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The Green Upgrading of Digital Infrastructure: The Impact of Green Data Centers on Air Pollution

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Abstract

The rapid expansion of the digital economy coincides with escalating environmental challenges, making Green Data Centers (GDC) an important form of digital infrastructure with potential implications for environmental governance. However, existing studies mainly evaluate data centers from the perspectives of energy efficiency, electricity consumption, and carbon emissions, while city-level evidence regarding their effects on ambient air pollution remains limited. Using panel data for 282 Chinese cities from 2013 to 2023 and a staggered difference-in-differences approach, this study provides quasi-experimental evidence on the air- pollution effects of GDC construction. The baseline results show that GDC construction reduces urban air pollution by approximately 1.5%. The findings remain robust across a series of alternative specifications and estimation strategies. Mechanism analysis indicates that GDC construction decreases air pollution by promoting informatization development and green technological innovation. Moreover, the pollution-reduction effect is stronger in cities with higher levels of economic development, administrative level, financial development, and tertiary industry proportion. By linking green digital infrastructure to urban air-pollution governance, this study extends the environmental assessment of data centers beyond conventional energy-efficiency and carbon-emission indicators.

Keywords: Air pollution; China; Digital infrastructure; Green data center.

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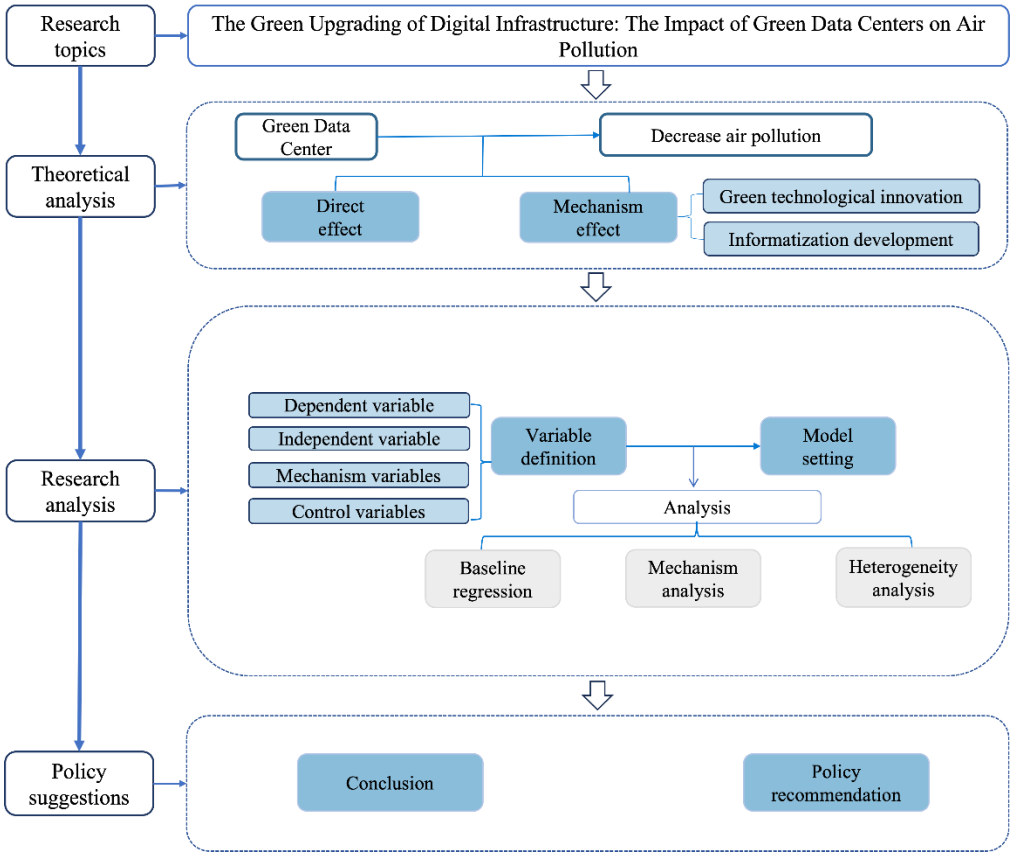
Graphical abstract



1. Introduction

A data center is an infrastructure that centrally deploys computing, storage, and network resources to provide a stable operating environment for large-scale data processing, storage, and transmission. Equipped with professional power supply, cooling systems, and network connections, they have also become points where energy emissions, material consumption, and local environmental externalities intersect. The power demand of data centers grew faster than the overall social electricity consumption between 2017 and 2024. According to data from the International Energy Agency, data centers already made up approximately 1% of the world's total electricity consumption in 2020, and this proportion is projected to rise to 1.2% by 2025 (Murino *et al.*, 2023). Currently, as generative artificial intelligence sees growing widespread use among data centers, the total energy consumption during training and inference phases has risen significantly (De Vries, 2023). The marginal emissions generated by electricity consumption in power systems significantly increase the externalities of air pollution (Istrate *et al.*, 2024). Air pollution, including volatile organic compounds and particulate matter, poses significant risks to human health (Abdipour *et al.*, 2026; Kamani *et al.*, 2023).

In China, digital infrastructure serves as a key driver for high-quality economic development and an important engine for the economy to move toward a new era of digitalization and intelligentization. However, it has long struggled to address its high energy consumption characteristics. Therefore, in February 2013, China's Ministry of Industry and Information Technology issued the *Guiding Opinions on Further Strengthening Energy Conservation and Emission Reduction in the Communications Industry*, which put forward relevant energy conservation and data center environmental protection requirements.[1]. In 2015, to strengthen the construction of green data centers (GDC), China formulated the *National Green Data Center Pilot Work Plan*, aiming to enhance energy efficiency and environmental protection standards for data centers by focusing on key areas, covering different sectors, and advancing in phases.[2]As of June 2024, China has built a total of 246 GDC, spanning multiple fields including energy, finance, telecommunications, intelligent computing, public institutions, and the internet. To clarify the green

[1] The official release website of the Guiding Opinions on Further Strengthening Energy Conservation and Emission Reduction in the Telecommunications Industry can be found at: https://www.gov.cn/zwgk/2013-02/20/content_2336279.htm

[2] The official release website of the *National Green Data Center Pilot Work Plan* can be found at: https://www.cac.gov.cn/2015-03/24/c_1114746732.htm

connotation, we define GDC as data centers that achieve energy savings and emission reductions in data storage and processing through improved energy efficiency, renewable energy utilization, and minimized environmental impact.

We can explore the dual attributes of GDC, namely their nature as a green policy initiative and a digital infrastructure. Green policies have rich connotations and diverse types, yet most scholars agree that environmental policy instruments exert a positive function in raising environmental protection standards and promoting eco-friendly development (Requate, 2005). Environmental policies exert impacts on micro-subject behavior, macroeconomic operation, and industrial structure adjustment. At the micro-subject level, the creation of environmental courts has prompted enterprises to expand environmental protection expenditures and advance the expansion of green innovation (Q. Zhang *et al.*, 2019). Green environmental regulations can promote green production methods and sustainable production models (Brown *et al.*, 2022) and urge enterprises to assume environmental responsibilities (B. Zhang *et al.*, 2023). Taking macroeconomic operation as a perspective, environmental regulatory instruments, including green credit and green finance, have been integrated into the policy system. Green structural policies can promote a green and low-carbon transition (Boneva *et al.*, 2021) while also reducing carbon releases (European Central Bank., 2022), thereby mitigating global warming. At the industrial level, these policies improve green total factor productivity and drive green transformation in the industrial sector (X. Li *et al.*, 2022). Meanwhile, they promote industrial structure optimization and contribute to regional carbon emission reduction (H. Li *et al.*, 2025). The degree of marketization and informatization can enhance policy effectiveness and enhance the environmental quality (Hou *et al.*, 2022).

