

Article

Integration of Data Elements and Artificial Intelligence for Synergistic Pollution and Carbon Reduction in 275 Chinese Cities

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Abstract

China's ecological civilization construction and the "dual-carbon" strategy highlight the urgent need for coordinated governance of pollution and carbon reduction. Whether data elements and artificial intelligence integration (DEAI) can serve as a new pathway to achieve this goal remains to be explored. This study investigates the dynamic effects of DEAI on pollution and carbon reduction using panel data from 275 prefecture-level cities in China during 2009–2021. An evaluation index system and a modified coupled coordination degree model are developed to measure DEAI, while an ordinary least squares (OLS) fixed effects model is applied to assess its impacts. The results show stage-specific effects of DEAI, including the phenomenon of "pollution reduction but carbon increase". Mechanism analysis indicates that improvements in green energy technology efficiency (GETE) and optimization of urban spatial structure are the main channels for achieving synergy. Heterogeneity analysis reveals that although government attention to environmental protection strengthens pollution control, it has limited effects on short-term carbon reduction. Moreover, the carbon reduction benefits of green energy transition pilots exhibit a time lag, and the "digital intelligence divide" generates negative spatial spillovers. These findings provide new evidence for the dilemma of "environmental protection without low-carbon benefits" and suggest policy directions for enhancing the coordinated governance of pollution and carbon reduction.

Keywords: data elements; artificial intelligence; integration; pollution reduction; carbon reduction



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1. Introduction

Over the past decade, China's ecological civilization construction has been characterized by a persistent inconsistency between pollution reduction and carbon reduction. The idea that "low carbon is not environmentally friendly, and environmental protection is not low carbon" has been prevalent in China's economic development [1]. During the "12th Five-Year (2011–2015)" and "13th Five-Year (2016–2020)" periods, China's ecological governance framework primarily emphasized pollution reduction. To meet environmental protection standards, enterprises often consume large amounts of energy, leading to increased carbon emissions and thus exacerbating the "environmental protection is not low carbon" issue [2]. However, during the "14th Five-Year (2021–2025)" period, China's approach to ecological governance has evolved toward prioritizing carbon reduction, with

regulatory targets shifting from “dual control of energy consumption” to “dual control of carbon emissions” [3]. Despite this shift, structural challenges and ongoing pressures related to environmental protection have not been fundamentally alleviated, and the goal of achieving “Carbon Peak and Carbon Neutrality” remains a formidable task [4]. In recent years, artificial intelligence (AI) has developed rapidly, profoundly reshaping human knowledge systems, credit mechanisms, and authority structures, thereby driving society toward an increasingly intelligent era. The development of industrial society has witnessed rapid progress in science and technology, but it has also been accompanied by serious problems of environmental pollution [5]. Similarly, while benefiting from the advancements brought by AI, an intelligent society faces numerous challenges [6]. The question of how to coordinate the digital and intelligent development of cities with green and low-carbon development has become a critical and urgent issue that requires immediate attention.

Data elements (DEs), as an indispensable and critical factor of production in the modern economy, are progressively becoming a central tool for advancing urban sustainable development and enhancing environmental governance efficiency. AI, an intelligent technology application grounded in data-driven principles, empowers production and decision-making processes through advanced technological means. DEs provide vast training datasets for AI, enabling it to more effectively reflect the complexities of real-world environments and production activities [7]. In turn, AI leverages its powerful data processing and analytical capabilities to further promote the in-depth application of DEs, improving the precision and efficiency of decision-making [8]. DEAI enhances the precision and efficiency of data collection, analysis, processing, and feedback, with its role in green and low-carbon development becoming increasingly evident [9].

DEs exhibit the characteristics of permeability, substitutability, and complementarity within the “technology–economy” paradigm, which is driving the widespread adoption of new types of production materials [10]. This results in a data-driven productivity model that facilitates the intensive transformation of green economic development approaches and has a significant effect on the ecological welfare [11]. Firstly, DEAI enhances machine perception and decision-making capabilities, substantially elevating the intelligence level of environmental governance [12]. Utilizing machine learning and deep learning algorithms, AI can precisely analyze environmental data, monitor pollutants such as air quality and water quality in real time, and automatically adjust governance measures [13]. Secondly, DEAI generates synergistic effects across entire industries. In areas such as traffic management, energy allocation, and urban planning, DEs and AI jointly contribute to pollution reduction and carbon reduction [14]. Furthermore, the thorough integration of DEs and AI has led to the emergence of numerous new green, intelligent, and integrated products, technologies, and business models [15].

However, in the process of DEAI, energy consumption has increased significantly, and the energy rebound effect may weaken or offset some of the gains made in pollutant and carbon emission reductions [16]. Data centers require substantial amounts of electricity to support computing and cooling systems [17]. With the explosive growth of data volumes and the continuous development of AI, the proportion of energy consumed by data centers relative to the global total is rising year by year [18]. Although some data centers have achieved green power procurement, many still rely on traditional energy sources, particularly coal-fired power, which directly contributes to increased carbon emissions [19]. The training of AI, especially deep learning models, demands extremely high computing resources, resulting in a significant increase in energy consumption [20]. Despite the potential of AI to improve energy efficiency, the rebound effect in a power structure dominated by fossil fuels may hinder the achievement of carbon reductions and could even lead to an increase in carbon emissions [21]. Therefore, in the context of digital and intelligent

transformation, energy and carbon rebound effects may significantly offset or diminish the progress in reducing carbon emissions [22].

As digital and intelligent technologies reshape urban development, notable differences emerge in how cities pursue pollution control and carbon reduction [23]. This research systematically investigates the varied impacts of DEAI on these two goals and examines the internal mechanisms driving its role in advancing environmental governance. The study contributes in the following ways:

- (1) Previous studies have predominantly examined DEs and AI in isolation, with limited efforts towards developing a comprehensive framework [24]. To address this gap, this study introduces DEAI, a unified framework capturing the interactive and synergistic relationship between DEs and AI. The theoretical contribution of DEAI lies in two aspects. First, it provides a conceptual integration linking DEs and AI across the generation, processing, and application chains, emphasizing their co-evolution in enabling digital intelligence and enhancing environmental governance. Second, it offers an operational and empirical innovation by constructing a life-cycle-based DE index and an AI capacity indicator system, integrated via a modified coupling coordination model to derive the DEAI index. This approach enriches theoretical understanding and provides a replicable quantitative framework.
- (2) While previous studies have primarily relied on conventional regression models to examine the correlations between DEs or AI and environmental performance, they often overlook synergistic interactions and spatial dynamics. To address these limitations, this study first employs a double fixed-effects OLS model to rigorously estimate the net impact of DEAI on urban pollution and carbon emissions across 275 Chinese cities from 2009 to 2021. Furthermore, we extend the analysis by investigating the spatial dynamics of DEAI, thereby uncovering its spatially heterogeneous effects—a critical dimension that has been largely neglected in the extant literature.
- (3) Existing research on the environmental implications of digitalization tends to focus on isolated mechanisms, such as technological progress or industrial restructuring, thereby constraining a holistic understanding of how integrated digital intelligence functions. To bridge this gap, our study examines the transmission channels through which DEAI mitigates pollution and carbon emissions from a dual perspective, simultaneously accounting for energy-related technological advancements and structural adjustments. This integrated methodological approach enables us to identify and compare the key synergistic factors that allow DEAI to achieve co-benefits for the environment, ultimately providing a more comprehensive and actionable framework for both theoretical inquiry and policy formulation.
- (4) The study also explores the differential effects of DEAI on pollution and carbon reduction. Moving beyond traditional analyses focused on city size and geographic location [25], it examines heterogeneity along three dimensions: government environmental concerns, the green energy transition, and spatial effects. This approach offers deeper insights into context-specific variations in the effectiveness of DEAI.

The remainder of this paper is organized as follows: Section 2 develops the theoretical framework and research hypotheses. Section 3 details the methodology, specifying the empirical model, definitions of the variables, and data sources. Section 4 presents the baseline regression results and a series of robustness tests. Section 5 investigates the underlying mechanisms, and Section 6 explores the effect of heterogeneity across critical urban dimensions. The findings and their wider implications are discussed in Section 7. Finally, Section 8 concludes the study by summarizing the core findings, discussing the corresponding policy implications, and noting the research limitations.

