

How Does Industrial Intelligentization Promote the Synergistic Reduction of Urban Pollution and Carbon Emissions? Evidence from Macro- and Micro-Level Mechanisms

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Abstract

Reconciling pollution abatement with carbon mitigation is central to China's green transition, yet the role of industrial intelligentization in advancing this synergy remains poorly understood. Drawing on panel data for 272 Chinese prefecture-level cities over 2011–2022, this study constructs a composite index of industrial intelligentization along three dimensions—intelligentization conditions, applications, and technologies—and empirically examines how it shapes the synergistic reduction of urban pollution and carbon emissions through both macro- and micro-level channels. Three main findings emerge. First, industrial intelligentization significantly enhances the synergistic reduction of urban pollution and carbon emissions, and this result is robust to a battery of robustness checks and to instrumental-variable estimation that addresses endogeneity. Second, mechanism tests show that at the macro level industrial intelligentization operates by raising urban green innovation, upgrading the industrial structure, and strengthening public environmental awareness, whereas at the micro level it works by reinforcing corporate environmental responsibility and easing firm-level information asymmetry. Third, the effect is heterogeneous: it is more pronounced in eastern and provincial-capital cities, in cities with higher economic development or lower industrialization, in cities with stronger environmental regulation or greater fiscal decentralization, and in non-resource-based and high-skill cities. By linking macro-level industrial and social channels to micro-level firm behavior, the study provides new evidence on the environmental dividends of industrial intelligentization and offers policy insights for building an intelligence-driven system of environmental governance.

JEL Classification: O33; Q55; Q56; R11

1. Introduction

China's economy is entering a stage of comprehensive green transformation, in which the coordinated advancement of carbon mitigation, pollution abatement, ecological expansion, and growth has become a defining goal of high-quality development. The report of the 20th National Congress of the Communist Party of China set out a strategic path for green transition, and successive national planning documents have emphasized the integrated development of intelligentization, greening, and cross-domain convergence, providing top-level guidance for aligning industrial upgrading with ecological civilization. As ecological governance and economic development enter a phase of deeper integration, how to organically unify pollution–carbon reduction with quality and efficiency improvement has become a pressing question of the transition period.

A new round of technological revolution and industrial transformation is unfolding, and the pervasive diffusion of industrial intelligentization is reshaping both the organization of production and the mode of environmental governance. Intelligent technologies represented by industrial robots exhibit capabilities of self-perception, self-learning, and self-decision, and can provide technological support for easing the twin constraints of development and emission reduction through whole-process production optimization, improvements in resource and energy efficiency, and precise pollution control. Against this backdrop,

systematically uncovering the internal mechanisms and realization pathways through which industrial intelligentization enables the synergistic governance of urban pollution and carbon emissions carries considerable theoretical and practical significance for advancing the green transformation of the development model and for reconciling high-quality economic growth with high-level environmental protection.

The synergistic reduction of pollution and carbon emissions lies at the heart of coordinating environmental protection with green, low-carbon development, and a rich literature has examined its realization pathways along three lines—technological, structural, and policy channels. On the technological side, the adoption of new-energy vehicles and advances in energy-saving technologies can effectively curb carbon emissions and air pollutants (Alimujiang and Jiang, 2020), while the development of digital technologies and digital finance also exerts a significant effect on the pollution–carbon synergy (Han et al., 2023; Guo and Wang, 2023). On the structural side, the optimization of the energy mix and the upgrading of the industrial structure are widely regarded as key pathways, and structural emission reduction has been shown to be more conducive to the synergy than technological emission reduction alone (Yang et al., 2022). On the policy side, most studies find that the setting of governmental environmental and economic targets (Li et al., 2022), emission- and carbon-trading schemes (Lu et al., 2022), and environmental regulations such as cleaner-production standards (Sun and Zheng, 2024) all help achieve the synergy, although some evidence suggests that environmental policy cannot simultaneously reduce carbon dioxide and air pollutants (Du and Li, 2020).

As research on the realization pathways of pollution–carbon reduction has matured and industrial intelligentization has advanced, scholars have begun to examine the environmental effects of intelligentization. However, most studies focus on a single dimension—either pollution abatement or carbon mitigation—and overlook the fact that the two share common roots and are inherently synergistic. On the carbon-mitigation dimension, most studies confirm that industrial intelligentization suppresses carbon emissions through technological progress and production intensification, with both industrial-robot adoption and industrial digital transformation exhibiting significant carbon-reduction effects (Jiang et al., 2022), although some research notes that the application of intelligent technologies can raise energy consumption and that the carbon-reduction effect displays a stage-specific pattern of diminishing marginal returns (Huang and Jiang, 2023). On the pollution-control dimension, the positive role of industrial intelligentization is widely recognized, as intelligent manufacturing and intelligent governance effectively lower firms' pollutant emissions and improve environmental performance (Sheng and Bu, 2022); urban industrial intelligentization has also been found to generate negative spatial spillovers that reduce the carbon intensity of neighboring cities (Wang and Luo, 2025).

