis	0.2237***	0.2240***	0.2200***	0.2259***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CO2	-0.0013	-0.0006	0.0003	-0.0024
	(0.0017)	(0.0018)	(0.0023)	(0.0025)
PS	-0.0053***	-0.0052***	-0.0078***	-0.0049*
	(0.0018)	(0.0018)	(0.0024)	(0.0030)
EN	0.0105***	0.0115***	0.0099***	0.0115***
	(0.0019)	(0.0020)	(0.0026)	(0.0029)
VC	-0.1183***	-0.1322***	-0.1303***	-0.1310***
	(0.0251)	(0.0260)	(0.0315)	(0.0396)
ER	0.0002	-0.0008	0.0024	-0.0013
	(0.0023)	(0.0023)	(0.0029)	(0.0039)
AIR	0.0299***	0.0265***	0.0382***	0.0240***
	(0.0033)	(0.0035)	(0.0044)	(0.0049)
pgdp	-0.0011	-0.0018	-0.0064**	0.0025
	(0.0023)	(0.0024)	(0.0029)	(0.0036)
size	-0.0016	-0.0032*	0.0017	-0.0033

	(0.0017)	(0.0019)	(0.0024)	(0.0026)
D	0.0823***	0.0820***	0.0613***	0.0943***
	(0.0015)	(0.0015)	(0.0019)	(0.0022)
City/Year FE	Yes	Yes	Yes	Yes
Cons	-0.6643***	-0.6624***	-0.5130***	-0.7499***
	(0.0096)	(0.0100)	(0.0127)	(0.0144)
R^2	0.9895	0.9897	0.9885	0.9904
N	97968	93024	48984	48984

Supplementary Note S3. Endogeneity test

Drawing on previous studies [59], we select terrain ruggedness (IV1) and the density of industrial robots in the United States during the same year (IV2) as instrumental variables for the AI gap between cities. Terrain ruggedness, as a relatively exogenous geographic feature, affects the cost and accessibility of digital infrastructure construction, thereby influencing AI development, but it does not directly determine the air pollution transmission intensity between specific cities. Similarly, the density of industrial robots in the United States serves as a proxy for global and leading nations' trends in AI and automation technology development. This external technological shock affects AI adoption and development in Chinese cities but is unlikely to directly influence air pollution transmission intensity between specific cities through channels other than its impact on the AI gap.

Table S4 presents the estimation results using the instrumental variable method. Column (1) shows the first-stage regression results, indicating that both IV1 and IV2 have highly significant positive effects on the AI gap (coefficients of 0.3535 and 0.9944, respectively). This demonstrates a strong correlation between the instrumental variables and the endogenous explanatory variable (AI gap), preliminarily satisfying the relevance requirement for instrumental variables. Furthermore, a series of diagnostic tests were conducted to assess the validity of the instrumental variables. The Anderson LM statistic is 2742.7134 (p-value =0.0000), strongly rejecting the null hypothesis of “under-identification of instrumental variables”, indicating that the model is identifiable. The Cragg-Donald Wald F statistic is as high as 1408.3348, far exceeding the commonly used Stock-Yogo critical value (e.g., 19.93 for 10% maximal IV size bias), strongly suggesting that the selected instrumental variables are not weak. The endogeneity test for the AI gap shows a corresponding statistic of 12.9119 (p-value = 0.0000), indicating that *AI_Gap* indeed has endogeneity issues, and using the instrumental variable method is necessary. In summary, the endogeneity test confirms the presence of endogeneity in the AI gap, validating the appropriateness of employing the instrumental variable approach.

Column (2) of Table S4 reports the second-stage estimation results from the 2SLS method. After addressing the endogeneity issue, the coefficient of the AI gap on air pollution transmission intensity is 0.1048, which remains highly significant and positive at the 1% level. The direction and significance of the 2SLS estimation results are consistent with those of the baseline regression and, to some extent, reinforce the conclusion that the AI gap exacerbates air pollution transmission. This once again demonstrates the robustness and reliability of the study's findings.

Table S4. Endogeneity test results

	(1)	**(2)**

Variable	*AI_Gap*	*CP*
IV1	0.3535***	
	(0.0100)	
IV2	0.9944***	
	(0.0275)	
AI_Gap		0.1048***
		(0.0177)
CP×D	0.0015***	0.2239***
	(0.0002)	(0.0001)
CO2	-0.1253***	0.0067***
	(0.0050)	(0.0023)
PS	-0.1421***	-0.0030
	(0.0056)	(0.0019)
EN	0.1913***	-0.0057*
	(0.0061)	(0.0035)
VC	1.6543***	-0.1686***
	(0.0613)	(0.0278)
ER	0.0687***	-0.0033
	(0.0077)	(0.0025)
AIR	-0.2365***	0.0365***
	(0.0097)	(0.0037)
pgdp	0.2965***	-0.0287***
	(0.0073)	(0.0054)
size	0.1133***	-0.0089***
	(0.0052)	(0.0022)
D	0.3528***	0.0488***
	(0.0046)	(0.0061)
Anderson LM statistic	2742.7134	
	(0.0000)	
Cragg-Donald Wald F statistic	1408.3348	
	[19.93]	
Sargan statistic		39.4279
		(0.0000)
Endogeneity test		12.9119
		(0.0000)
R^2		0.9879
N	97968	97968

Note: In the reported statistical tests in the table, values in parentheses ( ) represent the corresponding p-values, while values in square brackets [ ] denote the critical values of the Stock-Yogo weak instrument identification F-test at the 10% significance level.