2. Theoretical Analysis and Hypothesis

2.1. Direct Impact of DEAI

2.1.1. Direct Impact of DEAI on Reducing Urban Pollution

Urban pollution reduction, targeting pollutants such as SO₂ and PM_{2.5}, relies heavily on precise monitoring and source control. From the perspective of environmental economics and the theory of externalities, pollution reduction represents a form of positive environmental externality that requires both regulatory and technological interventions. On the one hand, DEAI plays a pivotal role in the precise prediction and monitoring of pollutant emissions. Advances in big data technologies not only generate vast data streams but also uncover the intricate diversity and complexity of pollution sources [26]. By analyzing historical environmental data, AI can effectively identify pollution sources, discern emission patterns, and predict potential pollution events [27]. Artificial intelligence employs advanced architectures, including deep neural networks (DNNs) and convolutional neural networks (CNNs), to autonomously extract high-dimensional information from large environmental datasets, supporting the development of robust predictive models in multifactor and complex environmental systems [28]. On the other hand, DEAI fosters a synergistic effect on green production and innovation [29]. AI facilitates real-time monitoring of production processes, enabling precise identification of resource inefficiencies and energy wastage, thereby improving firms' environmental performance [30]. Furthermore, AI-driven green technology applications extend beyond isolated production stages, promoting a holistic and industry-wide transition toward sustainable development [31].

H1. *DEAI can promote urban pollution reduction.*

2.1.2. Direct Impact of DEAI on Urban Carbon Reduction

The actual effect of DEAI on urban carbon reduction is theoretically ambiguous, framed by the tension between the efficiency gains predicted by endogenous growth theory and the potential countervailing force of the rebound effect.

Some studies show that AI significantly contributes to carbon reduction [32]. In the realm of energy consumption and production, AI enables precise forecasting of the spatial and temporal distribution of energy demand and supply, allowing energy management systems to optimize energy allocation during peak and off-peak periods, thereby enhancing overall energy efficiency [33]. In terms of low-carbon technological innovation, AI accelerates the discovery of new materials and the simulation-based testing of low-carbon technologies, effectively shortening research and development cycles. Moreover, carbon emission monitoring and management, DEs provide real-time, large-scale foundational datasets, while AI plays a pivotal role in data processing, analysis, and model construction [34].

However, some studies have found that AI may also induce a carbon rebound effect [35]. In the early stages of DEAI, these technologies significantly reduced energy consumption and carbon emissions by enhancing production efficiency, optimizing energy management, and minimizing resource wastage [36]. Increases in production capacity and continuous market expansion may reduce or counteract the initial emission savings, producing effective reductions that are below expected levels [37]. Additionally, the widespread adoption of low-carbon technologies drives shifts in industrial structure, potentially facilitating the expansion of carbon-intensive industries, thereby exacerbating the carbon rebound effect [38]. Given that the rebound effect can partially offset the gains from technological efficiency, the net direct impact on carbon reduction is hypothesized to be inhibitory in the studied context.

H2. *DEAII may inhibit urban carbon reduction.*

2.2. Indirect Impact of DEAII

2.2.1. *Mediating Role of Technological Effect*

DEAII significantly enhances green total factor energy efficiency (GTFEE), a key metric that captures the joint achievement of economic output and environmental performance [39]. Big data technology consolidates data from sensors, smart devices, and environmental monitoring systems, while AI conducts in-depth learning and intelligent analysis based on multi-source data to identify potential pollution sources, carbon emission trends, and energy consumption patterns [40]. Furthermore, AI leverages both historical and real-time data to forecast future pollutant and carbon emission trends, providing a scientific foundation for the formulation of green policies [41]. This integration not only improves the effectiveness of green technology applications but also fosters their continuous innovation.

The technological effects of DEAII on pollution and carbon reductions are transmitted through multiple pathways. Specifically, the contributions of green energy technology progress (GETP) and green energy technology efficiency (GETE) operate through distinct mechanisms. (1) One key mechanism through which DEAII reduces both pollutants and carbon emissions is by fostering technological innovation in green energy [42]. However, these innovations are often accompanied by the expansion of production scale, which leads to an increase in energy demand, triggering the “energy rebound effect” [43]. Even if the green technology itself is energy-efficient, the increase in demand due to production expansion and the diffusion of technology can offset the initial benefits of emission reductions, potentially leading to higher energy consumption [44]. (2) Improvements in green technology efficiency typically have a more direct and sustained impact on carbon reduction. While green technology innovation focuses on the research, development, and application of new technologies, the improvement of green technology efficiency emphasizes the optimization and upgrading of existing technologies [45]. This efficiency improvement achieves pollution and carbon reduction by enhancing the energy efficiency of existing technologies and production systems [46].

H3a. *DEAII promotes pollution and carbon reduction primarily by enhancing GTFEE.*

H3b. *The impacts of DEAII on pollution and carbon reduction differ between GETP and GETE due to their distinct technical pathways.*

2.2.2. *Mediating Role of Structural Effect*

The structural effect of DEAII can be analyzed through the framework of new structural economics, which emphasizes the role of factor endowments in driving industrial and spatial structural evolution. DEAII, by introducing data as a new key factor endowment, provides substantial support for the advanced transformation of a city’s industrial structure. AI facilitates this transformation by optimizing production processes, enhancing energy management, and improving overall production efficiency [47]. The integration of data advantages and AI enables accurate market demand analysis and environmental monitoring, thereby enhancing the scientific basis of decision-making and steering industries towards low-carbon and environmentally sustainable practices [48]. Furthermore, DEAII accelerates the emergence of new industries, including green finance, smart green buildings, and digital green agriculture, which continue to replace the traditional high-energy-consuming and high-polluting industrial model [49].

H4a. DEAI influences pollution and carbon reduction by promoting industrial structure upgrading.

With the acceleration of urbanization, inefficient urban spatial structures pose significant challenges to pollution and carbon reduction, including resource waste, environmental pollution, and traffic congestion [50]. In urban spatial optimization, DEAI is primarily reflected in two key aspects: intelligent urban planning and refined management. AI and big data technologies assist decision-makers in formulating more scientific and forward-looking urban spatial planning strategies by accurately predicting and simulating future urban development trends [51]. Additionally, by analyzing land-use data, building density, and climatic data, inefficient areas in urban spatial layouts can be identified, helping to avoid disorderly and inefficient urban expansion [52]. The rational allocation of urban space through data-driven intelligent planning not only alleviates traffic congestion and resource wastage but also effectively controls pollutant and carbon emissions [53]. As shown in Figure 1, this pathway is a core mechanism for DEAI to achieve pollution and carbon reductions.

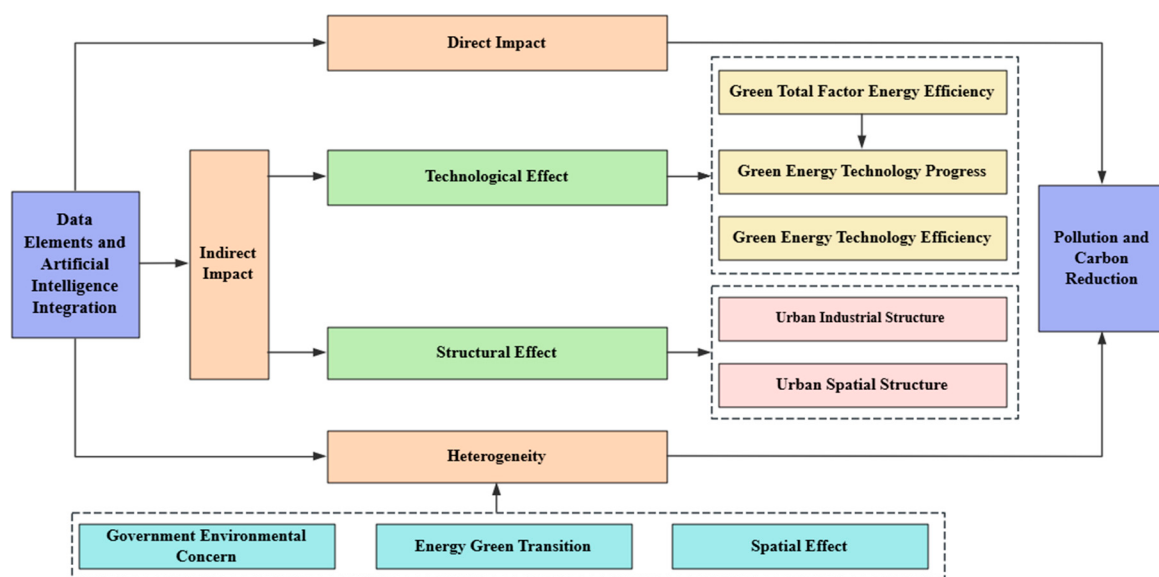


Figure 1. Theoretical framework for analyzing DEAI impacts.