Overall, the existing literature tends to treat the pollution-abatement and carbon-mitigation effects of industrial intelligentization separately, and dedicated studies of how industrial intelligentization drives their synergy remain scarce. The few related works either rely on provincial samples to verify macro transmission pathways such as industrial and energy structure (Fan, 2026) or use firm-level samples to explore micro channels such as corporate governance and production efficiency (Han et al., 2026). Few

studies integrate the macro and micro perspectives, and the complete logical chain—through which industrial intelligentization extends from the macro industrial and social levels to the micro firm level to enable the synergistic reduction of urban pollution and carbon emissions—has not been systematically articulated.

Motivated by these gaps, this study uses a sample of 272 Chinese prefecture-level cities over 2011–2022 to systematically examine the effect of industrial intelligentization on the synergistic reduction of urban pollution and carbon emissions and its underlying mechanisms. The marginal contributions are threefold. First, the analytical perspective is extended to the urban level. By incorporating industrial intelligentization and the pollution–carbon synergy into a unified framework and focusing on the meso-level of prefecture-level cities, the study addresses the limitation of prior work that concentrates on the provincial macro level or the firm micro level. Second, the treatment of mechanisms is more systematic and complete. By integrating the macro and micro perspectives, the study clarifies multiple transmission pathways—green innovation, industrial-structure upgrading, and public environmental awareness at the macro level, and the strengthening of corporate environmental responsibility and the easing of information asymmetry at the micro level—thereby providing systematic theoretical and empirical support for the internal logic through which industrial intelligentization drives the synergy. Third, the heterogeneity analysis is more comprehensive and targeted. The study conducts heterogeneity tests across four dimensions and eight sub-characteristics—urban location and administrative rank, economic-development foundation, institutional environment, and factor endowment—thereby identifying differences in effects across urban contexts and offering more granular and targeted evidence for advancing intelligentization in a locally adapted manner and for the precise implementation of urban pollution–carbon governance policies.

2. Theoretical Analysis and Research Hypotheses

2.1 The direct effect of industrial intelligentization on the urban pollution–carbon synergy

Industrial intelligentization refers to the deep integration of a new generation of information technologies with industrial manufacturing, whereby data-driven production achieves self-perception, self-learning, self-decision, and self-execution, moving industry toward the high end of the value chain, realizing society-wide intelligent manufacturing, and providing impetus for economic growth and structural change. On the one hand, relying on intelligent technologies, firms can conduct real-time dynamic monitoring of the entire production process, precisely identify energy- and pollution-intensive production stages, and optimize processes in a targeted manner (Li et al., 2024); while raising resource-use efficiency and reducing wasteful resource loss, they can also promote the recycling and harmless disposal of waste, effectively lowering energy consumption and pollution intensity per unit of output. On the other hand, industrial intelligentization markedly improves the precision and efficiency of production processes through high-precision control systems, avoids material waste caused by human error, and

reduces the excessive consumption of raw materials, thereby cutting the emission of greenhouse gases and pollutants in the production process (Yan et al., 2020).

H1: The development of industrial intelligentization significantly promotes the synergistic reduction of urban pollution and carbon emissions.

2.2 The mechanisms through which industrial intelligentization affects the urban pollution–carbon synergy

2.2.1 Macro-level mechanisms

(1) Green innovation

The deep integration of digital-intelligent technologies with industrial production breaks down long-standing barriers between industries and injects new momentum into urban green-technology innovation and the transformation and upgrading of the industrial structure (Zhang et al., 2024). On the one hand, the data-sharing dividends brought by digital-intelligent technologies strengthen inter-regional information exchange, and cross-region, cross-industry, and cross-firm collaborative R&D models provide an efficient organizational architecture for regional green innovation, improving the efficiency of green-technology communication among R&D departments; at the same time, more timely and accurate information on resource consumption and abatement costs obtained through intelligent technologies supports green-technology innovation. On the other hand, industrial intelligentization can secure an adequate supply of high-quality talent: the diffusion of intelligent technologies frees labor from repetitive and simple tasks, continuously lowering the share of low-skill jobs (Wang and Dong, 2020), while firms, given the stronger knowledge-absorption and technology-conversion capacity of high-skill workers, tend to employ more high-skill talent for intelligent manufacturing. This optimization of human capital helps reduce the uncertainty of applying external green technologies and accelerates their digestion, absorption, and imitation.