As for the attribute of digital infrastructure, digital infrastructure construction is often accompanied by significant economies of scale and network externalities, generating a series of identifiable economic consequences spanning the macro to micro levels. At the macro level, digital infrastructure exerts a marked positive influence on gross domestic product growth and labor productivity (Koutroumpis, 2019), and it improves total factor productivity (Q. Wang *et al.*, 2024), driving long-term economic growth (Jorgenson *et al.*, 2008). It also enhances economic resilience, reduces structural unemployment (Abrardi & Sabatino, 2023), and promotes industrial structure upgrading (P. Zhang, Wang, *et al.*, 2022). At the micro level, digital infrastructure enables full utilization of information (Bertschek & Niebel, 2016), improves redistribution efficiency (Jensen, 2007), boosts the efficiency of innovation and entrepreneurship (L. Zhang *et al.*, 2022), reduces transaction costs (Freund & Weinhold, 2004), and increases enterprise productivity (Fabling & Grimes, 2021). However, from the environmental perspective, the Internet may exacerbate air pollution at the early stage of development (X. Yang *et al.*, 2021). In the initial period of digital infrastructure expansion, owing to inadequate construction and supervision measures, it has a promoting effect on $PM_{2.5}$ emissions (Z. Yang, Gao, *et al.*, 2023). Digital and AI-driven technologies have been shown to improve regional productivity and resource allocation efficiency (Ma *et al.*, 2026), while intelligent energy systems supported by digital infrastructure can enhance low-carbon operation and energy efficiency (Guo *et al.*, 2025). In addition, high-energy-consuming computing facilities consume large amounts of electricity, leading to a significant increase in $PM_{2.5}$ pollution (Guidi *et al.*, 2025). The operation of diesel backup generators in data centers can significantly degrade air quality (Gilmore *et al.*, 2010), and fossil fuel power plants that supply electricity to data centers, along with diesel backup generators, emit hazardous pollutants such as fine particulate matter and nitrogen oxides (Olaguer *et al.*, 2016). In summary, while the constructive impacts on economic growth, employment, trade, and enterprise performance have been quite robust, digital infrastructure has come at a high environmental cost.

Air pollution has become one of the most severe environmental challenges worldwide (Mohandas *et al.*, 2025; Sivasubramanian *et al.*, 2025). It can cause plant death and disrupt ecological balance (Maruthai *et al.*, 2025; Selvanarayanan *et al.*, 2025; Vinayagam *et al.*, 2025). At the same time, prolonged exposure to polluted air significantly increases the risk of developing cardiovascular and respiratory diseases, as well as cancer. Air pollution demands urgent attention (Mohandas *et al.*, 2025). Against this backdrop, it is crucial to study whether the GDC construction reduces the negative externalities of air pollution. Data centers are currently at the intersection of rapidly expanding electricity consumption scale and a power source structure still dominated by fossil fuels, creating new pollution pressures. Thus, it is worthy of in-depth research to determine whether GDC construction, when compared with traditional data centers, effectively alleviates the dilemma of high energy consumption and better performs a function in the curtailment of airborne pollution.

Against this background, the rapid expansion of digital infrastructure and the substantial energy and environmental pressures associated with conventional data centers provide the principal motivation for this study. Although GDC construction is intended to improve energy efficiency and environmental performance, empirical evidence regarding its effects on air pollution remains limited. The principal aim of this study is therefore to evaluate whether GDC construction contributes to reducing air pollution. The scope of the study is defined geographically, temporally, and methodologically. Geographically, the analysis covers 282 prefecture-level cities in China. Temporally, it uses annual panel data from 2013 to 2023. In terms of policy scope, the study focuses on the phased implementation of the national GDC construction and treats it as a quasi-natural experiment, deploying a staggered difference-in-differences (DID) method.

2. Literature Review

2.1. *Digital Infrastructure, Data Center Expansion, and Air Pollution*

Among various forms of infrastructure, data centers play a critical role by providing the physical and computational foundation. Unlike conventional industrial facilities, data centers operate continuously and require substantial electricity supply and cooling capacity, leading to significant environmental externalities.

Early studies on the environmental impacts of data centers primarily focused on operational energy consumption. Global estimates suggest that data centers account for a rapidly growing share of electricity demand, although efficiency improvements have partially offset this growth (Masanet *et al.*, 2020). Traditional assessments have long relied on operational efficiency indicators, particularly Power Usage Effectiveness (PUE), to evaluate environmental performance. However, such indicators are limited in scope. Efficiency metrics like PUE fail to capture the full environmental burden (Van Heddeghem *et al.*, 2014). Similarly, PUE does not directly reflect air pollutant emissions, nor does it account for upstream environmental impacts embedded in energy production (Shehabi *et al.*, 2016). Therefore, relying solely on efficiency indicators may lead to an incomplete understanding of the environmental consequences of data centers. The environmental evaluation of data centers should incorporate life-cycle perspectives and pollution outcomes rather than focusing exclusively on operational performance. Digitalization does not inherently reduce energy demand or environmental pressure; its net impact depends on whether efficiency gains can offset scale effects (Lange *et al.*, 2020). In the Chinese context, the rapid expansion of data centers is closely intertwined with regional energy structures, industrial distribution, and environmental governance. Given China's heavy reliance on coal-fired power in certain regions, the indirect air pollution associated with electricity consumption is particularly significant. Data centers in China can generate substantial environmental impacts if powered by new energy sources (Bhavsar *et al.*, 2021). At the same time, policy instruments play a crucial role in promoting green transformation. Regulatory measures such as energy efficiency standards, renewable energy integration, and carbon reduction targets have been identified as key drivers for the GDC construction (Yin & Wang, 2024).

In addition, recent studies have increasingly applied advanced deep-learning techniques to air-pollution classification. A hybrid attention-enabled deep-learning model was developed to improve the identification of air-pollution levels (Sannasi *et al.*, 2026). In addition, a deep feedforward classification framework incorporating Sophia-G optimization was proposed to enhance classification performance (Mohandas *et al.*, 2025). A spatial attention-based MobileNetV2 framework was also introduced for the classification of air-pollution levels in Bangalore (Mohandas *et al.*, 2025). These studies demonstrate that attention mechanisms, optimization algorithms, and lightweight deep neural networks can improve the extraction of complex features from environmental data and support more accurate air-pollution classification.

2.2. *Pollution-Reduction Mechanisms of Green Data Centers*

Compared with traditional data centers, GDC places greater emphasis on clean energy use and environmental performance. GDC can reduce air pollution by improving energy efficiency. Since electricity generation is an important source of fine particulate pollution, reducing electricity demand through energy-efficient data center operation can indirectly mitigate air pollutant emissions associated with power generation (Thind *et al.*, 2019). Energy conservation strategies in data centers include advanced cooling technologies, low-power electronics, improved power distribution, automation, and equipment with extended thermal limits (Manganelli *et al.*, 2021). GDC can reduce pollutant emissions by optimizing the energy structure. The integration of renewable energy sources, such as solar, wind, and hydropower, can reduce dependence on fossil-fuel-based electricity and lower emissions at the source (Manganelli *et al.*, 2021). However, the environmental performance of GDC depends not only on annual renewable energy procurement but also on the dynamic carbon intensity of the electricity mix (F. Wang *et al.*, 2022). Recent research has systematically reviewed green-aware management techniques for sustainable data centers, including workload scheduling, virtualization, energy management, and waste heat recovery (Lin *et al.*, 2024). Renewable-energy-aware scheduling can further reduce the use of brown energy by adjusting computing tasks according to renewable energy availability and operational constraints (Grange *et al.*, 2018). The integration of data centers with comprehensive energy systems provides a new pathway for reducing environmental impacts and indirectly mitigating air pollution. The concept of data center integrated energy systems emphasizes renewable energy utilization and planning optimization (Y. Wang *et al.*, 2024). Such integration may reduce dependence on fossil-fuel-based electricity and improve regional environmental performance. GDC is evaluated through a holistic framework that includes energy efficiency, water consumption, and waste management (Murino *et al.*, 2023). A broader set of sustainability indicators includes energy efficiency, water use, waste heat utilization, renewable energy integration, hourly carbon-free energy matching, embodied carbon, and land-use impacts(Grochulska-Salak *et al.*, 2025), which are not limited to the operational stage (Whitehead *et al.*, 2015).

2.3. *Information, Technological Innovation, and Air Pollution Governance*

GDC affects air pollution not only through their own energy-saving and emission-reduction performance, but also through their role as information infrastructure that supports technological innovation and environmental governance. From the perspective of information development, GDC is important infrastructure for the digital economy and the digitalization of environmental governance. Digital economy development significantly reduces urban air pollution emissions, with a stronger effect in central and western China (Wu *et al.*, 2023). The

digital economy significantly reduces industrial dust (Y. Zhang & Ran, 2023) and promotes pollution reduction through mechanisms such as industrial structure upgrading (Z. Yang, Fu, *et al.*, 2023).

Technological innovation significantly reduces air pollution emissions, indicating that innovation can improve environmental quality (F. Chen *et al.*, 2022). GDC construction can also promote the informatization and intelligentization of air pollution governance. Air pollution governance has long faced problems such as information asymmetry, delayed regulation, and insufficient cross-regional coordination. Related research shows that digital infrastructure can promote green technology innovation and enhance urban green innovation capacity through talent agglomeration, R&D investment, and industrial upgrading. Digital infrastructure significantly promotes urban green innovation and produces spatial dynamic effects (C. Li *et al.*, 2024). For air pollution governance, this means that GDC construction can improve the precision of environmental governance.