H4b. DEAI influences pollution reduction and carbon reduction by optimizing urban spatial structure.

3. Research Design

3.1. Model Setting

To empirically examine the direct impact of DEAI on urban pollution and carbon reduction, the OLS fixed effects model is specified as follows:

$$POL_{it} = a_0 + \alpha_1 DEAI_{it} + \alpha_2 Controls_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

$$CO_{2it} = \beta_0 + \beta_1 DEAI_{it} + \beta_2 Controls_{it} + \mu_i + v_t + \varepsilon_{it} \quad (2)$$

where POL_{it} represents urban pollutant emissions, and CO_{2it} represents urban carbon emissions. $DEAI_{it}$ denotes the integration index of DEs and AI, i denotes city, and t denotes year. The coefficients α_1 and β_1 represent the effects of DEAI on urban pollutant emissions and carbon emissions, respectively. μ_i and v_t correspond to city-specific and province-year-specific fixed effects, ε_{it} is the error term.

To account for spatial interdependencies among urban pollutants and carbon emissions, a spatial Durbin model (SDM) is implemented to explore how DEAI affects environmental outcomes across neighboring cities.

$$POL_{it} = \rho_0 W \cdot Y_{it} + \gamma_1 DEAI_{it} + \gamma_2 X_{it} + \delta_1 W \cdot DEAI_{it} + \delta_2 W \cdot Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

$$CO_{2it} = \rho_1 W \cdot Y_{it} + \theta_1 DEAI_{it} + \theta_2 X_{it} + \vartheta_1 W \cdot DEAI_{it} + \vartheta_2 W \cdot Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (4)$$

where ρ_0 and ρ_1 represent the spatial autoregressive coefficients of urban pollutant emissions and carbon emissions, respectively, and W denotes the spatial weight matrix. The coefficients γ_1 and θ_1 measure the direct effects of DEAI on urban pollutant emissions and carbon emissions, while δ_1 and ϑ_1 capture the spatial spillover effects of DEAI.

3.2. Variables

3.2.1. Dependent Variables

In this study, pollutant and carbon emissions serve as the dependent variables. Pollutant emissions are represented by the logarithm of a synthesized index combining industrial wastewater, sulfur dioxide, and particulate emissions, while carbon emissions are measured as the logarithm of urban carbon output.

3.2.2. Independent Variable

Table 1 presents the measurement indicators for DEs and AI integration. DEs are assessed through a life-cycle-based evaluation index system encompassing three dimensions: generation and acquisition, processing and sharing, and application and associated benefits. Generation and acquisition are operationalized using metrics such as Internet users per 100 people, mobile phone users per 100 people, and per capita telecommunication service volume. Processing and sharing are evaluated using the share of employees in computer services and software industries, and per capita telecom revenue. Application and benefit realization are measured via DE utilization levels and the digital financial inclusion index [54], with utilization further determined by the disclosure frequency of five key technological indicators in corporate annual reports—AI, blockchain, big data, cloud computing, and big data applications.

Table 1. Measurement indicators for DE and AI integration.

Indicator	Secondary Indicator	Measurement	Property
DEs	DEs generation and acquisition	Internet users per 100 people	+
		Cell phone subscribers per 100 people	+
		Total telecommunications services per capita	+
	DEs processing and sharing	Percentage of Computer Services and Software Employees	+
		Per capita income from telecommunication services	+
	DEs application and benefits	Utilization Level of Data Elements Digital Inclusive Finance Index	+
AI	AI technology base and support	Robot Installation Density	+
	AI technology practice and application	Number of Artificial Intelligence Enterprises	+

Note: + denotes positive.

AI capacity is captured via the number of AI enterprises and the weighted density of industrial robot installations. Specifically, the density is derived by multiplying the number of robots installed in each sector, as reported by the IRF, by the sector's share of national employment. Employment figures are sourced from the China Labor Statistics Yearbook.

The entropy method is employed to calculate the comprehensive index of DEs and AI, respectively. This approach is chosen over alternatives such as Principal Component

Analysis (PCA) because the entropy method objectively determines the weights based on the variability of each indicator, without assuming linear relationships among variables, making it particularly suitable for heterogeneous urban panel data. On this basis, the modified coupling coordination degree model is applied to measure the degree of DEAI. The measurement process consists of the following steps:

- (1) Normalization of Indicators (r_{ij}): Since all measurement indices for DEs and AI are positive indicators, normalization is performed using the following formula:

$$r_{ij} = \frac{a_{ij} - \min_j \{a_{ij}\}}{\max_j \{a_{ij}\} - \min_j \{a_{ij}\}} \quad (5)$$

- (2) Calculation of Entropy Value (h_i): The entropy value of each indicator is computed to reflect its relative importance in the dataset.

$$h_i = -k \sum_{j=1}^n f_{ij} \ln f_{ij} \quad (6)$$

where $f_{ij} = r_{ij} / \sum_{j=1}^n r_{ij}$, $k = 1 / \ln n$.

- (3) Determination of Entropy Weight (w_i): The weight of each indicator is derived based on its entropy value, ensuring an objective distribution of indicator contributions.

$$w_i = \frac{1 - h_i}{m - \sum_{i=1}^m h_i} \quad (7)$$

where $0 \leq w_i \leq 1$, $\sum_{i=1}^m w_i = 1$.

- (4) Computation of the Composite Index (U): The comprehensive index is calculated using the entropy-weighted values of DE (U_i) and AI (U_j).

$$U = \sum_{j=1}^n r_{ij} w_{ij} \quad (8)$$

- (5) Application of the Modified Coupling Coordination Model: To assess DEAI, the modified coupling coordination model is applied to compute the coupling degree (C).

$$C = \sqrt{\left[1 - \frac{\sum_{i>j,j=1}^n \sqrt{(U_i - U_j)^2}}{\sum_{m=1}^{n-1} m} \right]} \times \left(\prod_{i=1}^n \frac{U_i}{\max U_i} \right)^{\frac{1}{n-1}} \quad (9)$$

- (6) Evaluation of System Coordination Degree: The overall coordination degree of DEs and AI is measured using the system's comprehensive coordination index (T).

$$T = \sum_{i=1}^n \alpha_i \times U_i, \sum_{i=1}^n \alpha_i = 1 \quad (10)$$

where α_i represents the weight of each system component, with $\alpha_1 = \alpha_2 = 0.5$.

- (7) Measurement of Integration Degree: The final degree of DEAI is determined.

$$DEAI = \sqrt{C \times T}, DEAI \in [0, 1] \quad (11)$$

where a higher value of DEAI indicates a stronger integration, while a lower value signifies weaker integration.

Based on the measurement results of urban DEAI, the mean change in DEAI from 2009 to 2021 is plotted for eastern, central, western, and national cities, as shown in Figure 2. From 2009 to 2021, the DEAI in eastern, central, western, and national cities exhibited a steady upward trend. The most significant growth in DEAI occurred in eastern cities, increasing from 0.071 to 0.261, with a higher average annual growth rate, reflecting eastern cities' leading position in digital technology application. In contrast, the DEAI in central cities increased steadily from 0.051 to 0.188, while in western cities,

it rose from 0.050 to 0.184. DEAI in central and western cities started at a lower level than in eastern cities but exhibited a significant acceleration in growth rate. The rapid growth of DEAI in central and western cities can be attributed to national policy support for balanced regional digital intelligence development, particularly through sustained investment in technological innovation, talent acquisition, and infrastructure construction, which has accelerated DEAI growth in these regions. Overall, eastern cities maintain a clear advantage in DEAI, but the growth potential in central and western cities is increasing.