Green innovation can reduce firms' resource loss and abatement costs and, by easing the constraints of renewable energy while reducing dependence on energy-intensive raw materials, lowers the emission of pollutants in the production process (Dai et al., 2025). Moreover, the widespread adoption of green-innovation technologies can further reduce the price of green products, shape public consumption preferences, and guide consumers toward green purchases, helping to foster a green and low-carbon consumption climate; rising recognition of green products in turn compels firms toward green production, thereby realizing the pollution–carbon synergy.

(2) Industrial-structure upgrading

Industrial intelligentization exerts a pronounced effect on industrial-structure upgrading in two ways. First, it can empower the transformation and upgrading of traditional industries (He and Zhao, 2021): by

introducing intelligent technologies, energy- and pollution-intensive traditional industries can achieve automated, intelligent, and networked renewal of their production processes, moving toward high-end, intelligent, and green development. Second, it helps give rise to new business forms and models, thereby optimizing the allocation of factors and the layout of the industrial structure (Guo, 2019): for emerging industries, industrial intelligentization has spawned clusters such as the industrial internet, intelligent-equipment manufacturing, and AI algorithm services, and this evolution of the industrial structure effectively reduces the share of traditional energy- and pollution-intensive industries. Meanwhile, sustained growth in consumer demand for intelligent products drives industries toward high value-added, technology-intensive transformation, further optimizing factor and industrial-structure allocation.

Industrial-structure upgrading helps cities meet their pollution–carbon reduction goals. On the one hand, upgrading necessarily drives the optimization of the energy mix, directly reducing greenhouse-gas and pollutant emissions (Shao et al., 2022): as energy- and emission-intensive traditional industries are gradually replaced by low-energy, low-emission emerging industries, firms are prompted to intensify the development and use of renewable energy, strengthening the regional synergy. On the other hand, upgrading promotes collaborative governance mechanisms among upstream and downstream firms, achieving the recycling of energy-intensive resources and the goals of energy conservation and emission reduction; through collaborative governance, the technological level and competitiveness of each node in the industrial chain are raised, and the entire chain is guided toward green, low-carbon transformation.

(3) Public environmental awareness

Amid the fourth industrial revolution, the application of artificial-intelligence technologies across production domains and the implementation of supportive government policies have made the development of industrial intelligentization a focus of broad social attention (Feng et al., 2024). Intelligent upgrading on the production side can optimize firms' operations and management and reduce wasteful resource loss; relying on fine-grained source pollution monitoring and low-cost process control, it helps firms actively assume environmental responsibility. This sense of responsibility is conveyed to the public through product philosophy and sales services, deepening public attention to environmental issues. In addition, industrial intelligentization broadens the channels for disseminating environmental information and, relying on digital platforms, gives rise to environmental projects that effectively lower the threshold for public environmental participation, further raising public environmental awareness and willingness to participate.

Rising public environmental awareness significantly strengthens the public's willingness to defend environmental rights and to exercise oversight, encouraging citizens to report local environmental problems to governments; this effectively remedies the information shortfall in governmental environmental supervision and eases the environmental information asymmetry between local governments and polluting firms. Public environmental demands help local governments improve their environmental-governance systems and introduce stricter environmental regulations (Liu and Yuan, 2024), constraining firms' emission behavior at the institutional level and promoting the coordinated

reduction of pollutants and greenhouse gases on the production side (Ma et al., 2024). Moreover, because environmental problems directly affect residents' quality of life and health, heightened awareness can guide the public toward green, low-carbon lifestyles, continuously supporting the synergy from the demand side.

H2: At the macro level, industrial intelligentization promotes the urban pollution–carbon synergy by raising urban green innovation, upgrading the industrial structure, and strengthening public environmental awareness.

2.2.2 Micro-level mechanisms

(1) Corporate environmental responsibility

Through technological empowerment and efficiency transformation, industrial intelligentization markedly enhances firms' willingness and ability to fulfill environmental responsibility. In terms of technological empowerment, the deep application of artificial intelligence and the industrial internet enables firms to exercise fine-grained control over energy use, material use, and pollutant emissions across the entire production process (Wang et al., 2026). This "precision" governance transforms traditional environmental spending from a pure compliance cost into a source of improved resource-use efficiency, strengthening the material basis for firms to assume environmental responsibility. In terms of responsibility internalization, intelligent transformation shifts the managerial logic from "end-of-pipe treatment" toward "source prevention": by using intelligent technologies to build green supply-chain management systems, firms can more proactively identify environmental risks in production and incorporate them into long-term development strategies (Fang and Zhang, 2024).