2.4. *Research Gaps and Contributions*

Existing studies provide an important foundation for understanding the environmental implications of digital infrastructure and data centers. Nevertheless, several research gaps remain. First, the environmental performance of data centers has primarily been evaluated through operational indicators such as power usage effectiveness, electricity consumption, renewable energy utilization, and carbon emissions. Relatively limited attention has been paid to their effects on ambient air pollution at the city level. Second, existing research is largely technology-oriented and focuses on energy-saving equipment, cooling systems, workload scheduling, and renewable energy integration. Less is known about how the environmental benefits of GDC construction are transmitted from facilities to broader urban environmental outcomes. Third, studies on digitalization and environmental governance generally examine the digital economy or digital infrastructure as a whole, without sufficiently distinguishing between conventional and green digital infrastructure. Finally, the urban conditions that shape the environmental effectiveness of GDC construction have not been systematically examined.

This study addresses these gaps in three respects. First, it treats the phased GDC construction in China as a quasi-natural experiment and provides city-level empirical evidence on the relationship between green digital infrastructure and air pollution. This extends the evaluation of data centers beyond energy-efficiency and carbon-emission indicators. Second, based on the dual attributes of GDC as both digital infrastructure and a green policy initiative, the study investigates informatization development and green technology innovation as two potential transmission mechanisms. Third, it examines heterogeneous effects across cities with different levels of economic development, administrative level, financial development, and tertiary industry proportion, thereby identifying the urban conditions under which the pollution-reduction effect of GDC construction is stronger.

3. Research Hypotheses

3.1. *Policy Background*

Being a core infrastructure for the digital economy, data centers have become increasingly prominent for their high energy consumption characteristics (Dwivedi *et al.*, 2022). How to facilitate the digital economy evolution while reducing the energy consumption and pollution of data centers has emerged as a major global challenge. By 2015, the total number of data centers had exceeded 400,000 in China. However, the power usage effectiveness lagged far behind the international advanced level, and the emission of large quantities of harmful substances caused significant air pollution in most data centers. Therefore, the Chinese government has guided data centers to take two key measures. On the one hand, it has improved the proportion of renewable energy usage and prioritizes the deployment of data center projects at the hub nodes of the east data and west computing initiative to tap into the strengths of clean energy in China's western regions. On the other hand, through government procurement standards, differential electricity pricing policies, and energy-saving renovation projects, it has upgraded the energy efficiency of existing data centers and imposed restrictions on high-energy-consuming projects. Building on the existing work on data centers, the government has selected several representative data centers in key application fields, including manufacturing, energy, telecommunications, the Internet, public institutions, and finance, to carry out GDC construction projects. In 2018, GDC was first established in 20 cities; subsequently, four additional batches of GDC construction pilot cities were designated in 2020, 2021, 2022, and 2023. The distribution of cities where the five batches of GDC construction are located is shown in **Figure 1**.

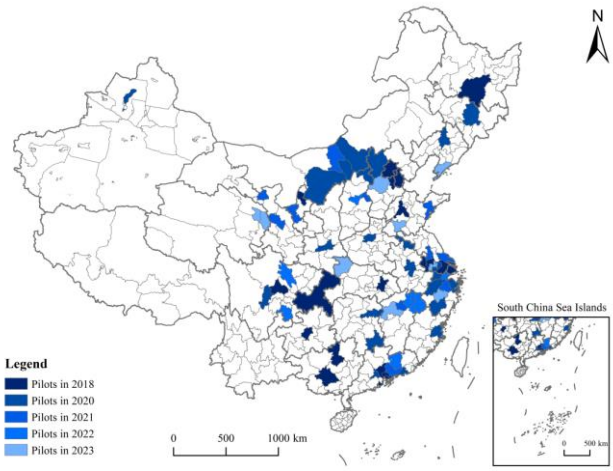


Figure 1. Spatial Distribution and Implementation Batches of GDC construction. Note: Different colors represent the cities included in different batches of the national GDC construction between 2018 and 2023. The map illustrates the geographical coverage and temporal expansion of GDC construction in China.

From the perspective of macro policy layout, the development of GDC construction can be divided into the following four phases: The first (2013–2016) was strategic exploration. The *Guiding Opinions on the Construction and Layout of Data Centers* was issued, emphasizing that data

center site selection should align with energy endowments and prioritize layout in regions rich in renewable energy. This initially established the policy orientation for GDC construction. The second (2017–2020) was preliminary implementation, focusing on dual efforts in standard construction and industry expansion, and witnessed the completion of the first batch of GDC construction. The third (2021–2024) was regional collaboration. The *14th Five-Year Plan for the Development of the Information and Communications Industry* clearly stated that efforts should be made to expedite the construction of GDC and advance the orderly transfer of computing resources to western China. GDC construction not only serves as a driver for the transformation of eastern regions but also becomes a new impetus to develop the economy in western regions. The fourth (2025–) is in-depth implementation. The first national standard for GDC evaluation was officially implemented on June 1st, prompting the continuous optimization and improvement of GDC construction during the large-scale development. The policy development process is shown in **Figure 2**.

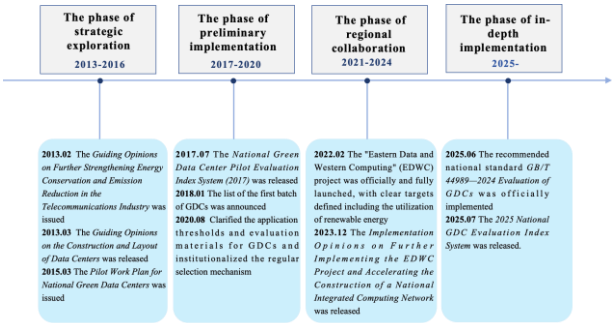


Figure 2 GDC Development Process. Note: The figure summarizes the four major stages of GDC policy development. The timeline highlights the principal policy documents and implementation milestones in each stage.

3.2. *Hypothesis Development*

The construction of GDC may facilitate the coupling between digital technology and energy-saving technologies. As a key infrastructure of the digital economy, data centers consume substantial electricity during operation, and the adoption of green electricity is considered important for achieving green development (Castro *et al.*, 2024). On the one hand, digital technologies can support the upgrading of energy-saving technologies in GDC, potentially generating environmental benefits (Bendig *et al.*, 2023). This may enable the use of green electricity to reduce energy consumption in data centers (Xu *et al.*, 2023), thereby lowering pollutant emissions associated with energy use. On the other hand, energy-saving technologies can reduce hardware energy consumption and improve operational efficiency, allowing digital devices to deliver stable computing power under lower energy intensity, which may contribute to improved air quality.

The development of GDC construction may also reflect the interaction between digital management and green governance. GDC can utilize digital management tools to enhance monitoring and coordination in environmental governance. For example, policies such as the eastern data and western computing initiative encourage the relocation of data centers to regions with abundant renewable energy resources, which may help reduce pollution from fossil fuel-based electricity generation[3]. In addition, full-process data collection can support more informed and data-driven environmental management, potentially improving the precision of emission reduction efforts (Y. Song *et al.*, 2024). From another perspective, environmental regulations may impose constraints that incentivize improvements in digital management systems (Renugadevi *et al.*, 2020), such as more efficient computing power allocation and operational optimization (Rostirolla *et al.*, 2022), which may further contribute to pollution reduction.

Following the convention of empirical economics research, the hypotheses in this study are formulated as concise, directional, and empirically testable propositions.

Therefore, Hypothesis 1 (H1) is proposed: The GDC construction can reduce air pollution levels.

Ecological modernization theory argues that environmental improvement can be achieved not only through restrictive environmental regulation, but also through technological progress, industrial upgrading, institutional optimization, and the modernization of governance systems. Green and digital infrastructure can play an important role in reconciling economic development with environmental protection. Therefore, based on Ecological Modernization Theory, this study identifies informatization development and green technology innovation as two potential mechanisms through which GDC construction may be associated with improvements in urban air quality. Informatization reflects the governance modernization channel, while green technology innovation reflects the technological upgrading channel.

First, the informatization mechanism embodies the governance modernization channel. GDC construction enhances digital infrastructure, improves data processing and information flows, and supports more efficient environmental monitoring and resource allocation. Second, the green technology innovation mechanism represents the technological upgrading channel. By stimulating investments in energy-saving technologies, low-carbon equipment, and cleaner digital operations, GDC promotes technological change that improves production efficiency and reduces emissions.