Supplementary Note S4. Economic development levels of cities

To further investigate the complex contextual effects of the AI gap on air pollution

transmission intensity, we grouped city pairs based on the economic development levels of the cities within the urban cluster. Specifically, city pairs were categorized into three groups: “Low-Low” (both cities have low economic development levels), “High-Low” (one city has a high level while the other has a low level), and “High-High” (both cities have high economic development levels). Regression analyses were then conducted for these three subsamples to examine whether the AI gap's effect on air pollution transmission intensity varies across different combinations of economic development levels.

Column (1) of Table S5 shows that for city pairs with low economic development levels (“Low-Low” group), the regression coefficient of *AI_Gap* is 0.0072 and is significant at the 1% level. Notably, this is the largest coefficient in absolute terms among the three groups. This result indicates that when both cities have relatively weak economic foundations, the AI gap's impact on air pollution transmission is the most pronounced. In this context, even the relative “AI leader” within the “Low-Low” group may face significant economic growth pressures, potentially neglecting environmental considerations when promoting AI applications or even adopting non-green AI technology paths [60]. Meanwhile, the “AI follower” in this group, with weaker economic and technological foundations, is likely to have the weakest environmental governance capacity and bargaining power, making it more susceptible to pollution spillovers from neighboring cities. In such cases, the “imitation lag period” of AI technology in the environmental governance domain may be prolonged, leaving both cities with low overall environmental management capabilities. Even minor technological differences can significantly amplify the risks of pollution transmission. Conversely, narrowing the AI gap between such cities would have the most pronounced inhibitory effect on air pollution transmission intensity, achieving the greatest impact.

Second, column (2) of Table 3 shows that in the “High-Low” city pair combination, the regression coefficient of *AI_Gap* is 0.0035 and is significant at the 5% level. While the coefficient is significantly positive, it is smaller than that of the “Low-Low” group. This situation can be seen as a typical manifestation of the “pollution haven” or industrial transfer effect described in technology gap theory. Economically developed and AI-leading cities possess stronger incentives and capabilities to use AI technology to promote local industrial upgrading and environmental quality improvement [61]. At the same time, they are more inclined to transfer high-pollution, low-value-added industrial activities outward. Economically underdeveloped and AI-lagging cities, on the other hand, may become potential recipients of pollution due to their economic structure, technological limitations (insufficient “absorptive capacity”), and relatively lenient environmental regulations. The existence of the AI gap has driven this economic and technological asymmetry to further exacerbate the uneven distribution of environmental burdens across cities. Given the stark disparity in economic strength and AI-driven environmental governance capacity between the two sides in the “High-Low” combination, the AI gap continues to significantly promote pollution transmission.

Column (3) of Table 3 shows that in the “High-High” city pair combination, the regression coefficient of *AI_Gap* is 0.0042 but is not statistically significant. This result suggests that when both cities in a pair have high economic development levels, the AI gap between them, though potentially present, does not appear to significantly translate into differences in air pollution transmission intensity. First, in the “High-High” group, even the relative “AI follower” typically has reached a high level of absolute economic strength, technological capabilities, and

environmental governance systems. This implies that they possess stronger "absorptive capacity" to learn and apply new environmental protection technologies (including AI-enabled environmental technologies) and are better equipped to mitigate or neutralize potential pollution spillovers from neighboring "AI leaders". Second, economically developed cities often face stronger public demands for environmental quality and stricter environmental regulatory pressures (a reflection of the "demand-pull" factor in technology gap theory). This may drive these cities, regardless of their relative AI development levels, to enhance their own environmental standards, creating a "race to the top" dynamic that weakens the pollution transmission effects potentially caused by the AI gap.

Supplementary Note S5. Low-carbon city pilot programs

To examine the potential role of environmental policies in the process by which the AI gap affects air pollution transmission intensity, we categorized city pairs based on whether they were part of the low-carbon city pilot program. The city pairs were divided into three groups: "Non-Pilot–Non-Pilot" (both cities are non-pilot cities), "Pilot–Non-Pilot" (one city is a pilot city and the other is a non-pilot city), and "Pilot–Pilot" (both cities are pilot cities).