The enhancement of corporate environmental responsibility is an important micro-level pathway for advancing the synergistic governance of urban pollution and carbon emissions. On the one hand, firms with a strong sense of environmental responsibility tend to adopt stricter green production standards and, by increasing coordinated investment in traditional pollutant-control facilities such as desulfurization, denitrification, and dust removal alongside energy-saving and low-carbon technologies, achieve the simultaneous reduction of pollutants and greenhouse gases at the production-process stage. On the other hand, stronger corporate environmental responsibility can stimulate employees' green-innovation behavior through an organizational-identity effect: when firms actively fulfill environmental responsibility, employees are guided to form green values that translate into voluntary low-carbon R&D and energy-saving practices (Xiong et al., 2025).

(2) Firm-level information asymmetry

With its powerful capacity for data collection and processing, industrial intelligentization breaks down the "information silos" between firms' internal management and external supervision. In terms of internal management, the application of intelligent platforms renders data from every production stage real-time and digital, allowing management to grasp true emission baselines and eliminating information gaps in internal decision-making. In terms of external interaction, automatic monitoring systems based on

sensor networks and cloud platforms can connect firms' real-time emission data and energy-consumption indicators directly to government regulators and third-party monitoring agencies, greatly lowering the difficulty of oversight by governments and consumers (Zhou and Liu, 2024).

Easing firm-level information asymmetry creates an efficient institutional environment and market climate for the synergistic governance of urban pollution and carbon emissions. On the one hand, greater information transparency strengthens the precision of environmental regulation: relying on the emission data they obtain, governments can formulate more targeted coordinated-abatement policies, compelling firms to accelerate the elimination of energy- and pollution-intensive obsolete capacity and improving the policy match between pollution abatement and carbon mitigation. On the other hand, easing information asymmetry activates the market mechanisms of green finance and public oversight and reduces corporate greenwashing (Wang et al., 2024): transparent environmental information enables financial institutions to accurately identify green-credit targets and channels funds toward firms with efficient coordinated-governance capacity.

H3: At the micro level, industrial intelligentization promotes the urban pollution–carbon synergy by strengthening corporate environmental responsibility and easing firm-level information asymmetry.

3. Research Design

3.1 Model specification

To examine the effect of industrial intelligentization on the synergistic reduction of pollution and carbon emissions, this study employs a two-way fixed-effects model specified as follows:

$$CP(i,t) = \alpha_0 + \alpha_1 \cdot INT(i,t) + \alpha_2 \cdot Control(i,t) + \mu(i) + \lambda(t) + \varepsilon(i,t) \quad (1)$$

where i indexes cities and t indexes years; $CP(i,t)$ denotes the level of the urban pollution–carbon reduction synergy; $INT(i,t)$ denotes the level of industrial intelligentization; $Control(i,t)$ is a set of control variables; $\mu(i)$ and $\lambda(t)$ capture city and year fixed effects, respectively; and $\varepsilon(i,t)$ is the random disturbance term.

3.2 Variable selection

Dependent variable: the urban pollution–carbon reduction synergy (CP). Following Lu et al. (2022), the synergy is measured by the interaction term between carbon emissions and an environmental pollution index. Following Yang et al. (2019), a composite environmental pollution index is constructed at the prefecture level from three categories of pollutant emissions—industrial wastewater, sulfur dioxide in industrial exhaust, and industrial solid waste. This is a reverse indicator: larger values indicate higher regional pollution. Carbon dioxide emissions are used to characterize each city's carbon-emission level.

Explanatory variable: the level of industrial intelligentization (INT). Following Wang et al. (2022), eight secondary indicators are selected across three aspects—intelligentization conditions, intelligentization

applications, and intelligentization technologies—and the entropy-weight method is used to measure the level of industrial intelligentization, as shown in Table 1.

Table 1
Indicator system for the level of industrial intelligentization

Primary dimension	Secondary indicator	Measurement
Intelligentization conditions	Optical-cable density	Provincial optical-cable data allocated to prefecture level using the share of municipal public-utility fixed-asset investment
Intelligentization conditions	Mobile-switch capacity	Share of prefecture telecom revenue in the province's telecom revenue
Intelligentization conditions	Internet broadband subscriber scale	Broadband subscribers as a share of year-end registered population
Intelligentization conditions	Mobile-internet subscriber scale	Mobile-phone subscribers as a share of year-end registered population
Intelligentization conditions	AI-firm scale	Number of AI firms aggregated at the prefecture level
Intelligentization applications	Robot penetration	Bartik-IV method
Intelligentization applications	Big-data collection and processing capacity	Share of employees in information transmission, computer services, and software in total employment
Intelligentization technologies	AI patents	Number of AI patents of listed firms in the prefecture divided by employees in scientific research, technical services, and geological prospecting

