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The Artificial Intelligence Paradox: Does Digital Progress Fuel Environmental Injustice via Transboundary Pollution?

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Abstract

The uneven proliferation of artificial intelligence (AI) presents unexamined challenges to sustainable regional development. This study provides robust empirical evidence on how the inter-city AI gap influences environmental dynamics, specifically via transboundary air pollution. Using a framework based on the Technological Gap Theory, the results demonstrate that a wider AI gap significantly intensifies air pollution transmission between cities. The primary mechanisms are widening disparities in digital infrastructure and imbalanced flows of capital and labor. This effect is context-dependent and most severe for economically underdeveloped cities, creating a new form of environmental inequity. The analysis further reveals that while environmental regulations can mitigate this negative impact, technology-centric policies lacking green synergy may amplify it. The research's findings offer a new theoretical lens on techno-environmental inequality and underscore the necessity of synergistic policies that simultaneously bridge the digital and environmental divides to foster equitable and sustainable development.

Keywords: Technological Gap Theory; artificial intelligence; air pollution transmission; urban agglomerations; new digital infrastructure; factor mobility

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1. Introduction

Worsening air pollution poses not only a serious threat to public health but also significantly constrains the sustainable development of regional economies and societies [1,2]. Air pollution is characterized by notable cross-regional transmission, making it difficult for individual cities to address the issue independently [3]. For example, in China, during heavy pollution episodes in the Beijing–Tianjin–Hebei region, the contribution of PM2.5 transported from surrounding areas often reaches 70% [4]. In the Pearl River Delta region, industrial emissions and volatile organic compounds from different cities mix and migrate under specific meteorological conditions, collectively elevating regional PM2.5 and ozone levels [5]. Globally, sulfur dioxide and nitrogen oxide emissions from the industrial belt in the Great Lakes region of North America have historically caused widespread acid rain [6], affecting multiple states and provinces in both the United States and Canada [7]. Similarly, pollutants emitted by several industrialized countries in Europe often cross national borders, creating regional air quality challenges and prompting international cooperation [8], such as the establishment of the Geneva Convention on Long-Range

Transboundary Air Pollution [9]. These cases clearly demonstrate that joint prevention and control of air pollution have become common challenges for regional and even global environmental governance. Against this backdrop, national urban agglomerations such as the Beijing–Tianjin–Hebei, Yangtze River Delta, Pearl River Delta, and Chengdu–Chongqing regions not only serve as core engines of China's high-quality economic development and hubs of cutting-edge technological innovation [10], but are also among the regions with the highest concentrations of air pollution [11]. Coordinated air pollution prevention and control among cities within these regions have thus become a national strategic imperative and a necessary step in advancing ecological civilization.

At the same time, the new generation of information technologies, represented by AI, is profoundly transforming urban governance and industrial development models [12]. While AI applications demonstrate significant potential for environmental benefits, such as enhanced pollution monitoring and energy optimization [13,14], their diffusion is far from uniform. This uneven proliferation creates a distinct form of regional inequality we term the "AI gap". This concept moves beyond the general notion of a "digital divide", which often focuses on access to digital tools. The AI gap is a more profound, structural disparity that manifests across several interconnected facets. It is rooted in foundational disparities in new digital infrastructure (e.g., 5G networks, cloud computing); it is amplified by technological and talent imbalances (e.g., R&D, skilled professionals); and it is ultimately realized through a gap in industrial integration, which reflects how deeply AI is embedded in a region's economic base.

Crucially, the AI gap is transformative because it is systemic and self-reinforcing. Unlike previous technology gaps that were often sector-specific, the AI gap, driven by a General-Purpose Technology, influences the entire urban economic ecosystem [15]. Cities with an initial advantage attract a disproportionate share of capital, talent, and data, creating a powerful feedback loop that rapidly widens the gap. It is this systemic power to reconfigure regional economic landscapes and drive imbalanced factor flows that forms the central premise of our study. While our main empirical analysis captures the overall effect of the AI gap, we conceptualize these distinct facets not as components of a single composite index, but as the key channels through which the gap operates. Our subsequent mechanism analysis is dedicated to unpacking the roles of these specific facets, such as digital infrastructure disparity and factor mobility. The core question we address is how this potent, multi-faceted AI gap influences, or even reshapes, the cross-boundary transmission patterns of regional air pollution.

Does it exacerbate, mitigate, or alter the intensity of pollution transmission between cities? Exploring these questions in depth not only helps uncover new mechanisms of regional environmental governance in the digital economy era but also provides critical scientific evidence for formulating precise and effective policies to coordinate emission reduction and promote differentiated development within urban agglomerations. Existing academic research has extensively and deeply examined the sources of air pollution [16], its physical and chemical transformation mechanisms [17], and the cross-boundary transmission patterns driven by meteorological and topographical factors [18], thereby laying a solid scientific foundation for the practice of regional joint prevention and control [19]. Additionally, the potential applications of AI in environmental governance have increasingly attracted attention [20], with numerous studies affirming AI's positive role in enhancing the accuracy of environmental monitoring [21], optimizing pollution control strategies, and enabling green production. However, within urban agglomerations—the core spatial units of regional development in China—the question of how the uneven development of AI technology, resulting in the "AI gap", affects the cross-boundary flow of air pollution between cities remains unanswered.