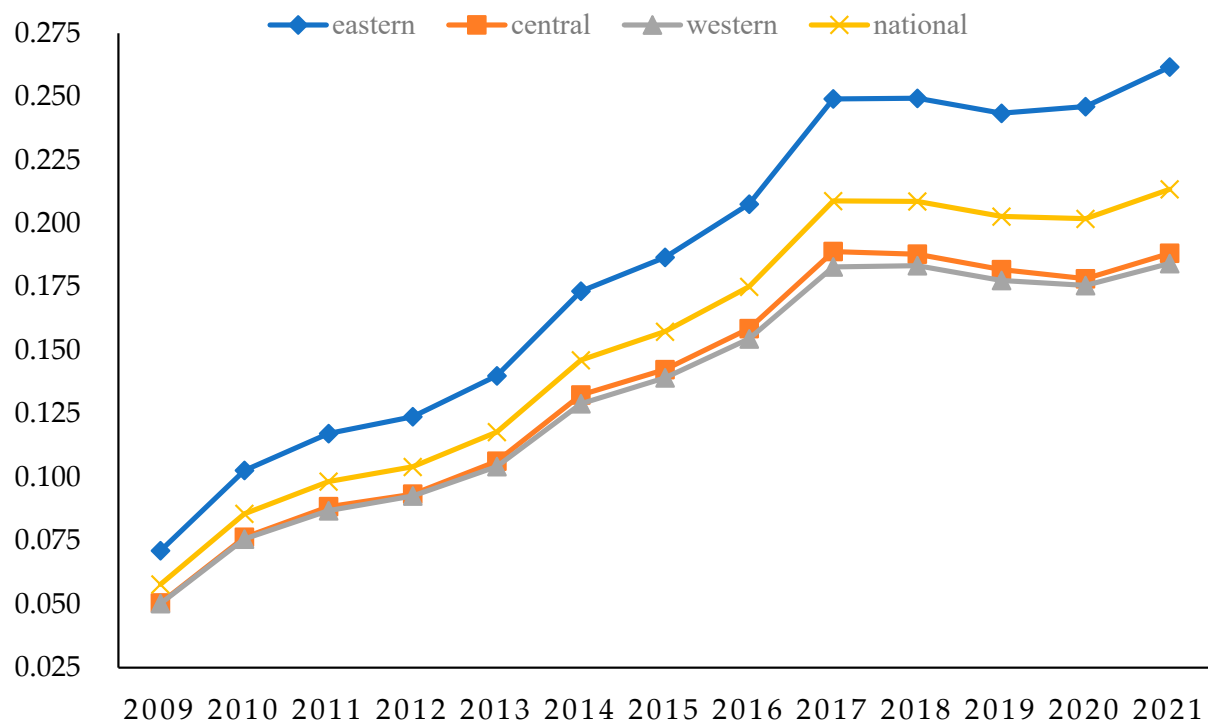


Figure 2. Annual average of DEAI in China (2009–2021).

Figure 3 presents the spatial distribution of China's DEAI from 2009 to 2021. Several distinct spatial evolution characteristics emerged. The eastern coastal region further solidified its DEAI advantage, as high-level clusters expanded in economically developed regions such as Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta. Meanwhile, disparities within central and western China intensified, with some provincial capitals and key economic hubs, including Chengdu, Wuhan, and Chongqing, experiencing substantial DEAI growth and accelerating their intelligent transformation. However, many cities in western China remained at lower levels, with regional development gaps persisting—or even widening—resulting in a “strong and getting stronger, weak and getting weaker” phenomenon. The northeastern region continued to lag behind, as traditional industrial cities such as Harbin, Changchun, and Dalian exhibited relatively slow progress in intelligent transformation, leading to DEAI growth significantly below the national average.

A notable trend was the increasing spatial diffusion of DEAI, wherein high-level cities extended their influence to surrounding second- and third-tier cities, forming regional growth poles. For example, cities such as Suzhou, Ningbo, and Dongguan experienced significant improvements in DEAI, indicating that DEAI is expanding beyond individual cities and permeating broader regions.

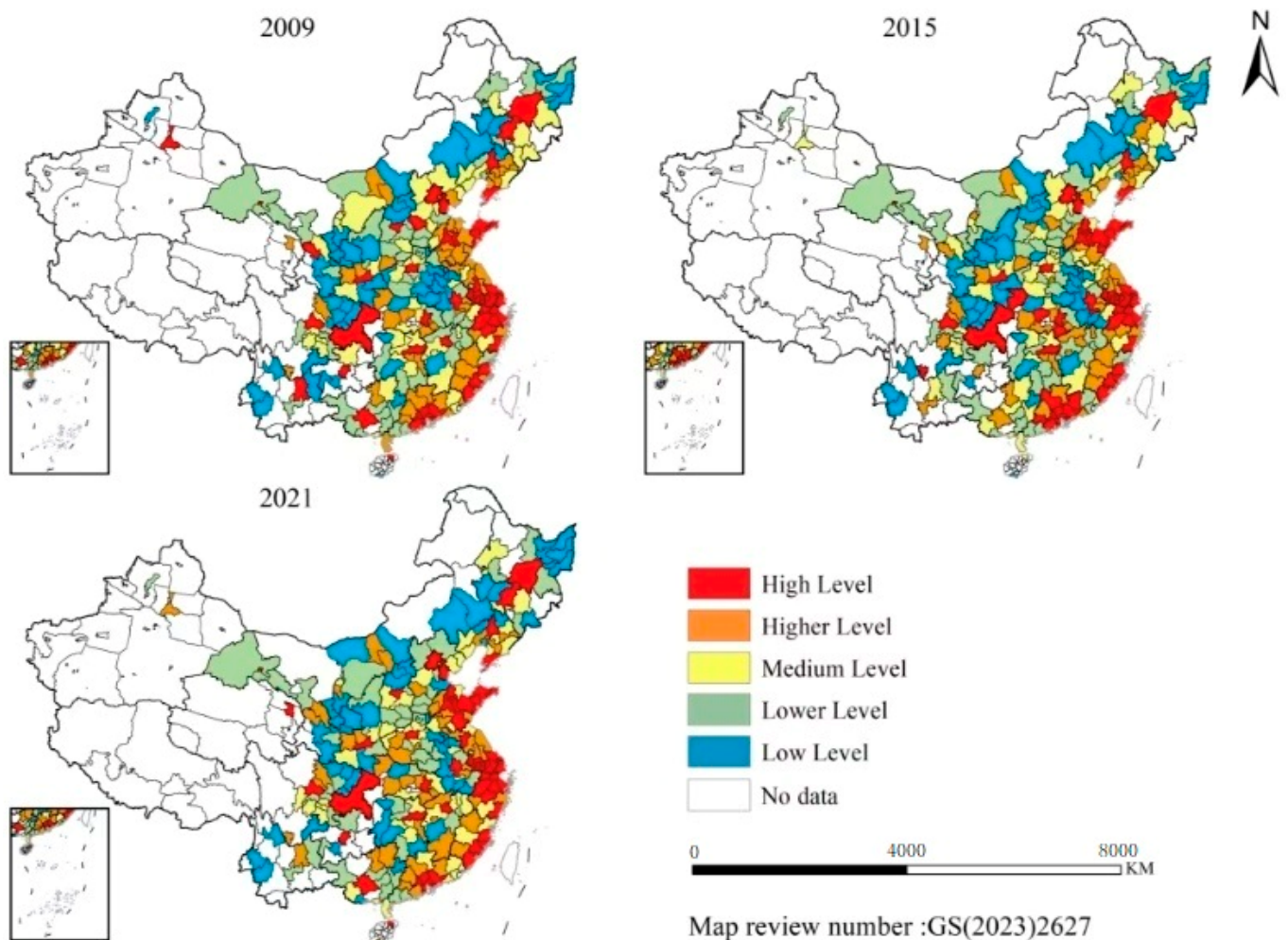


Figure 3. Spatial distribution of DEAII across Chinese prefecture-level cities (2009–2021).

3.2.3. Mechanism Variables

Theoretical analysis suggests that DEAII influences urban pollution reduction and carbon reduction through two key mechanisms: technological progress and structural optimization. In this study, GTFEE and its decomposition effects (GETP and GETE) serve as proxies for green energy environmental efficiency. Structural optimization encompasses both the upgrading of industrial structure and the optimization of urban spatial structure. Industrial structure upgrading is quantified through the measure of the advanced industrial structure (AIS), while urban spatial structure optimization is characterized by the degree of urban sprawl (US).

(1) GTFEE. To measure the level of green technological progress in urban areas, this study adopts GTFEE, which accounts for undesirable outputs. Table 2 presents the evaluation index system for urban GTFEE, where the input indicators include energy, land, capital, and labor, representing the essential resources required for achieving green technological advancement. Desired outputs consist of ecological and economic outputs, reflecting the dual objectives of economic growth and environmental improvement. Non-desired outputs include pollution and carbon emissions, which serve as critical indicators for monitoring the negative externalities arising during the transition process.