The construction of GDC may enhance urban informatization development by improving data processing capacity and promoting the adoption of energy-saving and resource-efficient technologies. As a result, GDC construction may strengthen cities' capabilities in

[3] As shown on the release website of the *Implementation Opinions on Supporting the Accelerated Development of Computing-Electricity Integration*: https://tzxm.sczwfw.gov.cn/zcfg/content/905

information processing and digital infrastructure (F. H. M. Liu *et al.*, 2025). This could further generate knowledge spillovers centered around GDC construction, facilitate inter-city factor flows, and improve the connectivity and collaboration of urban networks, thereby contributing to the overall development of informatization (J. Song *et al.*, 2024).

From the perspective of agglomeration economies, improved digital infrastructure may reduce spatial barriers between innovation agents and attract leading technology firms, thereby fostering comparative advantages in informatization (C. Li *et al.*, 2024). In turn, informatization development may support more efficient resource allocation and enable more refined and intelligent environmental governance. Government may utilize digital tools to monitor pollution emissions in real time, potentially improving the precision and effectiveness of air pollution control (J. Zhang *et al.*, 2025). In addition, informatization development may encourage traditional high-energy-consuming enterprises to accelerate digital transformation, which may help reduce pollution emissions (P. Zhang, Chen, *et al.*, 2022). It may also promote the upgrading of the environmental protection industry and enhance public participation in environmental governance, forming both top-down regulatory pressure and bottom-up supervision (Mai *et al.*, 2025).

Taken together, these arguments suggest that informatization development may serve as an important channel through which GDC construction affects air quality.

Thus, Hypothesis 2 (H2) is proposed: The GDC construction may reduce air pollution by improving informatization development.

China's *Evaluation of Green Data Centers* specifies several key indicators, including efficient energy and resource utilization and the implementation of green projects. These requirements may incentivize economic agents to meet regulatory standards through technological innovation and enhance their market competitiveness (Ouyang *et al.*, 2020). Under profit-maximizing behavior, firms may adopt substantive innovation when the expected benefits from regulatory compliance and cost savings outweigh the associated R&D costs. This process may also facilitate knowledge spillovers and mutual learning within the industry, generating positive externalities of technological innovation (Zhou, 2021).

Green technology innovation generally refers to innovations in processes, products, or management practices that aim to alleviate environmental pressure and improve resource efficiency (W. Li *et al.*, 2023). Such innovation may affect air pollution through several channels. First, it may reduce the cost and improve the efficiency of clean energy technologies, thereby facilitating the substitution of fossil fuels and reducing pollution at the source (Meng *et al.*, 2021;Carrión-Flores & Innes, 2010). Second, green technology innovation may lower pollutant emissions during production by optimizing processes and upgrading equipment, while helping firms comply with environmental regulations (Innes, 2006). Finally, even when source reduction and process improvements are insufficient, green technology innovation may enhance end-of-pipe treatment and monitoring technologies, improving pollutant removal efficiency and reducing ambient pollution levels (Dong *et al.*, 2023).

Therefore, Hypothesis (H3) is proposed: The GDC construction may reduce air pollution by enhancing green technological innovation.

The research hypothesis framework is shown in **Figure 3**.

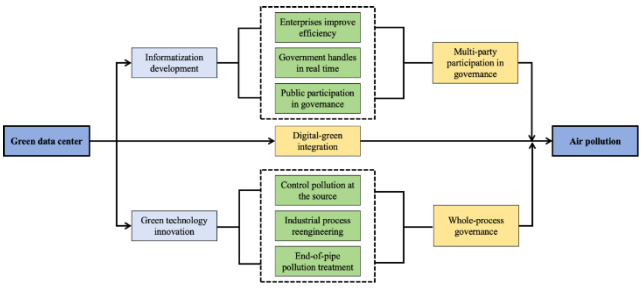


Figure 3. Research Hypothesis Framework. Note: The figure presents the hypothesized relationship between GDC construction and air pollution.

4. Research Design

4.1. *Method*

A quasi-natural experiment stemming from the construction of GDC serves as a sound one. To assess its effect on air pollution, the staggered DID method serves as the core empirical method in this study for examining the effect of GDC construction development on urban air pollution. The research uses a staggered DID method to assess the policy effect. This approach is suitable when the policy is implemented in phases across different units or regions over time. Its core idea is to use units not yet treated as the control group, comparing them with units newly treated in each period, thereby effectively isolating the net treatment effect from confounding time trends. The staggered DID approach is suitable for this study because GDC construction was introduced in different cities at different times. The baseline specification in Equation (1) estimates the effect of GDC construction using the treatment indicator, city fixed effects, year fixed effects, and control variables. To examine the dynamic effects of the policy and assess the parallel-trends assumption, Equation (2) incorporates indicators for relative time to policy implementation, with the year immediately preceding treatment (j = −1) serving as the reference period. This event-study specification allows us to examine pre-treatment trends and trace the evolution of the treatment effect after policy implementation. Unlike a conventional DID design that assumes a common treatment date, the staggered DID approach accommodates differences in treatment timing across cities.

As shown in Equation (1), it controls for year-fixed and city-fixed effects in the regression.

$$LnPM2.5_{it} = \alpha + \beta GDC_{it} + \gamma \sum \text{Controls}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

$LnPM2.5_{it}$ is the dependent variable, representing the natural logarithm of the annual average concentration of

$PM_{2.5}$ in city i and year t. GDC_{it} is the core independent variable, a binary treatment indicator that equals 1 for city (officially approved for the establishment of GDC construction) i in year t and all subsequent years after the launch of a GDC construction project, and 0 otherwise. The coefficient β is our primary parameter of interest. We hypothesize that β < 0, indicating that GDC construction contributes to a reduction in air pollution. $Controls_{it}$ denotes a vector that may confound the relationship between GDC construction and air pollution. Their inclusion is to isolate the net effect of GDC construction. λ_i represents city-fixed effect. μ_t represents year-fixed effect. α is the constant term of the equation. ε_{it} is the residual term.

The parallel trend test is a key step to verify the prerequisite for causal inference in the staggered DID method. Only when the trend of the outcome variable is consistent before the policy implementation, and there are no significant differences between the treatment group and the control group, can we ensure that the post-policy difference between the two groups mainly comes from the policy itself, rather than other trending factors. The parallel trend test Equation (2) is shown as follows:

$$LnPM2.5_{it} = \alpha + \sum_{j=-5}^{5} \beta_j GDC_j + \gamma \sum \text{Controls}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (2)$$

Among them, a time dummy variable is denoted by j, which reflects the relative time of when the policy is implemented. The base period is set at j = –1. Other parameters have meanings consistent with those in the Equation (1).

To verify the necessity of exploring the impact mechanism of GDC construction on air pollution, this study draws on the research design of Chen *et al.* (2020), and the mechanism test model is shown in Equation (3) below.

$$M_{it} = \alpha + \beta GDC_{it} + \gamma \sum Controls_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (3)$$

Among them, M_{it} represents the mediating variables. Same as Equation (1).

4.2. *Data*

Air pollution is the dependent variable, and this study uses $PM_{2.5}$ as a proxy variable for air pollution. First, $PM_{2.5}$ ranks as the key pollutant that causes the most widespread and severe harm to human health. Penetrating deep into the alveoli, an extremely small particle size can even move further to enter the blood circulation, triggering long-term impacts on the respiratory system, cardiovascular system, and overall health (Cohen *et al.*, 2017). The World Health Organization explicitly lists $PM_{2.5}$ as a core indicator for measuring air pollution and health risks. Second, the Chinese government places great emphasis on $PM_{2.5}$. Since the 12th Five-Year Plan, $PM_{2.5}$ has been incorporated into the air quality monitoring and assessment system. The *Air Pollution Prevention and Control Action Plan* has established a relatively complete $PM_{2.5}$ monitoring network nationwide and taken it as a key assessment indicator for environmental governance.[4] This high level of attention not only indicates that $PM_{2.5}$ is an important dimension for measuring air pollution but also ensures the authority, continuity, and availability of data, making it the most commonly used indicator in academic research and policy evaluation.

As the independent variable, we use a dummy variable for GDC. For any city selected as a GDC construction, this variable takes a value of 1 starting from that designation year; otherwise, it takes a value of 0. The significance and coefficient direction of this variable reveal the impact of GDC construction on air pollution.