The Technological Gap Theory (TGT), which explains the systemic impacts of uneven technological distribution [22], provides a foundational lens for our analysis. We acknowledge that the broader linkage between technological disparities and environmental outcomes is not entirely new territory. For instance, prior studies have explored how gaps in green-innovation capabilities or industrial automation affect environmental quality within nations or regions [23,24]. However, our study posits that the nature of the AI gap introduces a fundamentally distinct theoretical problem, especially concerning transboundary environmental dynamics. First, unlike more specialized industrial or environmental technologies, AI is a paradigm-shifting General-Purpose Technology that systemically reconfigures entire economic structures, production functions, and, crucially, the interregional mobility of capital and high-skilled labor [25]. The diffusion of AI is prone to creating stark "winner-takes-all" dynamics, leading to a more profound and persistent technological gap than previously studied technologies. Second, and central to our contribution, we move beyond examining the direct environmental impact within a technologically lagging or leading region. Instead, we apply TGT to a novel dependent variable: the intensity of pollution transmission between cities. This relational perspective is critical because the AI gap does not merely alter a city's own pollution profile; it reshapes the economic and industrial interdependencies that serve as conduits for transboundary pollution. Therefore, our work is not simply an application of TGT to a new context. Rather, we extend the theory by proposing and testing new mechanisms (i.e., imbalanced factor flows and digital infrastructure disparity) through which a General-Purpose Technology-driven technology gap specifically exacerbates relational environmental injustice via cross-boundary pollution flows. This approach offers a more nuanced understanding of the environmental externalities of the digital divide, contributing a distinct theoretical perspective to the TGT literature in the digital era.

The main contributions of this study are as follows: First, we construct a novel integrated theoretical framework by synthesizing the TGT with principles from economic geography. While the concepts of factor mobility and digital infrastructure are themselves well-established, our primary conceptual innovation lies in identifying and specifying them as the critical mediating pathways through which the AI gap, a modern General-Purpose Technology-driven disparity, influences the specific environmental outcome of transboundary pollution intensity. To our knowledge, this is the first study to propose and test this complete causal chain, thus building a new theoretical bridge between the literature on the digital economy and that on relational environmental justice. Second, our research deepens the understanding of these mechanisms. We move beyond intuitive assumptions by empirically demonstrating how the AI gap leads to imbalanced flows of capital and labor and how disparities in new digital infrastructure act as a foundational channel. This provides granular evidence on the environmental consequences of techno-economic inequality between cities. Third, on the empirical research level, the core innovation of this study lies in the construction of a large-scale paired city panel dataset, comprising 97,968 observations. By using city pairs as the unit of analysis, this approach enables a more direct examination of relative differences and interaction effects between cities. This refined research design, combined with large-scale sample empirical analysis, offers more direct and robust evidence for understanding the environmental effects of the AI gap. It also provides a scientific foundation for formulating precise policies aimed at promoting regional coordinated development and environmental governance.

2. Theoretical Analysis and Research Hypotheses

The Technology Gap Theory, first pioneered by Posner (1961) [26], provides a classical analytical framework for understanding the dynamic comparative advantage and trade

patterns arising from temporal lags in technological innovation and imitation between countries. The core of this theory lies in the notion that technological leaders gain temporary advantages through innovation, while technological followers strive to narrow the gap through learning and adaptation [27]. This dynamic "gap" profoundly shapes the behavioral patterns, production efficiency, and even welfare levels of economies [28]. The research framework is as follows (Figure 1):

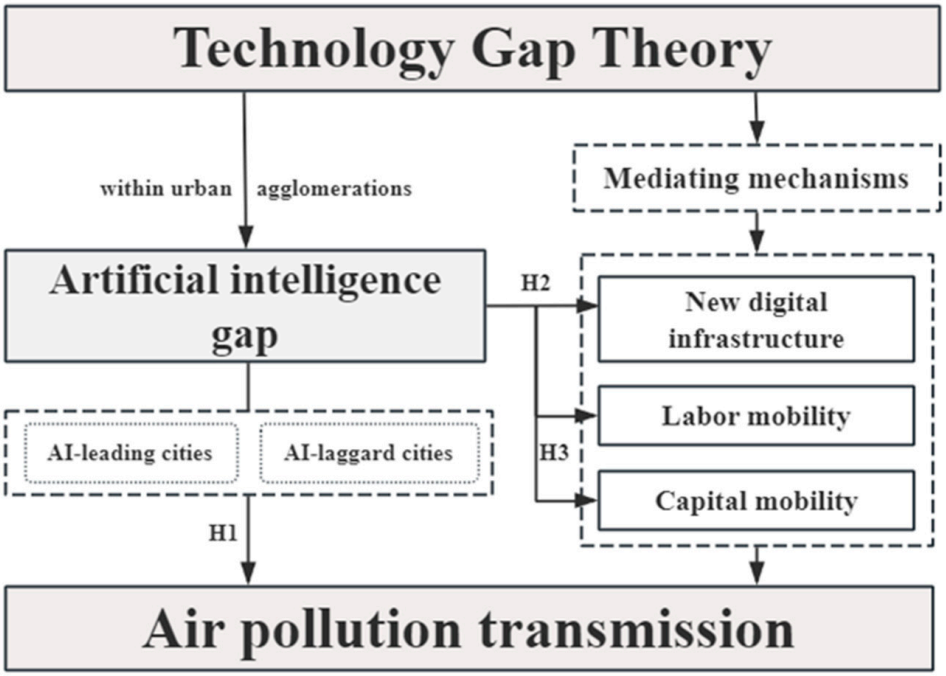


Figure 1. The research framework.

2.1. The AI Gap and Air Pollution Transmission

The TGT highlights how differences in capabilities between technological leaders and followers lead to variations in behavior and performance [29]. At the urban agglomeration level, the AI gap reflects substantial disparities in cities' capacities to harness AI for environmental governance, optimize industrial structures, and engage in coordinated regional pollution control [30]. These differences directly affect the intensity of cross-boundary air pollution transmission. Specifically, narrowing the AI gap between cities first implies that cities previously lagging in AI technology (followers) experience an endogenous enhancement in their environmental governance capabilities. These cities are better equipped to deploy AI-driven precision monitoring networks, pollution source identification systems, and intelligent early warning and emergency response mechanisms [31]. As a result, they can more efficiently control and reduce major pollution sources with high cross-boundary transmission potential, such as industrial point sources and regional area sources. This directly reduces the total volume of pollutants "exported" from these cities to neighboring areas and reciprocally limits the pollution "imported" from neighboring regions.