To quantify urban GTFEE, this study employs the super-efficiency Slack-Based Measure (SBM) model with undesirable outputs. Furthermore, the Global-Malmquist-Lupberger (GML) index method is applied to decompose GTFEE into GETP and GETE. This decomposition allows for a more precise investigation of how DEAII facilitates

technological spillovers, thereby influencing urban pollution reduction and carbon reduction pathways.

Table 2. Evaluation index system of GTFEE.

Indicator Type	Indicator	Measurement
Input	Energy	Total energy consumption
	Land	Built-up area
	Capital	Fixed capital stock
	Labor	Number of unit employees at the end of the year
Desired output	Ecological output	Green area of parks
	Economic output	Real GDP (real GDP at constant 2008 prices)
Undesired output	Pollutant emission	Composite index of industrial wastewater emissions, sulfur dioxide emissions and dust and fume emissions
	Carbon emission	Carbon dioxide emissions

(2) AIS. AIS denotes the process of advancing a region's industrial composition from a lower-order to a higher-order structure. This transformation is typically characterized by a shift in economic activity from agriculture-dominated sectors to those led by industry and services. It serves as a critical indicator of both economic development stages and the extent of industrial structure optimization. The calculation formula is as follows:

$$AIS_{it} = \sum_{n=1}^3 Y_{int} \times n, n = 1, 2, 3 \quad (12)$$

where AIS_{it} represents the AIS, and Y_{int} denotes the proportion of the n th industry in region i relative to GDP during period t . This index effectively captures the evolution of China's three-sector industrial structure, illustrating the gradual transition from primary industry dominance to secondary and tertiary industry dominance as reflected in the shifting proportions of these sectors over time.

(3) US. US refers to the phenomenon of uncontrolled urban expansion, typically characterized by the outward dispersal of population and economic activities from the urban core to surrounding areas. US is frequently associated with negative environmental and economic outcomes, including ecological degradation, inefficient resource utilization, and the intensification of the urban heat island effect. Night-time lighting serves as an objective proxy for industrial activity, commercial operations, and energy consumption, making it a valuable metric for assessing regional economic development. In this study, the spatial spread of 275 Chinese cities from 2009 to 2021 is quantified using nighttime lighting data combined with the LandScan global demographic analysis database. Urban areas are identified based on raster data where corrected nighttime lighting NPP-OLS brightness greater than or equal to 10 and population density greater than or equal to 1000 are taken as urban areas (raster). The measurement formula is as follows:

$$US_{it} = 0.5 \times (LA_{it} - LH_{it}) + 0.5 \quad (13)$$

where US_{it} represents the degree of US, LA_{it} denotes the proportion of urban areas with population density lower than the national average relative to total city area, and LH_{it} represents the proportion of urban areas with population density greater than or equal to the national average relative to total city area. The index ranges from 0 to 1, where values closer to 1 indicate a higher degree of US.

3.2.4. Control Variables

To account for factors affecting urban pollution and carbon reduction, the following control variables are included. Government Intervention (GI) is measured by local government expenditure relative to regional GDP, reflecting the extent of policy support. Industrialization (IND) is captured by the value added of the secondary industry as a proportion of regional GDP, indicating the industrial structure. Financial Development (FD) is represented by the ratio of year-end deposits and loans to the city's GDP, reflecting the availability of financial resources. Infrastructure (INF) is proxied by the logarithm of urban road area per capita, reflecting transportation capacity and spatial efficiency. Environmental Regulation (ER) is measured by the logarithm of investment in environmental pollution control, capturing the intensity of regulatory efforts. Finally, Openness (OPEN) is defined as the ratio of total imports and exports to city GDP, representing the level of economic openness.

3.3. Data Source

Data on AI enterprises and industrial robot installation density were sourced from the International Federation of Robotics (IFR) database, while the Digital Inclusive Finance Index was obtained from Peking University. Additional variables were collected from official statistical yearbooks, the China Research Data Service Platform, LandScan Global Vital Statistics Database, annual corporate reports, and government work reports. All empirical analyses were conducted using STATA 18. To address missing observations, linear interpolation was employed, yielding a complete panel dataset of 275 prefecture-level cities for 2009–2021.

Descriptive statistics are reported in Table 3. Mean values of POL and CO₂ reflect moderate pollution and carbon emission levels, with considerable cross-city heterogeneity. DEAI exhibits notable variation, indicating divergent trajectories in digital transformation and industrial upgrading. Control variables—including GI, IND, FD, INF, ER, and OPEN—also show substantial dispersion, capturing diverse economic structures, policy environments, and infrastructural conditions.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
POL	3575	4.018	1.437	0.000	8.871
CO ₂	3575	8.054	0.553	6.38	11.613
DEAI	3575	0.152	0.072	0.026	0.608
GI	3575	0.198	0.106	0.044	1.485
IND	3575	0.459	0.112	0.000	1.256
FD	3575	1.010	0.622	0.120	9.556
INF	3575	2.772	0.440	0.315	4.096
ER	3575	5.477	0.954	1.932	9.793
OPEN	3575	0.226	0.414	0.000	5.075
GTFEE	3575	0.228	0.179	0.014	1.311
GETP	3575	0.424	0.206	0.019	1.252
GETE	3575	0.692	0.209	0.031	1.469
AIS	3575	0.518	0.268	0.036	1.980
US	3575	0.774	0.140	0.165	0.975

4. Empirical Results

4.1. Baseline Results

Table 4 presents the regression results assessing the impact of DEAI on reductions in urban pollution and carbon emissions. Columns (1) and (2) display the results after

controlling for province-year and city fixed effects. The findings indicate that DEAI has a significantly negative effect on urban pollutant emissions, while it exerts a significantly positive effect on carbon emissions. This suggests that while the integration effectively promotes urban pollution reduction, it concurrently inhibits carbon reduction, thereby exhibiting the “pollution reduction but carbon increase” phenomenon. This outcome arises from two opposing mechanisms. On the one hand, DEAI enhances environmental governance and production efficiency through data-driven monitoring and intelligent regulation, effectively mitigating traditional pollutants. On the other hand, the operation of AI algorithms, data centers, and digital infrastructures demands substantial electricity for data processing and storage, much of which is still sourced from fossil fuels. Consequently, the energy consumption associated with digital-intelligent development offsets part of the carbon reduction benefits.

Table 4. Benchmark regression results.

Variable	POL	CO ₂	L.POL	L.CO ₂
	(1)	(2)	(3)	(4)
DEAI	−7.301 *** (−10.76)	1.013 *** (20.89)	−2.956 *** (−3.68)	0.992 *** (18.35)
Constant	−0.283 (−0.41)	7.848 *** (146.24)	−0.461 (−0.65)	7.824 *** (138.38)
City FE	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES
N	3575	3575	3300	3300
R ²	0.509	0.976	0.534	0.976

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

The regression analysis is re-conducted with the explanatory variables lagged by one period to assess the long-term impact of DEAI on urban pollution and carbon reductions. Columns (3) and (4) indicate that DEAI has a long-term positive effect on urban pollution reduction, but continues to increase carbon emissions in the long run. Consequently, this dual effect manifests as a “pollution reduction but carbon increase” phenomenon, underscoring the complex environmental trade-offs associated with digitalization and AI-driven technological advancements. Hypotheses 1 and 2 are validated.

4.2. Robustness Test

Table 5 presents the results of robustness tests conducted using three approaches: outlier treatment, exclusion of policy shocks, and replacement of the econometric model. The varying significance levels across specifications reflect the distinct challenges each test addresses: the 1% significance in columns (1)–(2) and (5)–(6) confirms strong robustness to outliers and measurement issues, while the 5% level in columns (3) and (4) indicates that policy shocks explain part of DEAI’s effect, yet its independent impact remains statistically meaningful.

Columns (1) and (2) report the results of outlier treatment tests. All continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values while retaining the full sample. Additionally, a robustness check excluded the four municipalities—Beijing, Tianjin, Shanghai, and Chongqing—to ensure that their exceptionally high DEAI levels and advanced digital infrastructure did not disproportionately affect the results. The estimated coefficients remain consistent in sign, magnitude, and significance with the baseline regressions, confirming the robustness of the findings against potential distortions from outliers and influential observations.

Table 5. Robustness test results.