Mediating variables: Green innovation (Inno), following Wang and Wang (2021), is proxied by the number of urban green-patent applications per 10,000 people. Industrial-structure upgrading (Isup), following Gan et al. (2011), is proxied by the ratio of value added of the tertiary industry to that of the secondary industry. Public environmental awareness (Enc), following Wu (2022), is proxied by the logarithm of the annual average Baidu search index for "haze." Corporate environmental responsibility (Enr), following Yu and Shi (2025), is measured by assigning values from 9 to 1 to the corporate environmental ratings (AAA–C) in the Huazheng ESG ratings. Information asymmetry (Ina), following Wang et al. (2009), is proxied by the degree of accrual-based earnings management, measured as the sum of the absolute values of discretionary accruals over the previous three years.

Control variables: To ensure precise identification of the effect of industrial intelligentization, the following controls are included: population size (PS), measured by the logarithm of the registered population; government intervention (GOV), measured by the ratio of local general budgetary expenditure to gross regional product; education expenditure (EDU), measured by the share of education spending in local general budgetary expenditure; financial development (FIN), measured by the ratio of year-end

deposit and loan balances of financial institutions to gross regional product; and the urbanization rate (URB), measured by the share of non-agricultural population in the registered population.

3.3 Data sources

The study uses a sample of 272 Chinese cities over 2011–2022. Within the industrial-intelligentization indicator system, industrial-robot data are drawn from the International Federation of Robotics (IFR) database, and firm-level AI-patent data are drawn from the IRPDB intellectual-property database. Urban carbon-emission data are the prefecture-level carbon dioxide emissions of Chinese cities extracted from the EDGAR resource; the "three industrial wastes"—wastewater discharge, sulfur dioxide emissions, and solid-waste emissions—are obtained from the China City Statistical Yearbook. Other data come from the official statistics of the National Bureau of Statistics, the China Environmental Statistics Yearbook, and the China Energy Statistics Yearbook. Prefecture-level cities with severe data gaps during the sample period are excluded, and the few remaining missing values are filled by linear interpolation. Descriptive statistics for the main variables are reported in Table 2.

Table 2
Descriptive statistics of the main variables

Symbol	Variable	N	Mean	SD	Min	Max
CP	Pollution–carbon synergy	3,264	12.80	1.901	4.142	18.05
INT	Industrial intelligentization	3,264	0.0456	0.0604	0.00740	0.552
PS	Population size	3,264	5.902	0.691	2.970	8.136
GOV	Government intervention	3,264	0.200	0.0999	0.0439	0.916
EDU	Education expenditure	3,264	0.175	0.0378	0.0436	0.356
FIN	Financial development	3,264	2.592	1.241	0.588	21.30
URB	Urbanization rate	3,264	0.395	0.207	0.0750	1
Inno	Green innovation	3,264	1.250	2.618	0	35.41
Isup	Industrial-structure upgrading	3,264	1.082	0.612	0.175	5.650
Enc	Public environmental awareness	3,264	3.128	1.297	0	7.020
Enr	Corporate environmental responsibility	32,946	1.944	1.156	1	9
Ina	Information asymmetry	24,059	0.181	0.135	0.00384	1.271

4. Empirical Results and Analysis

4.1 Baseline regression results

Table 3 reports the results for the direct effect of industrial intelligentization on the urban pollution–carbon synergy. Column (1) includes neither city nor year fixed effects; column (2) adds control variables; and column (3) includes all controls while simultaneously controlling for city and year fixed effects. Across all specifications, the coefficient on industrial intelligentization is negative and significant at the 1% level—that is, the development of industrial intelligentization promotes the synergistic reduction of urban pollution and carbon emissions, supporting Hypothesis H1. (Because CP is a reverse indicator that increases with pollution and carbon intensity, a negative coefficient indicates a stronger synergy.) A higher level of urban industrial intelligentization provides firms with robust technological support, enabling them to use intelligent technologies to optimize the efficiency of resource allocation and effectively mitigate the excessive loss of raw materials, thereby substantially reducing the emission of pollutants and greenhouse gases.

Table 3
Baseline regression results

INT	(1)	(2)	(3)
	-12.3251***	-8.9135***	-1.6067***
	(-10.3833)	(-7.4058)	(-2.6643)
Controls	Yes	Yes	Yes
City FE	No	No	Yes
Year FE	No	No	Yes
Observations	3264	3264	3264
Adjusted R2			0.753

4.2 Robustness checks

To verify the robustness of the findings, several checks are conducted, with results reported in Table 4.