In addition, narrowing the AI gap helps mitigate the "pollution haven" effect that may arise from disparities in environmental regulation enforcement capacity among cities within an urban agglomeration [32,33]. When cities with lower AI adoption (technology laggards) improve their environmental regulatory capabilities, enabled by AI-driven monitoring, data analysis, and enforcement assistance, their implicit "attractiveness" to high-pollution, high-emission industries decreases. This facilitates the optimization of regional industrial layouts toward more environmentally friendly configurations, preventing the over-concentration of pollution sources in areas with weaker regulatory capacity [34]. Consequently, the structural

foundation for large-scale and high-intensity cross-boundary pollution events is reduced. Finally, narrowing the AI gap among cities lays a technological foundation for building an efficient system of regional collaborative pollution control at the urban agglomeration level. Convergence in AI application levels across cities enables smoother and more effective cross-regional environmental data sharing [35], joint simulation of pollution diffusion models, collaborative forecasting of regional air quality, and coordinated prevention and control actions (e.g., unified warning standards and synchronized emergency responses). The improvement in regional environmental governance collaboration enhances the ability to address and buffer cross-boundary pollution flows, reducing the cumulative effects and impact scope during the transmission process.

Based on this analysis, the following hypothesis is proposed:

Hypothesis 1: *Narrowing the AI gap between cities within an urban agglomeration significantly reduces air pollution transmission intensity.*

2.2. New Digital Infrastructure

Within the framework of the TGT, disparities in AI capabilities between cities are not merely reflected in differences in algorithms, talent, or specific AI applications but are deeply rooted in the "absorptive capacity" and foundational environment that support the effective operation of these advanced technologies [36]. New digital infrastructure, as an indispensable "foundation" of AI technology, constitutes a critical dimension of cities' technological absorptive capacity [37]. The disparity in the level of digital infrastructure development itself is a key systemic feature of the technological gap. The TGT informs us that "technological innovators" (AI-leading cities), leveraging their first-mover advantages and comprehensive strengths, often take the lead in constructing and upgrading cutting-edge digital infrastructure, including 5G networks, big data centers, cloud computing platforms, and Internet of Things systems. These infrastructures provide fertile "soil" for the research, iteration, and efficient application of their AI technologies. In contrast, "technological followers" (AI-lagging cities) often face a "dual deficit"—a gap in both AI technology itself and the enabling digital infrastructure. This dual deficit creates greater challenges for lagging cities in narrowing the overall technological gap. Therefore, the magnitude of the AI gap between cities reflects not only disparities in core AI technologies but also reveals profound imbalances in critical "complementary assets" such as digital infrastructure.

When efforts are made to narrow the AI gap between cities, especially for AI "technological followers", their catch-up process, viewed through the lens of the TGT, is not merely about introducing or imitating AI technologies. More fundamentally, it is a systematic endeavor to enhance their "absorptive capacity" and address developmental shortcomings, with the synchronous construction and upgrading of new digital infrastructure being a critical prerequisite for successfully catching up and applying AI technologies. Advanced digital infrastructure provides the necessary computing power, data transmission, and storage capabilities for the efficient operation of AI technologies in complex scenarios, such as pollution tracing, intelligent monitoring, and early warning and emergency responses [38]. This establishes a robust technical foundation for leveraging AI in environmental governance. By improving digital infrastructure, AI-lagging cities can more effectively deploy and apply AI solutions—whether through independent innovation or learning from others—enabling broader environmental data collection, sharing, and intelligent analysis. This significantly enhances their precision control over local pollution sources and overall environmental governance efficiency. Thus, as the AI gap between cities narrows, accompanied by the strengthening of lagging cities' digital infrastructure as a core element of their "absorptive capacity", the effectiveness of AI applications in environmental governance

improves. This contributes to better pollutant control and mitigation capabilities, reducing local pollutant emissions and ultimately alleviating the cross-boundary transmission effects of air pollution.

Based on this, the following hypothesis is proposed:

Hypothesis 2: *Narrowing the AI gap between cities reduces air pollution transmission intensity through improvements in the level of new digital infrastructure.*

2.3. Labor and Capital Mobility

The TGT posits that technological disparities decisively shape the allocation of production factors [39]. As a knowledge-intensive field, AI development hinges on aggregating high-skilled talent and targeted capital investment [40]. Within the TGT framework, an AI gap creates a "siphoning effect": AI-leading cities (innovators) leverage first-mover advantages to attract talent and capital, while AI-lagging cities (followers) struggle to retain these resources, entrenching their disadvantage. This study, therefore, treats factor allocation imbalances as a consequence of the AI gap (cause) and examines the subsequent environmental effects. Consequently, as the AI gap narrows, the ability of follower cities to attract production factors is positively transformed. Regarding labor, narrowing the AI gap enhances the ability of lagging cities to attract and retain skilled professionals. This influx and retention of talent directly improves local environmental governance through more precise monitoring and data-driven decision-making [41], fosters green technology innovation, and facilitates the regional diffusion of advanced environmental knowledge. A stronger local talent pool reduces local pollution intensity, thereby diminishing the volume of pollutants available for cross-regional transmission. Regarding capital, narrowing the AI gap also optimizes capital allocation within the urban agglomeration [42]. As lagging cities demonstrate technological progress and new growth potential, they attract increased capital investment. This capital directly finances advanced environmental monitoring systems and the green upgrading of high-pollution industries [43]. Furthermore, it helps cultivate green, AI-driven industrial clusters and promotes a transition toward cleaner energy structures. By modernizing infrastructure and industry, these capital flows fundamentally reduce local pollutant generation.

Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3: *Narrowing the AI gap between cities reduces air pollution transmission intensity through the optimized allocation of labor and capital.*

3. Research Design

3.1. Model Specification

To examine the impact of the AI gap between cities on air pollution transmission intensity, this study constructs the following econometric model:

$$CP_{ij,t} = \alpha_0 + \alpha_1 AI_Gap_{ij,t} + \rho D_{ij} \times CP_{ij,t} + \alpha_n Controls_{ij,t} + u_i + u_j + v_t + \varepsilon_{ij,t} \quad (1)$$

In this study, $CP_{ij,t}$ represents the air pollution transmission intensity between city i and city j in period t, and $AI_Gap_{ij,t}$ denotes the AI gap between city i and city j during the same period. Given that air pollution transmission exhibits spatial spillover effects, this factor needs to be incorporated into the model. This concept is analogous to the "trade costs" in the gravity model of international trade, where distance is a key proxy for frictions that impede economic flows [44,45]. This study introduces the interaction term between the dependent variable (CP) and geographic distance (D) as a proxy for spatial spillover effects

and examines the coefficient ρ. $Controls_{ij,t}$ represents the control variables, u_i and u_j denote city fixed effects, v_t represents year fixed effects, and $\varepsilon_{ij,t}$ is the stochastic disturbance term.