Variable	POL	CO ₂	POL	CO ₂	POL	CO ₂
	(1)	(2)	(3)	(4)	(5)	(6)
DEAII	−7.764 *** (−11.09)	1.027 *** (20.15)	−7.035 *** (−9.64)	0.987 *** (18.38)	−7.281 *** (−11.10)	1.013 *** (21.76)
Constant	−0.473 (−0.68)	7.859 *** (145.78)	−0.548 (−0.79)	7.864 *** (144.97)	−0.330 (−0.50)	7.848 *** (152.38)
Controls	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES	YES	YES
N	3523	3523	3575	3575	3575	3575
R ²	0.501	0.957	0.511	0.976		

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

Columns (3) and (4) present the results of tests that account for policy shocks. Given that relevant pilot policies during the sample period may influence the regression outcomes, policy dummy variables are incorporated into the baseline regression model. Specifically, the regression controls for key pilot policies related to the construction of government data trading platforms, smart city initiatives, and the Broadband China pilot program. After accounting for these policy shocks, the signs of the regression coefficients remain largely unchanged, further validating the accuracy of the research findings.

Columns (5) and (6) report the results of the Tobit model test. Since DEAII is left-truncated, the Tobit model is employed to re-estimate the regression and enhance result reliability. The regression coefficients remain consistent with previous estimations, further confirming the robustness of the research conclusions.

4.3. Endogeneity Test

Table 6 presents the results of the endogeneity test, employing the instrumental variable (IV) method and the two-stage generalized method of moments (GMM) model to address potential endogeneity concerns. In this study, we construct interaction terms between the number of landline telephones per 100 people and DEAII as instrumental variables for the explanatory variable.

Table 6. Endogeneity test results.

Variable	DEAII	POL	CO ₂	POL	CO ₂
	(1)	(2)	(3)	(4)	(5)
IV	0.331 *** (31.55)				
DEAII		−5.472 *** (−4.34)	0.968 *** (9.32)	−8.273 *** (−11.11)	1.206 *** (19.85)
Constant	0.002 (0.13)	−1.020 (−1.54)	7.884 *** (144.90)	−0.571 (−0.95)	7.888 *** (161.52)
Controls	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES	YES
N	2532	2532	2532	3300	3300
R ²		0.479	0.980	0.501	0.977

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

Column (1) reports the first-stage regression results of the IV method, demonstrating that the instrumental variables pass both the correlation test and the weak instrument test, confirming their validity. Columns (2) and (3) present the second-stage regression results, showing that the regression coefficients of DEAII on pollutant emissions and carbon

emissions are -5.472 and 0.968 , respectively. These findings indicate that while DEAII significantly reduces urban pollutant emissions, it simultaneously contributes to increased carbon emissions.

To further ensure the robustness of the endogeneity test, the two-stage GMM estimation method is employed to account for potential heteroskedasticity. The results in columns (2) and (3) remain consistent with previous findings, further reinforcing the reliability of the research conclusions.

5. Mechanism Analysis

To investigate the underlying mechanisms driving the synergistic effects of pollution and carbon reduction facilitated by DEAII, and to accurately determine whether these effects stem from technological dividends or structural dividends, the following mechanism test model is as follows:

$$M_{it} = \tau_0 + \tau_1 DEAII_{it} + \tau_2 XControls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (14)$$

$$POL_{it} = \varphi_0 + \varphi_1 DEAII_{it} + \varphi_2 M_{it} + \varphi Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (15)$$

$$CO2_{it} = \omega_0 + \omega_1 DEAII_{it} + \omega_2 M_{it} + \omega_3 Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (16)$$

where M_{it} represents the mechanism variables, which include technological progress and structural optimization. Model (14) examines the impact of DEAII on these mechanism variables, while Models (15) and (16) assess the effects of the mechanism variables on urban pollutant emissions and carbon emissions.

5.1. Mediation Effect of GTFEE

Table 7 presents the results of testing the technological effects of DEAII. Column (1) reports the regression results for the impact of DEAII on urban GTFEE, with a significantly positive regression coefficient. This indicates that DEAII enhances urban GTFEE, demonstrating a technological progress effect.

Table 7. Mechanism test results of GTFEE.

Variable	GTFG	POL	CO ₂	POL	CO ₂	POL	CO ₂
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEAII	0.540 *** (7.75)	−5.915 *** (−8.80)	1.041 *** (21.35)	−7.318 *** (−10.75)	1.007 *** (20.76)	−7.102 *** (−10.42)	1.024 *** (21.09)
GTFEE		−2.567 *** (−10.26)	−0.051 *** (−3.29)				
GETP				0.036 (0.20)	0.013 (1.03)		
GETE						−0.555 *** (−4.09)	−0.029 ** (−2.48)
Constant	0.161 ** (2.42)	0.129 (0.19)	7.856 *** (145.04)	−0.285 (−0.42)	7.847 *** (146.76)	−0.182 (−0.27)	7.853 *** (145.54)
Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES	YES	YES	YES
N	3575	3575	3575	3575	3575	3575	3575
R ²	0.637	0.546	0.976	0.509	0.976	0.512	0.976

Note: The values of t are shown in parentheses. **, and *** indicate significance levels of 5%, and 1%, respectively.

Columns (2) and (3) provide the estimation results for the impact of DEAII and GTFEE on urban pollutant and carbon emissions. The negative and statistically significant effects of GTFEE suggest that DEAII has a synergistic effect on reducing both urban pollution and carbon emissions through green technological progress. Hypothesis 3a is validated.

To examine the technological transmission pathway through which DEAI influences urban pollution and carbon reductions, this study decomposes GTFEE into GETP and GETE using the GML index method.

Columns (4) and (5) present the regression results for GETP, where the regression coefficient is not statistically significant. This finding suggests that DEAI does not exert a substantial driving effect on GETP. The primary reason is that GETP captures the outward expansion of the technological frontier, representing breakthroughs in production possibilities. However, DE and AI remain predominantly applied within specific industries and have not effectively penetrated the realm of green technology research and development. Consequently, DEAI fails to push the boundaries of green technological innovation.

Columns (6) and (7) display the estimation results for GETE, revealing that its regression coefficients for pollutant and carbon emissions are both significantly negative. This indicates that DEAI significantly facilitates urban pollution reduction and carbon reduction by enhancing GETE. On the one hand, DEAI optimizes resource allocation and enhances data processing capabilities, thereby improving GETE. On the other hand, it fosters the intelligent management of pollution reduction and carbon reduction, making urban environmental governance more efficient. Hypothesis 3b is validated.

Therefore, the synergy between pollution reduction and carbon reduction primarily stems from improvements in GETE rather than advancements in GETP. This suggests that DEAI is more reliant on refining and applying existing technologies than on pioneering innovations that push the boundaries of green technology.

5.2. Mediation Effect of AIS and US

Table 8 presents the results of the industrial structure updating effect test of DEAI. Column (1) reports the estimated impact of DEAI on AIS, with a significantly positive regression coefficient. This finding suggests that DEAI effectively accelerates the transformation of urban industrial structures toward greater sophistication, confirming the presence of an industrial structure updating effect.

Table 8. Mechanism test results of AIS.

Variable	AIS	POL	CO ₂
	(1)	(2)	(3)
DEAI	0.414 *** (16.96)	−5.882 *** (−8.39)	0.905 *** (17.88)
AIS		−3.433 *** (−5.27)	0.262 *** (5.98)
Constant	2.352 *** (83.96)	7.792 *** (4.71)	7.231 *** (61.91)
Controls	YES	YES	YES
City FE	YES	YES	YES
Province × Year FE	YES	YES	YES
N	3575	3575	3575
R ²	0.939	0.516	0.977

Note: The values of t are shown in parentheses. *** indicates significance level of 1%.

Column (2) evaluates the influence of DEAI, in conjunction with AIS, on urban pollutant emissions. The results indicate that DEAI reduces urban pollutant emissions via its effect on AIS by promoting the shift from highly polluting industries to more efficient, environmentally sustainable sectors. This reflects enhanced production efficiency and stricter environmental compliance driven by digital-intelligent monitoring.

Column (3) assesses the impact of DEAI, as well as AIS, on urban carbon emissions. The positive impact of AIS on carbon emissions suggests that in the short term, industrial

upgrading may increase energy intensity and temporarily rely on fossil-fuel-based production, as advanced machinery, AI systems, and digital infrastructures require substantial electricity, leading to higher carbon emissions. This short-term increase is consistent with the “rebound effect” observed in technological transitions, where initial efficiency gains are offset by higher energy consumption. However, in the medium term, as production processes optimize, energy efficiency improves, and cleaner technologies are adopted, AIS is expected to mitigate carbon emissions, a pattern supported by studies showing delayed but positive environmental impacts of industrial and digital upgrading [55].