With reference to existing relevant studies (Su & Xie, 2023;Yu *et al.*, 2022;Y. Liu *et al.*, 2021), the selection of control variables is as follows: Economic development (ED) is measured by per capita GDP. Population density (PD) is calculated as the total population divided by land area. Greenspace coverage (GC) is defined as the urban greenspace area relative to the administrative area. Opening-up (OU) is measured by the actual utilization of foreign direct investment over regional GDP. Research expenditure (RE) is the proportion of research and development expenditure to total fiscal expenditure. Government intervention (GI) is computed as local general budgetary expenditure to the logarithm of regional GDP. From 2013 to 2023, this study employs a sample of 282 Chinese cities, where $PM_{2.5}$ data is sourced from the National Tibetan Plateau Scientific Data Center. From LandScan, we retrieve the population density data. Others are derived from the *China City Statistical Yearbook* and *the China Urban Construction Statistical Yearbook*. Except for the independent variable, all variables are converted to their logarithmic form, and descriptive statistics for the main variables are presented in **Table 1**. Data analysis and processing for this study are conducted using Stata software within the macOS operating system environment.

Table 1. Descriptive Statistics of Main Variables.

Variable	Obs	Mean	Std.dev.	Min	Max
$LnPM_{2.5}$	3,102	3.616	0.376	2.456	4.719
GDC	3,102	0.087	0.282	0.000	1.000
LnED	3,102	10.872	0.550	9.037	12.486
LnPD	3,102	5.437	0.979	1.469	8.396
LnGC	3,102	0.563	0.609	0.004	3.984
LnOU	3,102	0.002	0.003	0.000	0.029
LnRE	3,102	0.018	0.018	0.000	0.188

[4] As shown in the official document of the *Air Pollution Prevention and Control Action Plan* https://www.gov.cn/zwgk/2013-09/12/content_2486773.htm

LnGI	3,102	0.186	0.081	0.043	0.650

Note: Obs denotes the sample size, Mean represents the sample mean, Std.dev. stands for the sample standard deviation, Min indicates the minimum value, and Max signifies the maximum value.

5. Empirical Analysis

5.1. *Baseline Regression Results*

The results of Equation (1) are presented in **Table 2**. Column (1) includes only the core independent variable without fixed effects. In Column (2), city-fixed effects are included in the controls, whereas year-fixed effects are not. In Column (3), both fixed effects are controlled for, while all control variables are also incorporated. Across columns (1) to (3), the coefficients GDC consistently prove significantly negative, showing that the GDC construction can reduce air pollution levels. This verifies H1.

In Column (3), the coefficients of ED, GC, OU, RE, and GI are significantly negative. These factors help reduce air pollution by improving resource utilization efficiency, optimizing environmental governance, and upgrading industrial structures. In contrast, the coefficient for PD is positively significant, indicating that high population accumulation increases the energy consumption pressure and harmful releases from traffic, thereby exacerbating air pollution. These results are consistent with real-world logic and conform to basic economic principles.

Table 2. Baseline Regression Results.

	(1)	(2)	(3)
	$LnPM_{2.5}$	**$LnPM_{2.5}$**	**$LnPM_{2.5}$**
GDC	-0.265***	-0.019***	-0.015**
	(-15.394)	(-3.017)	(-2.353)
LnED			-0.038***
			(-3.161)
LnPD			0.971***
			(6.073)
LnGC			-0.061***
			(-3.604)
LnOU			-3.518***
			(-3.684)
LnRE			-0.470***
			(-3.595)
LnGI			-0.266***
			(-3.894)
City fixed effect	N	Y	Y
Year fixed effect	N	N	Y
Constant	3.639***	3.618***	-1.150
	(512.594)	(2839.416)	(-1.342)
Observations	3102	3102	3102
Adjusted R^2	0.039	0.969	0.970

*Note: ***, **, and * indicate significance levels at 1%, 5%, and 10% respectively; t-values are in parentheses. The same significance standards apply to the following tables.*

5.2. *Robustness Tests*

5.2.1. Parallel Trend Test

The results of Equation (2) are presented in **Figure 4**, which displays the parallel trend test results. Prior to the execution of GDC construction, the coefficients exhibit fluctuations around 0; furthermore, 0 is involved in the confidence intervals. Before the policy implementation, the trends of the treatment and the control group exhibit similarity, thus satisfying the prerequisite of the parallel trend assumption for the staggered DID method. The detailed coefficients are presented in **Table 3**.

After the policy implementation in the 4th year, the coefficient significantly declined, which suggests a certain lag. The construction of GDC is a systematic project; its effect on air pollution control is not immediate but gradually emerges in long-term continuous operation as the integration of technologies deepens.

5.2.2. Bacon Decomposition

Different treatment groups enter the pilot at diverse time points, and the traditional two-way fixed effects estimator may produce weighted average bias, leading to distorted estimation results. Bacon decomposition can decompose the overall staggered DID estimator to help identify whether there is abnormal weight or estimation bias. In **Table 4**, the weight of "Treatment vs. Never treated" is 0.908, accounting for an absolutely dominant weight and serving as the core source of the total effect. The treatment effect is -0.022, representing that the GDC construction has an overall negative influence on the outcome variable; due to the high weight, this is the main driver of the total staggered DID effect. The weights of "Earlier Treatment vs. Later Comparison" and "Later Treatment vs. Earlier Comparison" both contribute a relatively low proportion. The results have passed the analysis and verification of bacon decomposition.

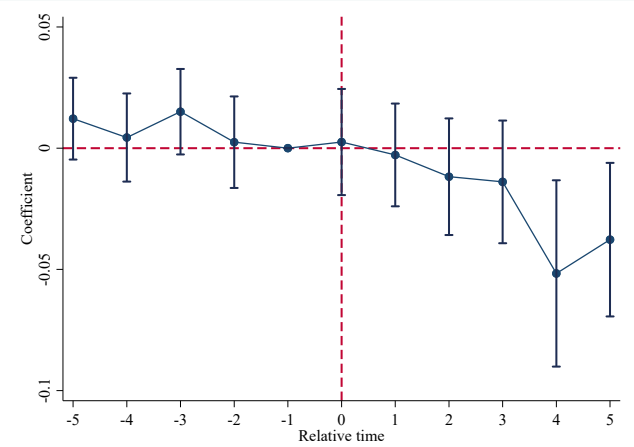


Figure 4. Parallel Trend Test. Note: The dots indicate the estimated coefficients at different relative time points. The line segments represent the 90% confidence intervals.

5.2.3. Placebo Test

Figure 5 presents the placebo test results from 500 simulations. The scatter points represent the distribution of estimated staggered DID coefficients obtained under a large number of random treatments.

The true estimated coefficient is the vertical dashed line, which is far below 0 and located in the tail, which verifies the reliability of the results. Random factors do not cause the effect estimated by the original results and thus pass the placebo test.

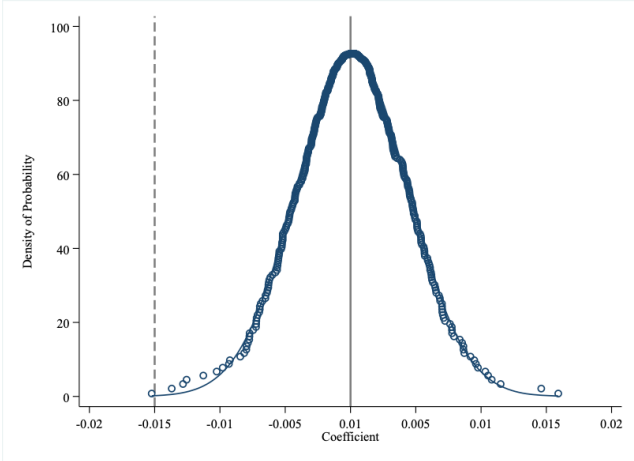


Figure 5 Placebo Test. Note: The scatter points represent the distribution of coefficient estimates from the placebo test. The vertical dashed line in the figure denotes the coefficient of -0.015 from the baseline regression of Equation (1).

Table 3. Relative time Results.

Relative time	Coefficient	T-value
-5	0.012	1.415
-4	0.004	0.472
-3	0.013	1.221
-2	0.002	0.255
0	0.003	0.236
1	-0.003	-0.261
2	-0.012	-0.960
3	-0.014	-1.078
4	-0.052***	-2.637
5	-0.038**	-2.336

Table 4. Results of Bacon Decomposition.