To examine the mediating effects of new digital infrastructure (*NIF*), labor mobility (*LM*), and capital mobility (*CF*) in the process by which the AI gap influences air pollution transmission intensity—and to avoid the potential endogeneity issues that may arise in the final step of the traditional stepwise regression approach to testing mediation effects—this study follows the methodology of Jiang (2022) [46] and constructs the following models:

$$M_{ij,t} = \partial_0 + \partial_1 AI_Gap_{ij,t} + \partial_n Controls_{ij,t} + u_i + u_j + v_t + \varepsilon_{ij,t} \quad (2)$$

In Equation (2), M represents the mediating variables, including new digital infrastructure (*NIF*), labor mobility (*LM*), and capital mobility (*CF*). ∂ represents the parameters to be estimated, while the remaining variables are consistent with those in Equation (1).

3.2. Variable Selection

3.2.1. Air Pollution Transmission Intensity

This study focuses on the air pollution transmission intensity between cities within urban agglomerations. To quantify air pollution transmission intensity, a comprehensive air quality assessment indicator capable of effectively covering the concentrations of major pollutants such as PM2.5, PM10, sulfur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), and ozone (O_3) is selected—namely, the Air Quality Index (AQI) [47]. The AQI is widely recognized internationally and is characterized by its standardization. It comprehensively reflects the concentration levels of multiple air pollutants and is used as a unified standard for evaluating air quality in many countries and regions [48]. Therefore, selecting the AQI to measure air pollution levels ensures data comparability and consistency, providing a standardized air quality indicator for cross-regional comparisons in the study (Supplementary Note S1).

3.2.2. AI Gap

Existing literature primarily measures regional AI levels using metrics such as the number of industrial robots, the number of AI enterprises, or the number of AI patents. AI patents, as a key indicator of technological innovation and application, effectively reflect R&D investments and technological advancements in the AI field. By using the natural logarithm of the number of AI patents in each city as a measure of the city's AI level, it is possible to accurately capture the technological accumulation and development trends of cities in the AI domain. Furthermore, the absolute value of the difference in AI levels between two cities is used as a proxy variable for the AI gap between paired cities during the sample period. To test the robustness of the results, alternative variables such as the number of industrial robots and the number of AI enterprises in each region are also employed in robustness checks.

3.2.3. Control Variables

The formation and intensity of air pollution transmission between cities are influenced by multiple factors [49]. Beyond geographic and meteorological factors such as geographical distance, altitude, wind speed, wind direction, and temperature, economic, social, ecological, and governance factors also play critical roles in the transmission mechanism of pollutants. Therefore, to avoid the influence of omitted variables on the research results, a series of control variables are introduced, with specific measurement methods provided in Supplementary Note Table S1.

As shown in Supplementary Note Table S2, the mean value of air pollution transmission intensity (*CP*) is 0.393, but its standard deviation (1.093) is much larger than the mean,

with a range from 0 to 7.655. This indicates substantial differences and significant volatility in pollution transmission intensity between cities, with some city pairs exhibiting very high transmission intensity. Similarly, the mean value of the AI gap (*AI_Gap*) is 1.296, and its standard deviation (1.012) also demonstrates considerable disparities in the degree of AI development imbalance across cities.

3.2.4. Data Sources

This study utilizes daily average AQI index data from 1 January 2015 to December 31 2022. The dataset includes 11 national-level urban agglomerations (the 11 national-level urban agglomerations are: Yangtze River Delta Urban Agglomeration, Central Plains Urban Agglomeration, Lanxi Urban Agglomeration, Hubao Eyu Urban Agglomeration, Guanzhong Plain Urban Agglomeration, Beijing–Tianjin–Hebei Urban Agglomeration, Beibu Gulf Urban Agglomeration, Urban Agglomeration in the Middle Reaches of the Yangtze River, Chengdu–Chongqing Urban Agglomeration, Ha Changcheng Urban Agglomeration, and The Pearl River Delta Urban Agglomeration) and the Beijing–Tianjin–Hebei Urban Agglomeration in China, encompassing a total of 157 cities. These data are obtained from the China Research Data Service Platform. In constructing the edges of the air pollution transmission network, meteorological factors such as temperature and wind direction are also considered. These data are sourced from the National Meteorological Information Center. Information on the location, altitude, and coordinates of each city is retrieved using the Geocoding API provided by the Baidu Map Open Platform. Additionally, the 157 prefecture-level cities in China from 2015 to 2022 are paired to form 97,968 city pairs. The databases for all control variables primarily include the CECI database and the Chinese Regional Economic Research Database.

4. Empirical Analysis

4.1. Baseline Regression Analysis

To test Hypothesis 1, we conducted an empirical analysis using model (1) (see Table 1). In column (1), without considering other influencing factors, the coefficient of the AI gap is 0.0188 and is significant at the 1% level. This preliminary evidence suggests that as the AI gap between cities widens, the air pollution transmission intensity between cities also increases. However, this result might be influenced by omitted variable bias. Therefore, in the model presented in column (2), we include a series of control variables, such as urban economic development level, environmental regulation, city size, and carbon emission intensity, to more accurately estimate the net effect of the AI gap. As shown in column (2), after controlling for other potential influencing factors, the coefficient of the AI gap remains significantly positive, with a value of 0.0041. This means that for every one-unit increase in the AI gap between cities, the air pollution transmission intensity between cities will increase significantly by an average of 0.0041 units. Given that our *AI_Gap* variable is measured as the absolute difference in the natural logarithm of AI patents, a literal "one-unit" increase represents a massive non-linear shift.