While DEAI facilitates cleaner production and pollution control via industrial transformation, the associated energy consumption or reliance on carbon-intensive processes may offset potential carbon reduction, highlighting the complexity of DEAI in achieving both pollution and carbon reduction [56]. Hypothesis 4a is partially supported.

Table 9 presents the test results for the urban spatial structure optimization effect of DEAI. Column (1) reports the estimated impact of DEAI on US, with a significantly negative regression coefficient. This finding suggests that DEAI effectively curtails urban sprawl and excessive spatial expansion, thereby confirming the existence of a spatial structure optimization effect. Columns (2) and (3) provide estimates of the effects of DEAI and US on pollutant emissions and carbon emissions, respectively. The significantly negative regression coefficients of US indicate that DEAI mitigates urban pollutant emissions and carbon emissions by constraining spatial expansion. On the one hand, DEAI optimizes the spatial configuration of urban development, reducing energy consumption and traffic-related emissions resulting from uncontrolled expansion while fostering a more compact and efficient urban growth model [15]. On the other hand, through intelligent urban space management and planning, DEAI enhances the efficiency of resource allocation and utilization within limited spatial boundaries, thereby further lowering urban pollutant emissions and carbon emissions [57]. Hypothesis 4b is validated.

Table 9. Mechanism test results of US.

Variable	US	POL	CO ₂
	(1)	(2)	(3)
DEAI	−0.205 *** (−9.10)	−10.120 *** (−17.14)	0.981 *** (19.46)
US		−13.736 *** (−16.01)	−0.156 *** (−2.93)
Constant	0.919 *** (61.12)	12.345 *** (12.40)	7.991 *** (109.50)
Controls	YES	YES	YES
City FE	YES	YES	YES
Province × Year FE	YES	YES	YES
N	3575	3575	3575
R ²	0.965	0.571	0.976

Note: The values of t are shown in parentheses. *** indicates significance level of 1%, respectively.

Therefore, the synergistic effect of DEAI on pollutant and carbon reductions stems primarily from the optimization of US rather than AIS.

6. Heterogeneity Test

6.1. Heterogeneity of Government Environmental Concern (Appendix A)

To accurately evaluate the impact of government environmental governance, keywords related to environmental governance in government reports were statistically analyzed using Python 3.11.5 web-crawling technology. This analysis quantified the government’s environmental concern index, which serves as a proxy variable to measure the level of

governmental attention to environmental issues. Based on the average values from a sample of 275 prefecture-level cities spanning the period from 2009 to 2021, the level of governmental environmental concern was classified into two groups: “low-level” and “high-level”. Regression estimations were then conducted separately for each group. Table 10 presents the results of the heterogeneity test of government environmental concern. Columns (1) and (2) present the results of the regressions for low levels of government environmental concern, while columns (3) and (4) show the results for high levels of government environmental concern.

Table 10. Heterogeneity test results of government environmental concern.

Variable	POL	CO ₂	POL	CO ₂
	(1)	(2)	(3)	(4)
DEAII	−5.879 *** (−5.96)	0.856 *** (11.84)	−7.927 *** (−7.72)	0.918 *** (15.00)
Constant	−1.710 (−1.18)	10.204 *** (90.24)	−1.780 * (−1.80)	7.743 *** (147.22)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES
N	1768	1768	1807	1807
R ²	0.489	0.978	0.523	0.967

Note: The values of t are shown in parentheses. *, and *** indicate significance levels of 10%, and 1%, respectively.

Column (1) indicates that at low levels of government environmental concern, the regression coefficient for pollutant emissions is −5.879, suggesting that a higher level of governmental concern for environmental protection significantly contributes to pollution reduction. Column (3) shows that at high levels of government environmental concern, the regression coefficient for pollutant emissions is −7.927, implying that the effect of pollution reduction is more pronounced when the government exhibits a stronger commitment to environmental governance. However, columns (2) and (4) reveal that carbon emissions exhibit an increasing trend under both low and high levels of environmental concern. This finding suggests that the “pollution reduction but carbon increase” effect associated with DEAII persists regardless of variations in governmental environmental governance intensity. DEAII reduces pollutants by improving industrial efficiency, optimizing production, and enabling real-time monitoring, enhancing the effectiveness of government environmental policies. However, AI systems, data centers, and digital infrastructures require substantial energy, often from fossil fuels, which increases carbon emissions and offsets pollution gains.

Consequently, even under high government attention, DEAII simultaneously achieves cleaner production while raising carbon output, highlighting a trade-off between air quality improvement and low-carbon objectives in the digital and intelligent transformation.

6.2. Heterogeneity of Green Energy Transition

The level of urban green energy transition is assessed by the establishment of new-energy pilot cities; Table 11 presents the results of the heterogeneity test. Columns (1) and (2) display the regression results for non-new-energy pilot cities, while columns (3) and (4) show the results for new-energy pilot cities.

The regression coefficients for DEAII on urban pollutant emissions in columns (1) and (3) are −7.751 and −9.875, respectively. The regression coefficients for DEAII on carbon emissions in columns (2) and (4) are 1.033 and 0.480, respectively. The heterogeneity results suggest that DEAII significantly reduces urban pollutant emissions, with stronger effects in new-energy pilot cities. This is because pilot cities typically implement cleaner energy

infrastructures, higher shares of renewable electricity, and stricter emission standards, which amplify the pollution reduction effects of DEAI. At the same time, the increase in carbon emissions associated with DEAI is notably lower in pilot cities, as renewable energy adoption reduces the carbon intensity of AI operations, data centers, and industrial processes. Therefore, while DEAI drives cleaner production and efficiency gains universally, the presence of supportive renewable energy policies in pilot cities mitigates the carbon rebound effect.

Table 11. Heterogeneity test results of green energy transition.

Variable	POL	CO ₂	POL	CO ₂
	(1)	(2)	(3)	(4)
DEAI	−7.751 *** (−9.91)	1.033 *** (18.70)	−9.875 *** (−3.68)	0.480 ** (2.45)
Constant	−0.707 (−0.99)	7.843 *** (143.37)	−26.525 *** (−6.63)	7.048 *** (24.56)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES
N	3087	3087	488	488
R ²	0.540	0.976	0.468	0.981

Note: The values of t are shown in parentheses. **, and *** indicate significance levels of 5%, and 1%, respectively.

6.3. Heterogeneity of Spatial Effect

Under the economic–geographical nested matrix, the global Moran’s I values for urban pollution reduction and carbon reduction from 2009 to 2021 are all significantly positive, indicating a strong positive spatial correlation between urban pollution reduction and carbon reduction throughout the study period. The results of the spatial heterogeneity test are presented in Table 12.

Table 12. Heterogeneity test results of spatial effect.

Variable	POL	Direct Effect	Indirect Effect	Total Effect	CO ₂	Direct Effect	Indirect Effect	Total Effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEAI	−3.452 *** (−7.45)	−3.338 *** (−7.15)	3.308 *** (2.75)	−0.030 (−0.03)	0.196 ** (2.35)	0.206 ** (2.44)	0.610 *** (5.16)	0.816 *** (9.01)
W * DEAI	3.452 *** (4.25)				0.507 *** (4.44)			
ρ	0.427 *** (14.24)				0.130 *** (3.75)			
Controls	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Province × Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3575	3575	3575	3575	3575	3575	3575	3575
R ²	0.336	0.336	0.336	0.336	0.631	0.631	0.631	0.631

Note: The values of t are shown in parentheses. **, and *** indicate significance levels of 5%, and 1%, respectively.

Regarding local effects, columns (1) and (5) show that DEAI effectively promotes local urban pollution reduction, but also leads to increased local carbon emissions. This can be attributed to two main factors: first, DEAI drives the transformation of high-carbon industries and technological advancements [58]. While this reduces pollutant emissions, the expansion of high-carbon industries and technological upgrades increases energy demand, contributing to higher carbon emissions. Second, the widespread application of technologies such as big data and AI facilitates the establishment of numerous data centers and servers, which require significant energy resources, further driving up carbon emissions [59]. Consequently, while DEAI promotes urban pollution reduction, the total carbon emissions rise due to the increased output value driven by these new technologies.

In terms of spatial effects, columns (1) and (5) indicate that DEAI exerts a positive spillover effect on pollutant and carbon emissions in neighboring cities, suggesting that

these cities have not fully benefited from DEAI-driven green transformations. Instead, they experience negative externalities, resulting in increased pollutant and carbon emissions. This phenomenon is conceptualized as the digital–intelligence divide, defined as the disparity across regions in the capacity to generate, process, share, and apply data elements and artificial intelligence for productive purposes.