(1) Excluding municipalities directly under the central government. To rule out the potential influence of high-leverage observations, the four municipalities—Beijing, Shanghai, Tianjin, and Chongqing—are excluded and the regression is re-estimated (column 1). The coefficient on industrial intelligentization remains significantly negative, indicating that the baseline result is robust.

(2) Excluding extreme values. To reduce the possible interference of outliers, all continuous variables are winsorized at the 1st and 99th percentiles and the regression is re-estimated (column 2). The coefficient remains significantly negative, further supporting the reliability of the baseline result.

(3) Lagging the explanatory variable by one period. Given that industrial-intelligentization technologies may take time to move from introduction and digestion to environmental benefit, the core explanatory variable is lagged by one period (column 3). The lagged coefficient remains significantly negative, indicating that the promoting effect is persistent rather than merely contemporaneous.

(4) One-sided effects on carbon dioxide and pollutants. To rule out the possibility that the synergy is driven by a single environmental dimension, the effects of industrial intelligentization on carbon mitigation and pollution abatement are tested separately. As shown in columns (4) and (5), industrial intelligentization exerts a significant promoting effect on both, ruling out single-channel drivers and confirming its dual environmental dividend.

(5) Replacing the dependent variable. Following Chung and Liu (2025), the pollution–carbon synergy is re-measured using a coupling-coordination model, with values between 0 and 1 (higher values indicate a stronger synergy). The re-estimated result (column 6) shows a significantly positive coefficient on industrial intelligentization, confirming the robustness of the result and again supporting H1.

Table 4
Results of the robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Excl. municipalities	Excl. extreme values	Lagged one period	One-sided CO2	One-sided pollutants	Replaced dependent var.
INT	-1.5829**	-1.6782**		-0.4204***	-0.1733***	0.0902***
	(-2.3817)	(-2.2224)		(-3.4650)	(-2.9340)	(2.7010)
L.INT			-1.8445**			
			(-2.5757)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.3810**	11.1032***	6.9807*	16.3548***	-0.0269	1.0206***
	(2.0554)	(4.6487)	(1.8275)	(31.3340)	(-0.1949)	(13.6260)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3216	3136	2992	3264	3264	3264
Adjusted R2	0.750	0.781	0.756	0.261	0.467	0.158
Note: t-statistics in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.						

4.3 Endogeneity analysis

Following the practice in the existing literature, the penetration of industrial robots in the same industries in Germany (A_INT) is used as an instrumental variable for industrial intelligentization (Sheng and Bu, 2022). The rationale is twofold. First, China and Germany have comparable levels of industrial intelligentization and both rank among the world's five largest markets, so Germany's industrial layout and policy orientation in the intelligentization field influence China's investment in intelligent equipment

and technological R&D, satisfying the relevance requirement. Second, Germany's intelligentization inputs can hardly act directly on the synergistic governance of urban pollution and carbon emissions in China, satisfying the exclusion restriction. As reported in Table 5, the Kleibergen–Paap rk LM statistic indicates no under-identification problem, and the Kleibergen–Paap rk Wald F statistic of 18.68 rejects the weak-instrument hypothesis at the 1% level. The first stage shows that the instrument is significantly and positively correlated with industrial intelligentization; the second stage shows that industrial intelligentization has a significant effect on the urban pollution–carbon synergy at the 1% level, consistent with the baseline result and confirming robustness.

Table 5
Results of the endogeneity (IV) regression

INT	(1) First stage	(2) IV
		-17.2972***
		(-2.9551)
A_INT	0.0111***	
	(4.3219)	
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen-Paap rk LM statistic	15.62***	15.62***
Kleibergen-Paap rk Wald F statistic	18.68***	18.68***
Observations	3264	3264
Adjusted R2	0.004	0.601

4.4 Mechanism tests

4.4.1 Macro-level mechanisms

Green innovation. Prior research confirms that green innovation positively affects the urban pollution–carbon synergy (Liu et al., 2025), mainly because green innovation promotes the R&D and application of cleaner-production technologies, cutting pollutant emissions while reducing carbon emissions. In Table 6, column (1), the coefficient on green innovation (Inno) is positive and significant at the 1% level. In the process of industrial intelligentization, the labor-substitution effect of "machines replacing workers" helps firms save production costs and provides ample human and financial support for capital-intensive, long-horizon green R&D, and the resulting green-innovation effect advances the urban pollution–carbon synergy (Lin et al., 2023).

Industrial-structure upgrading. Prior research confirms that optimizing the industrial structure positively affects the synergy (Li et al., 2025), mainly because upgrading shifts energy-intensive industries toward low-energy industries, reducing pollutants and carbon dioxide at the source. In Table 6, column (2), the coefficient on industrial-structure upgrading (Isup) is significantly positive, indicating that higher industrial intelligentization drives regional industrial transformation and upgrading. The application of intelligent technologies raises the degree of production automation and drives structural optimization, helping the development model shift toward a low-energy, low-pollution, environmentally friendly mode (Ye and Ye, 2022) and thereby improving the synergy.