This result suggests that a larger technological gap is indeed associated with stronger pollution transmission. Conversely, narrowing the AI gap, meaning that the AI development levels of cities become more balanced, significantly contributes to reducing the intensity of transboundary air pollution transmission. Although the coefficient of the AI gap decreases after adding control variables (from 0.0188 to 0.0041), this is consistent with expectations, as part of the initial effect is absorbed by the control variables. Nonetheless, the significance and direction of the core effect remain unchanged, which strengthens the robustness of our findings.

Table 1. Baseline regression results.

	(1)	(2)
Variable	***CP***	***CP***
AI_Gap	0.0188 ***	0.0041 ***
	(0.0010)	(0.0010)
$CP \times D$	0.2215 ***	0.2237 ***
	(0.0001)	(0.0001)
CO_2		−0.0013
		(0.0017)
PS		−0.0053 ***
		(0.0018)
EN		0.0105 ***
		(0.0019)
VC		−0.1181 ***
		(0.0251)
ER		0.0002
		(0.0023)
AIR		0.0299 ***
		(0.0033)
pgdp		−0.0011
		(0.0023)
size		−0.0016
		(0.0017)
D		0.0823 ***
		(0.0015)
City/Year FE	Yes	Yes
Cons	−0.1178 ***	−0.6645 ***
	(0.0015)	(0.0096)
R^2	0.9891	0.9895
N	97968	97968

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard errors.

The true importance of this finding, however, lies in its systemic and forward-looking implications. When this effect is aggregated across the thousands of city pairs in our study, it points to a systematic widening of environmental inequality. Furthermore, as AI is an emerging technology, this result serves as a critical "early warning" for policymakers, highlighting that if technological disparities are left unchecked, the resulting environmental injustices could become far more severe. Although the coefficient's magnitude decreases after adding controls, its statistical significance and direction remain stable, reinforcing the robustness of our findings. Therefore, the baseline regression results strongly support Research Hypothesis 1, namely that the widening AI gap between cities is a significant factor exacerbating air pollution transmission intensity between cities.

4.2. Robustness Checks

To ensure the reliability and stability of the baseline regression results presented earlier, we conducted a series of robustness checks. The results are shown in Supplementary Note Table S3. Based on model (1), we performed additional verification by replacing the measurement of the core explanatory variable, excluding special samples, and dividing the analysis into different time periods.

4.2.1. Replacing the Explanatory Variable

In this study, we use the natural logarithm of the number of industrial robots in cities as an alternative variable [50] and calculate the absolute value of the difference between

paired cities (*AI_Gap1*) to measure the AI gap. As shown in column (1), using *AI_Gap1* to measure the AI gap between cities, the results indicate that narrowing the AI gap still has a significant positive effect on air pollution transmission intensity (coefficient: 0.0042). This finding is consistent with the baseline regression results, suggesting that the core conclusion of this study does not depend on a specific method of measuring the AI gap.

4.2.2. Excluding Special Samples

Considering that municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing) hold unique administrative status, economic scale, and policy resources, their AI development and pollution control patterns may systematically differ from those of other cities. Therefore, we excluded the samples of these four municipalities and re-estimated the model. The results in column (2) show that after excluding these special samples, the coefficient of the AI gap is 0.0057 and remains significant at the 1% level. This indicates that the research conclusions are not driven by these unique megacities and demonstrate good generalizability across the sample.

4.2.3. Different Time Periods

We divided the sample period into two sub-periods, 2015–2018 and 2019–2022, and conducted separate regressions for each. Column (3) presents the results for the 2015–2018 period, where the coefficient of the AI gap is 0.0015 but is not statistically significant. This may suggest that in the early stages of AI technology development and application, its impact on air pollution transmission intensity had not yet fully materialized. However, examining the results for the 2019–2022 period in column (4), the coefficient of the AI gap is 0.0066, which is not only significant at the 1% level but also exhibits a stronger effect compared to the baseline regression result for the full sample (0.0041). This finding likely reflects that as AI technology has rapidly advanced and been more deeply integrated into environmental governance in recent years, the impact of imbalanced AI development between cities on air pollution transmission has become more pronounced.

In summary, although the effect of the AI gap is not significant in the 2015–2018 subsample, the positive impact of the AI gap on air pollution transmission intensity remains highly significant when the core explanatory variable is replaced, special samples are excluded, and in the more recent 2019–2022 period. This suggests that the core conclusion of this study—that the AI gap exacerbates air pollution transmission—is robust.

4.3. Endogeneity Test

Considering the potential bidirectional causality between the AI gap and air pollution transmission intensity, or the possibility that both are influenced by unobservable factors, we address endogeneity issues by employing the two-stage least squares (2SLS) method. This approach aims to obtain more consistent estimates of the impact of the AI gap. 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.

4.4. Mechanism Analysis

To further explore the pathways through which the AI gap affects air pollution transmission intensity, we examined the potential mediating roles of disparities in new digital infrastructure levels (*NIF*), labor mobility (*LM*), and capital flows (*CF*). Based on model (2),

we empirically tested the direct impact of the AI gap on these three mediating variables. The results are presented in Table 2.

Table 2. Mechanism test results.

	(1)	(2)	(3)
Variable	***NIF***	***LM***	***CF***
AI_Gap	0.0100 ***	−0.1200 ***	−0.9278 ***
	(0.0005)	(0.0117)	(0.0287)
CO2	0.0008	−0.0134	−0.2349 ***
	(0.0007)	(0.0184)	(0.0493)
PS	−0.0008	−0.1456 ***	−0.2833 ***
	(0.0008)	(0.0218)	(0.0519)
EN	−0.0015 *	0.0663 ***	0.2658 ***
	(0.0008)	(0.0215)	(0.0550)
VC	−0.0149	−2.5121 ***	0.8719
	(0.0110)	(0.2915)	(0.7232)
ER	0.0023 **	−0.0146	−0.0412
	(0.0010)	(0.0290)	(0.0650)
AIR	0.0007	0.3685 ***	0.5238 ***
	(0.0015)	(0.0358)	(0.0955)
pgdp	0.0064 ***	−0.0838 ***	−2.3294 ***
	(0.0010)	(0.0257)	(0.0658)
size	−0.0012	0.0128	−4.3973 ***
	(0.0008)	(0.0194)	(0.0500)
D	0.0014 **	−1.0739 ***	−0.8047 ***
	(0.0006)	(0.0147)	(0.0388)
City/Year FE	Yes	Yes	Yes
Cons	0.0930 ***	7.6611 ***	13.3323 ***
	(0.0037)	(0.0936)	(0.2481)
R^2	0.1629	0.1472	0.3659
N	92872	97968	97968

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard errors.