Comparison	Weight	Coefficient
Earlier Treatment vs. Later Comparison	0.066	0.011
Later Treatment vs. Earlier Comparison	0.026	0.016
Treatment vs. Never treated	0.908	-0.022

5.2.4. Instrumental Variables Method

To alleviate potential endogeneity concerns in the model, this study further employs an instrumental variable approach as a robustness check. Specifically, the logarithm of the number of employees in the information transmission software, and information technology services industry per 10,000 people (LnIPT) is used as an instrumental variable for GDC development. The rationale for this instrumental variable lies in two aspects. First, the employment scale in the information transmission, software, and information technology services industry reflects a region's digital economy foundation, level of

information technology application, and development environment of related industries, and is therefore closely associated with the construction GDC. Second, this indicator is expected to affect air pollution mainly through its influence on GDC construction, thereby satisfying the exogeneity requirement of an instrumental variable to some extent. By introducing this instrumental variable, the estimation bias caused by omitted variables, reverse causality, and other endogeneity sources can be mitigated, thus improving the reliability of the empirical findings.

Table 5 reports the estimation results of the instrumental variable approach. The first-stage regression shows LnIPT has a significantly positive effect on GDC construction, with a coefficient of 0.361 significant at the 1% level. This result indicates that a larger scale of talent in the information transmission software, and information technology services industry is conducive to the construction of GDC. Therefore, the selected instrumental variable is strongly correlated with the endogenous explanatory variable. The Anderson canonical LM statistic rejects the null hypothesis of under-identification. The second-stage regression results show that the coefficient of GDC is -0.085 and statistically significant at the 1% level. This finding suggests that GDC construction significantly reduces air pollution. Overall, the instrumental variable results further support the main conclusion of this study: the construction of GDC contributes to air pollution decrease, and this conclusion remains robust after alleviating potential endogeneity concerns.

Table 5. Instrumental Variables Method.

Dependent Variable	(1)	(2)
	GDC	LnPM2.5
LnIPT	0.361***	
	(10.703)	
GDC		-0.085***
		(-2.959)
City fixed effects	Y	Y
Year fixed effects	Y	Y
Control Variables	Y	Y
Constant	17.588***	-.0378
	(5.574)	(-0.032)
Observations	3102	3102
Anderson canon. LM statistic	121.66[0.0000]	
F-value	114.42	

Notes: The t-statistics are reported in parentheses. The p-value for the Anderson canonical LM statistic is reported in square brackets.

5.2.5. Considering the crash of the COVID-19 Pandemic

Production suspension in numerous enterprises and restrictions on transportation significantly reduced energy consumption and industrial production activities, leading to a marked short-term decrease in pollutants during the pandemic period. To avoid confounding effects, this study excludes the period in the empirical design, confirming that the estimation results can truly reflect the GDC construction itself on air pollution. In **Table 6**, samples related to the pandemic period are excluded; after isolating the net effect, GDC remains significant in column (1). This proves that the policy can still significantly reduce pollution even when affected by the pandemic.

Table 6. Robustness Test.

	(1)	(2)
	$LnPM_{2.5}$	$LnPM_{2.5}$
GDC	-0.021*	-0.015**
	(-1.856)	(-2.353)
Province fixed effects	N	Y
City fixed effects	Y	Y
Year fixed effects	Y	Y
Control Variables	Y	Y

Constant	7.416***	-1.150
	(4.342)	(-1.343)
Observations	1974	3102
Adjusted R^2	0.973	0.970

Table 7. Robustness Test.

	(1)	(2)
	$LnPM_{2.5}$	**$LnPM_{2.5}$**
GDC	-0.014**	-0.016***
	(-2.166)	(-2.698)
Additional control variables	N	Y
City fixed effects	Y	Y
Year fixed effects	Y	Y
Control Variables	Y	Y
Constant	-1.957	-1.150
	(-1.610)	(-1.343)
Observations	2277	3102
R^2	0.972	0.974

5.2.6. Incorporating Provincial Fixed Effects

Structural differences at the provincial level may lead to omitted variable bias. Different provinces exhibit long-term disparities in aspects such as resource endowments, population size, and climatic conditions—these differences are often difficult to fully capture through explicit control variables. Therefore, based on the origin, the provincial fixed effects are controlled. In column (2) of **Table 6**, all adding provincial fixed effects, the core independent variable still yields a significant result.

5.2.7. PSM-DID

In the robustness test, we further employ the propensity score matching method (PSM) to alleviate potential sample selection bias. Therefore, failing to control for initial differences between the treatment and control groups may lead to biased estimates. Column (1) of **Table 7** reports the robustness test results based on propensity score matching, with kernel matching used as the matching method. The results show that, after kernel matching, the coefficient of GDC is -0.014 and is significant at the 5% level, indicating that GDC construction reduces urban air pollution. This finding suggests that, after alleviating sample selection bias caused by observable differences between the treatment and control groups, the inhibitory effect of GDC construction on air pollution remains valid.

Table 8. Incorporating Climate Control Variables.

	(1)	(2)	(3)	(4)
	$LnPM_{2.5}$	**$LnPM_{2.5}$**	**$LnPM_{2.5}$**	**$LnPM_{2.5}$**
GDC	-0.018***	-0.014**	-0.014**	-0.017***
	(-2.828)	(-2.322)	(-2.286)	(-2.705)
Ln precipitation	-0.051***			-0.049***
	(-5.730)			(-5.488)
Ln temperature		0.069**		0.058***
		(2.421)		(2.632)
Ln wind speed			-0.022	-0.029
			(-1.023)	(-1.362)
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y

Constant	-0.771	-1.324	-1.135	-0.908
	(-0.882)	(-1.543)	(-1.325)	(-1.037)
Observations	3102	3102	3102	3102
R^2	0.971	0.971	0.970	0.971

5.2.8. Include Additional Control Variables

We additionally include two control variables: environmental governance capacity and government attention to environmental protection. Specifically, environmental governance capacity is measured by the harmless treatment level of domestic waste, while government attention to environmental protection is measured by the proportion of environment-related words in government work reports to the total number of words. The inclusion of these variables allows for a more comprehensive control of the effects of local environmental governance foundations and government policy attention on air pollution, thereby reducing potential estimation bias caused by omitted variables. The results in column 2 of **Table 7** indicate that the coefficient of GDC remains significant even after controlling for the control variables.

5.2.9. Incorporating Climate Control Variables

Climatic factors are key natural variables that affect the diffusion, deposition, and formation of atmospheric pollutants. Columns (1) to (3) of **Table 8** control for precipitation, temperature, and wind speed, respectively. Above all, the three aforementioned climatic factors are concurrently controlled for in column (4). The core independent variable remains significantly negative.

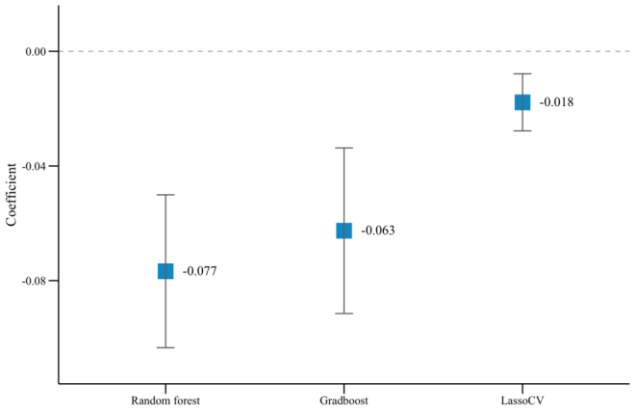


Figure 6. Double Machine Learning. Note: The horizontal axis represents different machine learning models, and the vertical axis denotes coefficient. The blue squares represent the coefficient values of different models, and the line segments represent the 90% confidence intervals.

5.2.10. Double Machine Learning

To further examine the robustness of our baseline results and alleviate concerns regarding model specification, we employ the Double Machine Learning (DML) approach. DML allows for flexible control of high-dimensional covariates and reduces potential bias arising from functional form misspecification. Specifically, we use Random Forest, Gradient Boosting, and Lasso machine learning algorithms to estimate the nuisance functions. A 6-fold cross-fitting procedure is implemented, in which the sample is randomly partitioned into six subsets. The final estimates are obtained by averaging across all folds, thereby reducing overfitting and ensuring robustness. **Figure 6** presents the DML estimation results based on different machine learning methods. The direction of the estimated effects remains stable and is consistent with the baseline DID results. The consistency between DML and DID findings suggests that our results are not driven by model specification or functional form assumptions. Overall, the DML results provide additional evidence supporting the robustness of our main findings.

5.3. *Mechanism Test*

The results of Equation (3) are presented in **Table 9**, which presents the mechanism test.