Public environmental awareness. Prior research confirms that heightened public environmental awareness positively affects the synergy (Yang et al., 2023), mainly because stronger awareness reflects greater public willingness to supervise and participate in ecological governance, thereby compelling local governments and firms to strengthen environmental management. In Table 6, column (3), the coefficient on public environmental awareness (Enc) is significantly positive, indicating that higher industrial intelligentization raises public environmental awareness. Intelligent digital platforms such as AI and big data help the public obtain environmental information and, by virtue of their strong dissemination capacity, expand the influence of environmental topics and stimulate public environmental awareness, exerting a positive effect on the urban synergy. Hypothesis H2 is thus supported.

Table 6 Regression results for the macro-mechanism tests			
INT	(1) Inno	(2) Isup	(3) Enc
	19.1354***	0.8785**	0.7065**
	(7.4315)	(2.5001)	(2.0611)
Controls	Yes	Yes	Yes
Constant	-25.7538*	3.2810**	-0.7745
	(-1.8431)	(2.2287)	(-0.4893)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3264	3264	3264
Adjusted R2	0.454	0.630	0.938

4.4.2 Micro-level mechanisms

Corporate environmental responsibility. Prior research confirms that firms' active assumption of environmental responsibility positively affects the synergy (Jiménez-Parra et al., 2018), mainly because stronger responsibility prompts firms to internalize environmental costs into operating decisions and to

reduce pollution and carbon emissions by proactively adopting clean technologies and improving abatement facilities. In Table 7, column (1), the coefficient on corporate environmental responsibility (Enr) is significantly positive, indicating that higher industrial intelligentization strengthens firms' environmental responsibility. Intelligent monitoring systems render firms' emission data transparent and raise the regulatory efficiency of managers and governments, compelling production departments to comply with regulations; to pursue a favorable long-term reputation, firms actively assume environmental responsibility, thereby reducing urban pollutant and carbon dioxide emissions.

Information asymmetry. Prior research confirms that easing firm-level information asymmetry positively affects the synergy (Yang and Han, 2023), mainly because it lowers the principal–agent costs of environmental governance and strengthens regulators' ability to constrain firms' emission behavior, yielding better governance outcomes. In Table 7, column (2), the coefficient on information asymmetry (Ina) is significantly negative, indicating that higher industrial intelligentization eases firm-level information asymmetry. Supported by intelligent technologies, firm managers can adjust production plans on a data-driven basis, reducing resource waste and ineffective emissions, and can strengthen upstream–downstream cooperation along the supply chain, optimizing the coordinated-abatement mechanism and accelerating the urban synergy. Hypothesis H3 is thus supported.

Table 7
Regression results for the micro-mechanism tests

INT	(1) Enr	(2) Ina
	0.5098**	-0.0460*
	(2.2984)	(-1.8846)
Controls	Yes	Yes
Constant	-0.1748	0.058**
	(-0.3210)	(2.356)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	32946	24059
Adjusted R2	0.020	0.018

4.5 Heterogeneity analysis

4.5.1 Urban location and administrative rank

To examine heterogeneity arising from geographic location and administrative rank, the 272 cities are split into eastern versus central-and-western cities by location and into provincial-capital versus non-

capital cities by administrative rank, with grouped regressions reported in Table 8. By location, industrial intelligentization significantly improves the synergy in both eastern and central-and-western cities, with a stronger effect in the east—largely because the east has a more rational industrial structure, a lower emission base in high-tech and tertiary industries, and better technological infrastructure that enables faster deep application and iteration of intelligentization. By administrative rank, the effect is significant only in provincial-capital cities. A plausible reason is that provincial capitals typically enjoy priority access to intelligentization-upgrading subsidies and policy support, together with higher administrative-resource allocation capacity, better infrastructure, and stronger talent-agglomeration effects, giving them greater organizational-coordination capacity and technology-conversion efficiency; non-capital cities face factor outflow and investment-attraction thresholds, so the scale dividends of intelligentization are hard to translate into governance outcomes in the short run.