4.4.1. New Digital Infrastructure Level

To capture the supply-side strategic priority for new digital infrastructure—a variable for which standardized physical data at the city-level is scarce—we adopt a mainstream quantitative text analysis approach using authoritative Government Work Reports [51]. Our systematic protocol involves quantifying the frequency of keywords related to new digital infrastructure (e.g., "5G", "Industrial Internet"), which were derived from national policy documents to ensure objectivity. A city's strategic focus is measured as the ratio of this keyword frequency to the report's total word count [52]. The final variable, *NIF*, is the absolute difference in this measure between city pairs, representing the disparity in strategic commitment.

On this basis, we examined the impact of the AI gap on disparities in new digital infrastructure levels. The results in column (1) show that the coefficient of *AI_Gap* is 0.0100 and is highly significant at the 1% level. This result indicates that the larger the AI gap between cities, the greater the disparity in their new digital infrastructure levels. This finding aligns closely with our theoretical expectations. It reveals that cities leading in AI development tend to have more advanced digital infrastructure, while cities lagging in AI development may also fall behind in digital infrastructure. Consequently, when the AI gap is large, the disparity in new digital infrastructure levels between cities also widens. This provides strong empirical support for the mechanism by which the AI gap influences pollution transmission through its impact on disparities in new digital infrastructure levels.

This finding resonates deeply with the discussion in the technology gap theory regarding "absorptive capacity" and the prerequisites for technology diffusion. As a frontier technology, AI diffusion and application do not occur in isolation but are highly dependent on whether the receiving parties (AI-lagging cities) possess the necessary "soil", such as new digital infrastructure, including 5G networks and data centers. The empirical results show that "innovators" in AI technology (AI-leading cities) often simultaneously maintain leadership in new digital infrastructure, while "imitators" or "catch-up cities" (AI-lagging cities) may face dual disadvantages in AI technology and digital infrastructure. This co-evolution and mutual reinforcement of the AI gap and the digital infrastructure gap reflect the multidimensional and systemic nature of the "technology gap" as described in the theory. It highlights that the AI gap is not merely a gap in software algorithms or technology but a comprehensive ecosystem gap that includes new digital infrastructure. Therefore, to narrow the AI gap and realize its positive environmental externalities, it is essential to acknowledge and address the deeper disparities in new digital infrastructure caused by the technology gap and to enhance the overall technological absorptive capacity of catch-up cities.

4.4.2. Labor Mobility

To analyze the impact of the AI gap on labor mobility, we use population migration data from the Baidu Migration Big Data Platform as a proxy for labor mobility. Column (2) shows that the regression coefficient of *AI_Gap* on labor mobility is −0.1200 and is significant at the 1% level. This indicates that the widening AI gap between cities significantly suppresses labor mobility. This finding is consistent with Hypothesis 3, which posits that a larger technological gap may lead to excessive concentration of labor in AI-leading cities, hindering the balanced allocation of labor across regions or its flow to areas lagging in AI development. As such, the mechanism through which the AI gap influences pollution transmission via its impact on labor mobility receives preliminary support.

Although rooted in international trade, technology gap theory's insights into how technological differences induce changes in factor allocation are equally applicable at the urban cluster level. AI-leading cities, as "technological innovation hubs" within urban clusters, often create more attractive employment prospects and more dynamic economic environments, thereby exerting a strong "siphon effect" on production factors, including labor. The empirical results showing the AI gap's effect on labor mobility reflect this theoretical logic. Cities lagging in AI development are not only in a catch-up position technologically but also tend to exhibit weaker overall economic vitality and attractiveness to labor, leading to net labor outflows or insufficient inflows. This imbalance in labor mobility, indirectly triggered by the AI technological gap, further weakens the economic and social development potential of AI-lagging cities, including their capacity to effectively govern the environment due to a lack of human resources and fiscal support. This reflects how the technological gap, through its influence on the regional allocation of core production factors, ultimately affects air pollution transmission between cities.

4.4.3. Capital Flows

To better capture intercity capital flows, we utilized corporate cross-regional investment data obtained from the China Stock Market & Accounting Research database. This data was matched to the city level, and cross-regional investments between cities were used as a proxy for capital flows. An empirical analysis based on model (2) was conducted, with the results presented in column (3). The regression coefficient of *AI_Gap* on capital flows is −0.9278, which is also significant at the 1% level. This indicates that a larger AI gap between cities is associated with reduced or more uneven capital flows. This finding aligns

with Hypothesis 3, which posits that technological gaps may hinder the flow of capital to cities where the potential for AI development has yet to fully materialize or reduce the efficiency of regional capital allocation. Thus, the mechanism by which the AI gap influences air pollution transmission through the channel of capital flows is also supported.

Capital, as a key production factor that seeks efficiency and returns, is heavily influenced by the level of technological development and prospects for innovation [53]. The underlying logic of technology gap theory is that technologically advanced regions, due to their innovation capabilities and higher expected returns, are more likely to attract external capital. Our empirical findings support this: cities that are "technological hubs" in the AI field are more likely to become centers of capital accumulation, while cities that are "technological lowlands" may face challenges such as capital "passing through" or even outflows. This imbalance in capital flows implies that AI-lagging cities may experience slower progress in advancing their AI technological development, upgrading industries, or leveraging AI to enhance environmental governance due to a lack of essential financial support. This reflects what the technology gap theory reveals: technological disparities influence the efficiency of capital allocation, further reinforcing or even widening development gaps between cities within urban clusters. Ultimately, these disparities manifest in various areas, including differences in environmental governance capabilities.