We use the number of mobile phone users (MPU) and the number of Internet broadband access users (IBAU) in a city to measure the level of informatization development. The rationale is that these two indicators directly reflect the construction of information and communication infrastructure and the extent of information technology usage among residents. The number of mobile phone users captures the penetration of mobile communication networks and the convenience of information acquisition, transmission, and processing. The number of Internet broadband access users reflects the coverage of fixed Internet infrastructure and the city's network access capacity. Together, these two indicators characterize informatization development from the perspectives of mobile communication and fixed network access, thereby providing a comprehensive measure of a city's digital infrastructure and information technology application environment. Informatization development is presented in Column (1)-(2). The coefficient of GDC is significantly positive, which indicates that the GDC construction promotes the informatization development. This verifies H2.

We use the number of green patent applications (GPA) and green invention patents (GIP) to measure the level of green technology innovation. Patent data can directly reflect green technology R&D activities and innovation outputs at the city level. Specifically, the number of green patent applications captures the overall activity, scale, and breadth of green innovation, thereby reflecting the quantitative dimension of green technology innovation. In contrast, green invention patents generally involve higher technological content, stronger originality, and stricter examination standards than utility model or design patents, and thus better represent the quality of green technological innovation. Therefore, using both green

patent applications and green invention patents provides a more comprehensive measure of urban green technology innovation from both the quantity and quality dimensions. The results of green technology innovation are presented in Column (3)-(4). Among the results, the coefficient of GDC is significantly positive. This verifies H3.

The Sobel test also passes the significance test, indicating that the mediating effect is statistically valid. This result further confirms that GDC construction can affect air pollution through the relevant mediating mechanism, thereby strengthening the reliability of the mechanism analysis.

Table 9. Mechanism Test.

	(1)	(2)	(3)	(4)
	MPU	**IBAU**	**GPA**	**GIP**
GDC	0.657***	0.574***	1.174***	0.635***
	(6.255)	(9.171)	(9.249)	(7.964)
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y
Constant	31.635**	-1.720	35.315**	21.822***
	(2.047)	(-0.240)	(2.442)	(2.788)
Observations	3102	3102	3102	3102
R^2	0.982	0.909	0.882	0.881
Sobel Z	-4.735***	-5.703***	-4.052***	-4.729***

6. Heterogeneity Analysis

Heterogeneity analysis is conducted because differences among cities in reality lead to variations in the core effect across different groups and regions. Identifying which cities experience more significant effects from GDC construction not only prevents the average effect from masking real patterns but also provides a basis for targeted policy-making. The climate variables were matched with the main panel dataset by region and year to ensure spatial and temporal consistency between the climate controls and the empirical sample. This study conducts heterogeneity analysis from four perspectives: economic development level, administrative level, financial development, and tertiary industry proportion, as shown in **Figure 7**.

GDP is used to measure the level of economic development, and cities are divided into high and low economic development cities. Using the median of the sample, we divide the observations into two groups. High economic development cities have a significantly negative coefficient, while the low ones do not. A region's developed economic system addresses the constraints of energy, technology, and cost in data center emission reduction through investment in clean energy and the attraction of high-tech talents. This improves energy efficiency and thereby reduces air pollution (Dinda, 2004).

Cities with high administrative levels are defined as municipalities directly under the central government and sub-provincial cities, while the rest cities are of low administrative levels. The coefficient of high administrative level cities is significantly negative, whereas the other is not. The phenomenon is attributed to the Chinese promotion tournament incentive mechanism for local officials, which leads green performance assessment to be more prominent in higher-level cities with greater political attention (H. Li & Zhou, 2005). Stricter supervision in high administrative level cities enables the construction of GDC to better play its role in reducing air pollution.

Financial development is measured by the ratio of the balance of deposits and loans of financial institutions to the regional GDP. Cities are divided into high and low financial development cities based on the median of the sample. As shown in **Figure 7**, the coefficient for high financial development cities is significantly negative, while the coefficient for low ones is not significant. In high financial development cities, policy signals are more likely to provide capital expenditure for GDC transformation through tools such as green credit. This accelerates the implementation of technological transformation of GDC, thus air pollution is reduced (Tamazian & Bhaskara Rao, 2010).

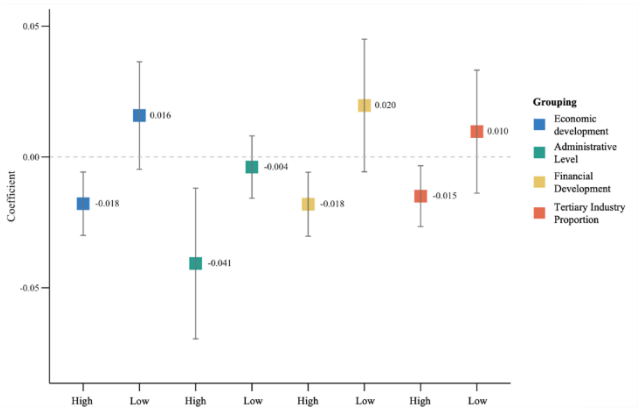


Figure 7. Heterogeneity Test. Note: The horizontal axis shows different groups, and the vertical axis represents coefficient. The

blue squares represent the coefficient values grouped by economic development, the green squares represent the coefficient values grouped by administrative level, the yellow squares represent the coefficient values grouped by financial development, and the orange squares represent the coefficient values grouped by tertiary industry proportion. The line segments indicate the 90% confidence intervals.

Tertiary industry proportion is defined as the ratio of the added value of the tertiary industry to GDP. Cities are divided into high and low tertiary industry proportion cities according to the median of the sample. The coefficient for high tertiary industry proportion cities is significantly negative, while the coefficient for low ones is not. Cities with a high tertiary industry, green digital computing power, accurately convert physical activities into digital streams in the virtual. This directly reduces high-emission physical links in these service activities, making GDC more effective in optimizing energy efficiency and reducing air pollution emissions (Savona & Ciarli, 2019).

7. Discussion

This study provides robust empirical evidence that the construction of GDC significantly contributes to the reduction of urban air pollution. Building upon the baseline regression, mechanism analysis, and heterogeneity tests, this section further interprets the findings, situates them within the broader literature, and discusses their theoretical and practical implications.

First, the finding that GDC construction significantly reduces air pollution concentrations reinforces the view that digital infrastructure can generate positive environmental externalities when embedded with green attributes. Unlike traditional data centers, which are often criticized for their high energy consumption and associated emissions, GDC integrates energy-saving technologies and cleaner energy sources, thereby mitigating the environmental costs of digitalization. This result contributes to reconciling the long-standing debate on whether digital infrastructure exacerbates or alleviates environmental pressure. Existing studies have shown that early-stage digital infrastructure expansion may increase pollution due to scale effects and fossil energy dependence (Belkhir & Elmeligi, 2018). However, our findings suggest that when digital infrastructure evolves toward a greener paradigm, its technological and structural effects can dominate, leading to net environmental benefits (Oró *et al.*, 2015). This highlights the importance of distinguishing between conventional and green digital infrastructure in environmental assessments (Rong *et al.*, 2016). Recent research has increasingly emphasized that environmental improvement depends not only on pollution control but also on broader economic, technological, and institutional conditions. Air pollution can impose substantial health and economic costs (Ding *et al.*, 2025), while urban–rural integration and stronger green transition capacity may help improve regional environmental quality (Lu & Yoon, 2026; Y. Wang *et al.*, 2025). Effective environmental governance also requires public supervision, stakeholder coordination, and integrated ecological planning (Q. He *et al.*, 2026; Zhi *et al.*, 2026). Meanwhile, digital monitoring and cross-regional regulation have created new opportunities for carbon management and pollution control (Hu *et al.*, 2026).

Second, the effect observed in the parallel trend analysis indicates that the pollution-reduction impact of GDC construction is not immediate but exhibits a lagged effect, becoming significant several years after policy implementation. This temporal pattern reflects the inherent characteristics of infrastructure investment and technological diffusion. The construction of GDC involve complex processes, including equipment upgrading, energy structure optimization, and system integration (Avgerinou *et al.*, 2017). Moreover, the environmental benefits depend on the gradual accumulation of technological improvements and operational efficiency gains (Aslan *et al.*, 2018). This finding aligns with the notion that environmental policies and technological interventions often exhibit delayed effects, suggesting that policymakers should adopt a long-term perspective when evaluating the effectiveness of GDC construction initiatives.