The results in column (1) of Table 4 show that when neither city in the pair has implemented the low-carbon city pilot program, the regression coefficient of *AI_Gap* on air pollution transmission intensity is 0.0167 and is significant at the 1% level. This finding suggests that in the absence of specific and strengthened environmental policy guidance, the differences in AI capabilities between cities, as described by the technology gap theory, have the most pronounced negative effects on air pollution transmission. AI-leading cities, lacking sufficient constraints for green development, may indirectly contribute to pollution spillovers, while AI-lagging cities, due to their weaker technological and management capacity, are more vulnerable to such effects. In this scenario, technological disparities are more likely to translate directly into differentiated environmental burdens.

Columns (2) and (3) of Table 4 show that when at least one city in the pair is a low-carbon pilot city (i.e., in the "Pilot–Non-Pilot" and "Pilot–Pilot" groups), the AI gap's impact on air pollution transmission intensity is no longer significant. The results from these two groups reveal an important finding: proactive environmental policies, such as the low-carbon city pilot program, can effectively "mitigate" or "buffer" the negative cross-regional pollution transmission effects of the AI gap. From the perspective of technology gap theory, this may be attributed to the fact that low-carbon pilot policies are often accompanied by stricter environmental objectives, more comprehensive monitoring and evaluation systems, and policy support for green technologies. These factors enhance the environmental governance standards and capacities of pilot cities (whether AI leaders or followers), thereby weakening the potential for AI technological disparities to translate into pollution transmission. Moreover, low-carbon pilot programs incentivize the application of AI technologies in green areas such as energy conservation, emissions reduction, clean production, and intelligent environmental protection [62]. Even AI-leading pilot cities are more likely to leverage their technological advantages to reduce their own pollution rather than externalize it. Particularly in the "Pilot–Pilot" group, shared policy goals may foster mutual learning and cooperation between cities in low-carbon development and pollution governance,

forming a “policy convergence” or “green consensus” that transcends the competition and divergence typically driven by technological gaps.

Supplementary Note S6. Smart city pilot programs

To further investigate how specific policy contexts—particularly the “smart city pilot” policy, which is closely related to technology application and the modernization of urban governance—affect the relationship between the AI gap and air pollution transmission intensity, we categorized city pairs based on their participation in the “smart city pilot” program. The city pairs were classified into three groups: “Non-Pilot–Non-Pilot” (both cities are non-smart city pilots), “Pilot–Non-Pilot” (one city is a pilot and the other is not), and “Pilot–Pilot” (both cities are smart city pilots).

The results in column (1) of Table 5 show that when neither city in the pair is part of the smart city pilot program, the regression coefficient of *AI_Gap* on air pollution transmission intensity is 0.0023, but it is not statistically significant. When both cities have not systematically promoted smart city construction, although there may be a gap in their AI development levels, this gap does not appear to significantly influence air pollution transmission intensity. This may indicate that, in the absence of the smart city policy as a driver, cities' overall ability to use advanced technologies such as AI for integrated city management—including environmental governance—may remain generally low or fragmented. As a result, while the AI gap objectively exists [12], its actual impact on pollution transmission remains underdeveloped, and the significant environmental externalities described in the technology gap theory are weakened in this context.

Column (2) of Table 5 shows that when one city is a smart city pilot and the other is not, the regression coefficient of *AI_Gap* is 0.0045 and is significant at the 1% level. The smart city pilot policy often accelerates the development, application, and integration of AI and other information technologies in pilot cities (which can be viewed as “innovators” in the context of technology gap theory). If this technology-driven “smart” development process fails to fully and synchronously integrate environmental protection and green development goals—or if its “smartness” is primarily focused on improving internal operational efficiency while neglecting regional environmental collaboration—then AI-leading pilot cities may, unintentionally, transfer part of their environmental pressure or pollution risks to non-pilot cities with relatively weaker technology adoption and management capacities (i.e., “followers” or “imitators”). In this scenario, the AI gap is compounded by the policy identity differences of “smart” versus “non-smart” cities, further highlighting the asymmetry in their environmental management and pollution response capacities, thereby significantly amplifying pollution transmission effects. This finding suggests that technology-enabled policies like smart cities, if lacking sufficient environmental considerations, may inadvertently exacerbate regional environmental inequalities.

Column (3) of Table 5 shows that when both cities are smart city pilots, the regression coefficient of *AI_Gap* is 0.0017 and is not statistically significant. When both cities are committed to smart city development, the AI development gap between them no longer significantly affects air pollution transmission intensity. This may be because both being pilot cities implies that they are actively enhancing their overall capacity to use modern information technologies for urban governance. Even if an AI gap exists, the relatively less advanced pilot city may still have a higher baseline level of “smart” governance compared to non-pilot cities, thereby improving its ability to

absorb cross-border pollution or its willingness to engage in collaborative governance. Another possibility is that both cities' pursuit of “smartness” may align their urban management philosophies, technological standards, and policy tools, fostering a consensus on regional pollution co-governance rather than leading to significant one-way pollution transmission due to technological gaps.

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