5. Extended Analysis

5.1. Economic Development Levels of Cities

To investigate the heterogeneous impact of the AI gap on air pollution transmission, we conduct a subsample analysis by categorizing city pairs based on their economic development levels into three groups: "Low–Low", "High–Low", and "High–High". The findings reveal that the environmental effect of the AI gap exhibits significant contextual dependence.

The core results indicate that the adverse impact of the AI gap on air pollution transmission is most severe in economically underdeveloped regions. For the "Low–Low" group, the regression coefficient of *AI_Gap* is 0.0072 (see Table 3) and is significant at the 1% level, suggesting that in regions with weaker economic foundations, the technological gap more readily translates into significant environmental risks. Furthermore, for the "High–Low" group, the effect of the AI gap remains significantly positive (coefficient = 0.0035, $p < 0.05$), albeit with a diminished magnitude, reflecting a typical "pollution haven" dynamic driven by the technological gap.

Notably, within the "High–High" group, the coefficient for *AI_Gap* (0.0042, see Table 3) is not statistically significant. This result suggests that once both cities in a pair achieve high levels of economic development and governance, they possess stronger "absorptive capacity" for environmental technologies and face stricter regulatory pressures. This enables them to effectively neutralize the pollution transmission effects arising from a relative technological gap, potentially fostering a "race to the top" dynamic.

In summary, this heterogeneity analysis reveals that the environmental costs of the AI gap are disproportionately borne by economically underdeveloped cities, highlighting the issue of environmental equity amidst unbalanced regional development. For brevity, this section reports only the key findings from the subsample regressions. The detailed criteria for sample categorization, complete regression results, and an in-depth discussion of the mechanisms are available in Supplementary Note S4.

Table 3. Impact test results based on economic development levels of cities.

	(1)	(2)	(3)
	Low–Low	**High–Low**	**High–High**
Variable	**CP**	**CP**	**CP**
AI_Gap	0.0072 ***	0.0035 **	0.0042
	(0.0024)	(0.0016)	(0.0034)
Control variable	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes
Cons	−0.3005 ***	−0.8956 ***	−0.3823 ***
	(0.0200)	(0.0159)	(0.0317)
R^2	0.9827	0.9931	0.9901
N	24648	39816	15624

Note: In this analysis, we use the annual per capita GDP of cities as a proxy for economic development levels. The annual average is used as the threshold for categorization: cities with values above the average are classified as high-level, while those below the average are classified as low-level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard errors. The symbol "–" in the table is used to distinguish between different elements before and after in the future, for grouping purposes.

5.2. Low-Carbon City Pilot Programs

This study further examines the moderating effect of environmental regulation, using the low-carbon city pilot program as a quasi-natural experiment. We categorize the city-pair sample into three groups—"Non-Pilot–Non-Pilot", "Pilot–Non-Pilot", and "Pilot–Pilot"—to investigate whether this policy intervention alters the impact of the AI gap on pollution transmission.

The analysis yields a valuable insight. In the group where neither city is a low-carbon pilot ("Non-Pilot–Non-Pilot"), the impact of the AI gap on pollution transmission is at its peak, with a regression coefficient of 0.0167 that is highly significant at the 1% level (see Table 4). This indicates that in the absence of targeted policy guidance, the negative environmental externalities of the technological gap are fully realized.

Table 4. Impact test results of the low-carbon city pilot policy.

	(1)	(2)	(3)
	Non-Pilot–Non-Pilot	**Pilot–Non-Pilot**	**Pilot–Pilot**
Variable	***CP***	***CP***	***CP***
AI_Gap	0.0167 ***	−0.0020	0.0035
	(0.0018)	(0.0013)	(0.0033)
Control variable	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes
Cons	−0.2975 ***	−0.3918 ***	−0.8743 ***
	(0.0161)	(0.0134)	(0.0281)
R^2	0.9858	0.9853	0.9955
N	38780	45680	13508

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard errors. The symbol "–" in the table is used to distinguish between different elements before and after in the future, for grouping purposes.

A crucial shift occurs with policy intervention. As soon as at least one city in a pair is a pilot city (i.e., in the "Pilot–Non-Pilot" and "Pilot–Pilot" groups), the coefficient of the *AI_Gap* becomes statistically insignificant. This result provides compelling evidence that proactive environmental policies, such as the low-carbon city pilot program, can effectively buffer or decouple the cross-regional pollution risks arising from uneven technological development. The policy appears to function by steering AI applications toward green

sectors and fostering "policy convergence" or a "green consensus" between cities, thereby mitigating the adverse effects.

For brevity, this section reports only the key findings on the policy's moderating effect. The complete regression results for the group analysis and a more in-depth discussion of the mechanisms are provided in Supplementary Note S5.

5.3. Smart City Pilot Programs

Finally, this study investigates the complex role of technology-oriented policies, using the "smart city pilot" program as a case study. The results reveal a striking non-linear relationship, suggesting the smart city policy acts as a "double-edged sword".

We find that when neither city in a pair is a pilot, the effect of the *AI_Gap* is insignificant. This suggests that without a specific policy catalyst, the potential impact of the AI gap on pollution transmission may remain "dormant".

However, when the policy is asymmetrically implemented (the "Pilot–Non-Pilot" group), the negative effect of the AI gap is significantly "activated" and amplified, with a coefficient of 0.0045 (significant at the 1% level, see Table 5). This key finding serves as a caution: a purely technology-oriented policy, if lacking sufficient green synergy, can inadvertently exacerbate regional environmental inequality by enabling technology-leading pilot cities to shift environmental pressures to their non-pilot neighbors.

Table 5. Impact test results of the smart city pilot policy.