Within the spatial Durbin model, the digital–intelligence divide is operationalized through the positive and statistically significant spatial lag coefficient for DEAI. A positive coefficient indicates that higher DEAI levels in one city are associated with increased emissions in neighboring cities, providing empirical evidence of the divide’s constraining effect. The digital–intelligence divide impedes the flow and sharing of technology and innovation resources across regions, thereby hindering the diffusion of green technologies and innovations to neighboring areas [60]. Consequently, the digital–intelligence divide not only limits the spatial diffusion of green transformation effects but also exacerbates regional disparities in the realization of environmental improvements.

Columns (2)–(4) and (6)–(8) display the results of spatial effect decomposition. The regression results for direct, indirect, and total effects further confirm the spatial variability in the impact of DEAI on reducing urban pollution and carbon emissions.

7. Discussion

This study examines the effects and pathways through which DEAI influences reductions in urban pollution and carbon emissions, highlighting the dynamic contradictions and complexities inherent in its mechanism of action—factors that have been largely overlooked in traditional synergistic effect research paradigms. In contrast to the existing literature, which predominantly emphasizes the unified idea of “pollution reduction and carbon reduction synergy” [1], this study reveals that the impact of DEAI on urban pollution and carbon reductions exhibits significant phase heterogeneity. Specifically, during the observation period, a phenomenon of “pollution reduction but carbon increase” emerges.

While traditional studies have predominantly focused on the synergistic effects of the digital economy on reducing pollution and carbon emissions [61], this study underscores that the “pollution reduction but carbon increase” phenomenon observed in DEAI indicates significant phase differences in its environmental effects. From the perspective of technology life cycle theory, this finding can be explained as follows: In the early stages of DEAI, the application of DEs is primarily concentrated on pollution monitoring and production process optimization, which directly contributes to pollution reduction. However, the growth in AI-driven energy consumption leads to a temporary increase in carbon emissions [54]. As the technology matures, the optimization of AI algorithms for energy efficiency and the enhanced adaptability of clean energy sources serve to reduce carbon emissions, thereby diminishing their marginal growth [62]. Notably, the enhancement of GETE, rather than GETP, emerges as the core driver of synergies, suggesting that Chinese cities primarily rely on improving the efficiency of existing technological systems rather than achieving original technological breakthroughs to realize pollution and carbon reduction synergies [63].

Existing research has frequently examined the synergistic effects of pollution reduction and carbon reduction from the perspective of AIS [64]. However, this study identifies that AIS, in fact, produces a “pollution reduction but carbon increase” effect. This contradiction may stem from the rigidity of the energy consumption structure in high-value-added industries during the digitization process, where reliance on energy-intensive infrastructure—such as data centers—implicitly increases carbon emissions. In contrast, the optimization of urban spatial structure demonstrates a significant synergistic effect on pollution and carbon reductions [65]. By strategically planning the layouts of functional zones in urban

areas and optimizing transportation and logistics networks, DEAI can effectively mitigate eco-land encroachment and reduce carbon emissions associated with commuting, which result from US [66]. This finding unveils a previously overlooked dimension of spatial governance in the literature, suggesting that DEAI generates an environmental synergistic dividend by restructuring the spatial structure of cities.

8. Conclusions and Limitations

8.1. Conclusions

This study identifies the differential impacts of DEAI on urban pollution reduction and carbon reduction by constructing an evaluation index system for DEs and AI and applying a modified coupled coordination degree model to measure DEAI. From the perspectives of technological dividends and structural dividends, the study explores the mechanisms through which DEAI synergistically promotes urban pollution reduction and carbon reduction. Additionally, the heterogeneous characteristics of DEAI's effects on urban pollution reduction and carbon reduction are analyzed in relation to government environmental concern, energy transition policy, and spatial dynamics. The study's conclusions are as follows:

First, the baseline regression results demonstrate that DEAI significantly reduces urban pollutant emissions but increases carbon emissions, confirming Hypotheses 1 and 2 and highlighting the phenomenon of “pollution reduction but carbon increase.” Over the long term, DEAI continues to drive urban pollution reduction while sustaining carbon emissions growth, though the marginal effect of the carbon emissions increase exhibits a declining trend.

Second, from the perspective of technological effects, the mechanism analysis indicates that DEAI significantly enhances GTFEE, confirming Hypothesis 3a. The associated reductions in urban pollution and carbon emissions mainly occur through improvements in GETE rather than GETP, thereby validating Hypothesis 3b.

The structural effect analysis indicates that, from the perspective of industrial structure optimization, DEAI significantly advances AIS, thereby exerting an industrial structure optimization effect. However, AIS also leads to the short-term phenomenon of “pollution reduction but carbon increase,” as DEAI alone does not fully achieve carbon reduction through industrial restructuring, partially supporting Hypothesis 4a.

From the perspective of urban spatial structure optimization, DEAI effectively curtails the disorderly expansion of urban areas, demonstrating a clear spatial structure optimization effect. Furthermore, by mitigating urban sprawl, DEAI fosters simultaneous reductions in both pollutant and carbon emissions, validating Hypothesis 4b.

Overall, the primary drivers of DEAI's synergistic effect on pollution and carbon reduction are improvements in GETE and the optimization of urban spatial structure, rather than industrial restructuring alone.

Third, the heterogeneity analysis reveals the following insights: (1) Regarding government environmental concern, while urban pollutant emissions decline under both high- and low-policy intervention scenarios, carbon emissions consistently exhibit an increasing trend. This suggests that government environmental concern exerts a dual moderating effect on both pollution reduction and carbon reduction. (2) In terms of green energy transition, pilot cities for new energy initiatives demonstrate superior pollution reduction performance but fail to effectively curb short-term carbon emissions growth. In contrast, non-pilot cities exhibit weaker pollution reduction effects and more pronounced carbon emissions growth, underscoring the critical role of the implementation intensity of energy transition policies. (3) Regarding spatial heterogeneity, DEAI effectively promotes pollution reduction in local cities but inhibits carbon reduction. Additionally, DEAI increases both pollutant emis-

sions and carbon emissions in neighboring cities, indicating that the “digital intelligence divide” constrains the intercity flow of technological and innovation resources, thereby exacerbating disparities in green and low-carbon transitions among cities.

8.2. Limitations

While this study provides a comprehensive analysis of the environmental effects of DEAI, several limitations should be acknowledged. First, the construction of the DEAI index, though based on a systematic life-cycle framework, relies on proxy indicators at the city level; future studies could benefit from more granular, firm-level data to capture integration dynamics more precisely. Second, our spatial econometric model employs a conventional geographical distance matrix, which, while well-established, may not fully capture complex intercity relationships based on economic or informational linkages. Furthermore, institutional factors such as the definition of DEs’ property rights and the ethical regulation of AI algorithms may influence the environmental effects of DEAI, opening new avenues for interdisciplinary research.

These factors indicate that the results may not be directly generalizable to regions with substantially different legal, technological, or policy environments. Future studies could investigate the role of firm-level data, sectoral differences, and city-specific institutional frameworks to better understand the mechanisms through which digital technologies drive sustainable urban development, thereby extending the insights of the current study and informing policy design.

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Abbreviations

The following abbreviations are used in this manuscript:

DEAI	Data Elements and Artificial Intelligence Integration
GTFEE	Green Total Factor Energy Efficiency
GETP	Green Energy Technology Progress
GETE	Green Energy Technology Efficiency
AIS	Advanced Industrial Structure
US	Urban Sprawl

Appendix A

Government Environmental concern Keywords:

Emissions, Ammonia, PM10, Intensive, Green, Emissions, Energy, Air Quality, Particulate Matter, Dust, Pollution Control, Environmental Quality, Coal to Gas, Water Consumption, Coal to Electricity, Household Waste, Energy Consumption, Carbon Dioxide, Air Pollution, Environment, Low Carbon, Central Heating, PM2.5, Pollution, Pollution Control, Conservation, Haze, Consumption, New Energy, Sewage Treatment, Dust Reduction, Emission Reduction, Nitrogen Oxides Reuse, Pollution Prevention, Clean Energy, Sustainable Development, Pollutants, Recycling, Air, Environmental Protection, Sulfur Dioxide, Greenhouse Gases, Renewable, Resources, Ecological Pollution Control, Environmental Protection, Greening, Waste, Garbage, Green Development, Environmental Protection Inspectors.

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