Third, the mechanism analysis provides important insights into how GDC construction translates into decreased air pollution. The results show that informatization development and green technology innovation serve as two key transmission channels. On the one hand, GDC promotes urban informatization development by enhancing data processing capacity and digital connectivity, which in turn improves the efficiency and precision of environmental governance. Digital tools enabled by advanced infrastructure facilitate real-time monitoring, data sharing, and coordinated regulation, addressing long-standing issues such as information asymmetry and fragmented governance (Cui & Cao, 2022; Zou & Pan, 2023). On the other hand, GDC stimulates green technology innovation by creating incentives for firms to invest in energy-efficient technologies and environmentally friendly processes. The increase in green patent applications suggests that GDC construction not only directly reduces emissions but also fosters a broader innovation ecosystem that supports sustainable development (Z. Zhang *et al.*, 2023). In addition, the importance of online knowledge is highlighted in knowledge-based work in Chinese technical R&D teams (W. Zhang *et al.*, 2023). Evidence from technical applications further illustrates the operational value of digital infrastructure (J. He *et al.*, 2025), while data-driven frameworks can transform complex and fragmented flow information into fine-grained predictions that support operational decision-making (H. Liu *et al.*, 2026). They provide a useful technical analogy for the present findings. GDC construction may improve cross-departmental information exchange, real-time environmental monitoring, and coordinated pollution governance. These findings extend the literature by empirically validating the dual pathways through which digital infrastructure can influence environmental outcomes.

Fourth, the heterogeneity analysis reveals that the pollution-reduction effects of GDC construction are not uniform across cities but depend on local economic and

institutional conditions. Specifically, the effects are more pronounced in cities with higher levels of economic development, administrative hierarchy, financial development, and a larger tertiary sector. This heterogeneity can be explained from several perspectives. Economically developed cities possess better technological capabilities, infrastructure foundations, and human capital, enabling them to more effectively utilize GDC for environmental improvement. Cities with higher administrative levels often face stronger regulatory pressure and performance evaluation incentives, which enhance policy implementation. Financially developed regions provide better access to funding for green transformation, reducing the cost constraints associated with GDC construction. Meanwhile, cities with a larger tertiary sector rely less on heavy industry and are more compatible with digital and low-carbon development pathways (Antweiler *et al.*, 2001). These findings highlight that the effectiveness of GDC construction is contingent upon complementary conditions, suggesting that a "one-size-fits-all" approach may be suboptimal.

Fifth, the robustness checks, including placebo tests, instrumental variable estimation, and double machine learning methods, collectively strengthen the credibility of the results. The placebo test confirms that the estimated effects are not driven by random shocks, while the instrumental variable approach alleviates concerns about potential endogeneity. The consistency between traditional econometric models and machine learning-based estimates further indicates that the findings are not sensitive to model specification. This methodological rigor enhances confidence in the causal interpretation of the results and underscores the reliability of the conclusion that GDC construction contributes to air pollution reduction.

Compared with prior studies, our findings provide new insights in several ways. Earlier research has largely focused on energy consumption, carbon emissions, and operational efficiency at the facility level (Dayarathna *et al.*, 2016; Gill & Buyya, 2019; Kliazovich *et al.*, 2012). Some city-level studies have analyzed the effect of digital infrastructure on energy demand and emissions, but causal evidence of air pollution reduction remains scarce (Peng *et al.*, 2024). In addition, prior work often assumes uniform environmental effects, while our study highlights heterogeneity across cities with different economic, administrative, financial, and industrial conditions. Moreover, previous research primarily considered direct technological effects (Bieser & Hilty, 2018), whereas our study identifies informatization and green technology innovation as key mediating mechanisms, extending theoretical understanding of how green digital infrastructure contributes to environmental governance. Our findings also complement regional studies on energy-saving digital infrastructure in developed countries, but indicate stronger contextual dependence in China, reflecting variations in local institutional capacity and industrial structure.

Finally, the differences across estimation methods should be interpreted in light of their distinct assumptions rather than simply regarded as evidence that one model performs better than another. The staggered DID model captures the average change in air pollution associated with GDC construction after controlling for observable city characteristics and fixed effects, whereas the IV approach addresses potential policy-selection and reverse-causality concerns, which may lead to a larger estimated effect. The PSM-DID estimate is close to the baseline result, suggesting that differences in observable characteristics between treated and untreated cities are unlikely to be the main driver of the estimated effect. The variation among the double machine learning estimates may result from differences in model flexibility. Random forest and gradient boosting can capture nonlinear relationships, threshold effects, and complex interactions among economic development, industrial structure, financial conditions, and environmental regulation. In contrast, Lasso assumes a relatively sparse linear relationship and may generate a smaller estimate when the actual treatment effect is nonlinear or heterogeneous. In summary, the consistency in the direction of the estimates is more important than the exact equality of their magnitudes.

8. Conclusions

Unlike previous studies that primarily evaluate data centers using operational efficiency or carbon-emission indicators, this study examines their broader environmental externalities from the perspective of urban air pollution. By combining the green-policy and digital-infrastructure attributes of GDC construction, the study further explains how their environmental benefits are generated and under what urban conditions these benefits become more pronounced.

Using panel data from 282 Chinese cities over the period 2013–2023, this study examined the relationship between GDC construction and urban air pollution through a staggered DID method. The baseline estimate is −0.015 and statistically significant at the 5% level, indicating that GDC construction is associated with an approximately 1.5% reduction in air pollution. The estimated effect remains negative under alternative identification strategies. Specifically, the PSM-DID estimate is −0.014, while the instrumental-variable estimate is −0.085. Double machine learning models also produce negative estimates ranging from −0.018 to −0.077. Although the magnitude varies across estimation methods, the overall direction of the results is consistent. The mechanism results suggest that improvements in informatization development and green technology innovation are two potential channels through which GDC construction is associated with lower air pollution. The heterogeneity analysis further shows that the estimated pollution-reduction effect is stronger in cities with higher levels of economic development, administrative level, financial development, and tertiary industry proportion.

Drawing on them, the following policy recommendations are proposed.

First, GDC construction should be incorporated into the coordinated policy framework of digital infrastructure development and air pollution governance. GDC construction should be regarded as an important policy tool for improving environmental quality. Local governments should integrate GDC construction into urban green development plans, air pollution control strategies, and new infrastructure policies.

Second, policymakers should strengthen the role of GDC construction in improving informatization development and digital environmental governance. The government should promote the integration of GDC with smart environmental monitoring, pollution source identification, online regulatory platforms, and real-time air quality warning systems. By improving the collection, processing, and application of environmental information, GDC can better support precise and intelligent air pollution governance.

Third, GDC construction should be combined with green technology innovation policies. Governments should encourage data center operators, digital enterprises, research institutions, and manufacturing firms to participate in collaborative green technology innovation. Policy support can be provided for energy-saving servers, advanced cooling technologies, waste heat recovery, renewable energy integration, and intelligent energy management systems. At the same time, fiscal subsidies, tax incentives, green credit, and innovation funds can be used to guide enterprises to transform the environmental benefits of GDC into broader regional green technology innovation capacity.

Fourth, differentiated GDC construction should be designed according to local development conditions. Developed cities and central cities can be encouraged to take the lead in building high-standard GDC demonstration zones and promoting replicable governance models. For less developed cities, policy support should focus on improving digital infrastructure, expanding green financing channels, and strengthening technical capacity. Such differentiated policies can help avoid a situation in which only advanced cities benefit from GDC construction, while less developed regions face barriers in accessing green digital infrastructure.

The findings have several limitations. First, the city-level data do not capture differences in the operational scale, electricity consumption, cooling technology, or energy mix of individual GDC. Future studies could combine city-level information with facility-level operational data to identify which technical characteristics generate stronger environmental benefits. Second, future research could examine spatial spillover effects, because data-center construction and air pollution may affect neighboring cities through electricity transmission, industrial relocation, and atmospheric transport. Third, meteorological conditions, regional electricity structures, and renewable-energy utilization could be incorporated to provide a more detailed explanation of the observed effects. The staggered DID method depends on several identifying assumptions. In this method, these procedures may not completely eliminate the influence of unobserved time-varying factors. $PM_{2.5}$ measurements may contain spatial or temporal measurement errors, while city-level indicators of informatization and green technology innovation may not fully capture the proposed mechanisms. Finally, future studies could assess additional pollutants, such as PM_{10}, SO_2, NO_2, CO, and ozone, and use longer observation periods or evidence from other countries to evaluate the external validity and long-term effects of the findings.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Jingbao Cao: Methodology, Visualization, and Writing-original draft. **Shenghao Bi**: Conceptualization, Methodology, Visualization, and Writing- review & editing.

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