	(1)	**(2)**	**(3)**
	Non-Pilot–Non-Pilot	**Pilot–Non-Pilot**	**Pilot–Pilot**
Variable	***CP***	***CP***	***CP***
AI_Gap	0.0023	0.0045 ***	0.0017
	(0.0017)	(0.0015)	(0.0024)
Control variable	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes
Cons	−0.5427 ***	−0.7821 ***	−0.2389 ***
	(0.0161)	(0.0138)	(0.0264)
R^2	0.9869	0.9920	0.9814
N	32760	48048	17160

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard errors. The symbol "–" in the table is used to distinguish between different elements before and after in the future, for grouping purposes.

Reassuringly, this adverse effect is once again neutralized when both cities are smart city pilots, with the coefficient becoming statistically insignificant. This implies that a shared policy framework can foster collaborative governance, mitigating the risk of competitive pollution spillovers driven by technological gaps.

Taken together, this analysis underscores the critical importance of embedding "green synergy" in the design of technology-driven development policies. For brevity, this section reports only these key findings. The complete regression results and related discussions are detailed in Supplementary Note S6.

6. Discussion and Conclusions

6.1. Discussion

This study confronts a critical challenge of the 21st century: the risk that the burgeoning "digital divide", epitomized by the artificial intelligence gap, is systematically creating a new and pernicious "environmental divide". Moving beyond traditional analyses, we employ the technology gap theory as a lens to reveal how disparities in AI capabilities among cities do not merely reflect economic inequality but actively drive the cross-regional

transmission of air pollution. Our findings offer a sobering perspective on how regional imbalances in the digital era engender tangible environmental injustices.

The study's primary finding is that the AI gap is a significant catalyst for air pollution transmission. This empirically validates our central thesis, demonstrating that the uneven diffusion of a frontier general-purpose technology like AI generates profound negative environmental externalities. This insight contributes a vital new dimension to the technology gap theory. We extend its application from classic domains of trade and industrial competition to the intra-regional environmental consequences of technological disparity within urban agglomerations. In doing so, we provide a novel theoretical framework and robust evidence for understanding how a digital chasm morphs into a physical, breathable environmental burden, offering a new narrative for the evolution of the theory in an age of intelligent systems.

Furthermore, our research delineates the precise pathways through which this transformation occurs. The AI gap does not operate in a vacuum; it is mediated by a cascade of systemic disadvantages. We find that the AI gap widens disparities in new digital infrastructure—the very bedrock of the digital economy—and triggers an imbalanced flow of labor and capital. This aligns with and modernizes classic technology gap assertions about "absorptive capacity" and resource siphoning. AI-laggard cities, hobbled by inferior digital infrastructure, cannot fully leverage AI for environmental governance. Simultaneously, the "polarizing" effect of the AI gap drains them of the talent and capital needed for a green industrial transition. These mechanisms are the gears that convert a technological advantage in one region into an environmental liability in another, effectively operationalizing the transition from a digital to an environmental divide.

Crucially, the translation of the AI gap into environmental harm is not deterministic; it is profoundly shaped by local socioeconomic conditions and policy architecture. Our heterogeneity analysis reveals that the environmental costs are most severe in economically underdeveloped regions, exposing a double jeopardy where the digitally disadvantaged are also the most environmentally vulnerable. This finding underscores the role of economic capacity as a critical buffer. More importantly, it highlights the power of policy. Proactive environmental regulations, such as the "low-carbon city pilot", effectively decouple the AI gap from its negative environmental consequences, proving that institutional guardrails can guide technology toward equitable outcomes. In stark contrast, technology-first policies like the "smart city pilot", when devoid of green synergy, act as an accelerant. They can inadvertently amplify the environmental divide by intensifying resource concentration, serving as a powerful "double-edged sword". This demonstrates that technological progress is not inherently benign; its environmental dividend is contingent on deliberate and synergistic policy design.

6.2. Conclusions

Drawing on the technology gap theory, this study systematically investigates how the AI gap between cities drives air pollution transmission, providing robust evidence for the emergence of an "environmental divide" from a "digital divide" within China's urban agglomerations. The main conclusions are as follows:

First, the AI gap is a key driver of cross-border air pollution. This finding confirms that the uneven regional development of emerging technologies creates significant negative environmental externalities. By extending the technology gap theory to the environmental sphere at a sub-national level, this study offers a new and critical lens for understanding and combating regional environmental inequality in the digital age.

Second, the pathway from a digital to an environmental divide is mediated by structural disparities. The AI gap solidifies its impact by widening the chasm in new digital

infrastructure and inducing a skewed allocation of essential production factors like labor and capital. These mechanisms reveal how technological leadership translates into a tangible capacity to externalize environmental costs.

Third, the link between the digital and environmental divides is context-dependent and policy-sensitive. The effect is most pronounced in economically weaker cities, highlighting a critical vulnerability. Crucially, policy intervention is decisive. Targeted environmental policies (e.g., "low-carbon city pilots") can successfully sever the link between technological disparity and pollution transmission. Conversely, technology-focused policies (e.g., "smart city pilots") lacking environmental alignment can paradoxically strengthen it. This underscores the imperative for policymakers to move beyond simply promoting technological advancement and toward designing synergistic policies that close the digital divide while actively preventing the formation of a new, entrenched environmental divide, thereby fostering truly sustainable and equitable regional development.

6.3. Research Limitations and Future Directions

This study has several limitations. For instance, there is room for improvement in the quantification of the urban AI gap, the precise measurement of air pollution transmission intensity, and the causal identification of mediating mechanisms.

Future research can deepen these investigations along the following directions: First, future work could dynamically trace the evolution of the AI gap and assess the long-term dynamic changes in its environmental effects as well as the potential lagged effects of these environmental impacts. Second, it is valuable to disaggregate different types and application scenarios of AI technologies to examine their potentially differentiated environmental impacts within the framework of the technology gap theory. Third, further studies could explore the micro-foundations of how the AI gap affects environmental quality from more granular perspectives, such as firm behavior and individual choices. Finally, efforts could focus on developing and evaluating integrated policy solutions aimed at bridging both the digital and environmental gaps, providing actionable recommendations to promote the coordinated development of regional technological progress and ecological conservation.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su17209169/s1. This includes: Supplementary Notes S1–S6, and Tables S1–S4, [12,54–62].

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