Table 8
Heterogeneity by urban location and administrative rank

INT	(1) Eastern	(2) Central- western	(3) Provincial capital	(4) Non- capital
	-3.0403**	-1.3065*	-2.3111**	-0.3512
	(-2.2903)	(-1.6991)	(-2.6587)	(-0.3263)
Controls	Yes	Yes	Yes	Yes
Constant	-0.9025	14.1766***	13.8330	7.7119**
	(-0.1266)	(5.7498)	(1.5935)	(2.0482)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1164	2100	360	2904
Inter-group difference	5.87***	5.87***	1.46*	1.46*
Adjusted R2	0.750	0.765	0.896	0.737

4.5.2 Economic-development foundation

Differences in the economic-development foundation lead to divergent environmental effects of industrial intelligentization. The sample is grouped along two dimensions—economic-development level and degree of industrialization. First, per-capita GDP measures the economic-development level, and the sample is split at the mean into high- and low-development cities (Table 9, columns 1–2). Industrial intelligentization significantly improves the synergy in high-development cities but not in low-development ones—likely because high-development cities possess stronger fiscal support and a more advanced technological base, allowing faster implementation, whereas low-development cities are constrained by funding and technology shortfalls. Second, following Wang et al. (2019), the share of

industrial value added in gross regional product measures the degree of industrialization, and the sample is split at the annual mean into higher- and lower-industrialization cities (Table 9, columns 3–4). Industrial intelligentization significantly promotes the synergy in low-industrialization cities but not in high-industrialization ones—likely because high-industrialization cities have a high share of heavy and chemical industries, high "sunk costs" of traditional production, and severe technology lock-in and exit barriers, so the marginal difficulty of intelligent transformation is higher and traditional abatement space is largely exhausted.

Table 9
Heterogeneity by economic-development foundation

INT	(1) High development	(2) Low development	(3) Low industrialization	(4) High industrialization
	-1.5278**	12.9215	-2.8527**	-0.2316
	(-2.1812)	(1.6401)	(-2.2462)	(-0.2155)
Controls	Yes	Yes	Yes	Yes
Constant	6.0601*	0.7339	-4.8747	9.5468***
	(1.8574)	(0.0893)	(-0.3704)	(3.4699)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1498	1766	1649	1615
Inter-group difference	3.82***	3.82***	3.03***	3.03***
Adjusted R2	0.829	0.672	0.668	0.748

4.5.3 Institutional environment

Differences in local environmental-regulation intensity and fiscal-decentralization arrangements also yield divergent effects. First, following Shao et al. (2024), environmental-regulation intensity is measured by the share, in each city's government work report, of the number of characters in sentences containing environmental-protection terms; the sample is split at the annual mean into high- and low-regulation cities (Table 10, columns 1–2). Where regulation is stronger, strict rules compel firms to reduce pollution and carbon emissions through both rewards and penalties: to obtain green-production subsidies and operating returns, firms proactively introduce green intelligent equipment and optimize processes. Where regulation is weak, insufficient incentives and constraints make it difficult for intelligentization to advance the regional synergy. Second, following Lu and Qi (2012), fiscal decentralization is measured by prefecture-level per-capita fiscal revenue divided by the sum of prefecture-, provincial-, and central-level per-capita fiscal revenue; the sample is split at the mean into high- and low-decentralization cities (Table 10, columns 3–4). The coefficient on industrial intelligentization is significantly negative in high-

decentralization cities but insignificant in low-decentralization ones—likely because greater fiscal decentralization gives local governments more budgetary autonomy to build financial support for the R&D and application of intelligent technologies and to rapidly reallocate resources, whereas low-decentralization cities are constrained by fiscal resources.

Table 10
Heterogeneity by institutional environment

INT	(1) Strong regulation	(2) Weak regulation	(3) High decentralization	(4) Low decentralization
	-2.6582***	-1.2604*	-2.3606**	1.0966
	(-2.6687)	(-1.8561)	(-2.5903)	(0.5631)
Controls	Yes	Yes	Yes	Yes
Constant	2.6194	9.5674***	5.0049	9.6645***
	(0.2541)	(4.0458)	(0.9129)	(2.8997)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1385	1879	1408	1856
Inter-group difference	1.70***	1.70***	1.43***	1.43***
Adjusted R2	0.689	0.787	0.760	0.733

4.5.4 Factor endowment

Considering that natural-resource and human-resource endowments may differentially shape the environmental effects of industrial intelligentization, the sample is grouped along these two dimensions. First, following the National Sustainable Development Plan for Resource-Based Cities (2013–2020), cities are divided into resource-based and non-resource-based groups (Table 11, columns 1–2). The coefficient is significantly negative for non-resource-based cities but insignificant for resource-based ones—likely because, despite an urgent need for green transition, resource-based cities face path lock-in and rigid industrial structures from resource dependence, so intelligentization cannot systematically restructure traditional production in the short run. Second, following Hao (2017), human-resource endowment is measured by the share of workers with a junior-college degree or above, and the sample is split at the annual mean into high- and low-skill cities (Table 11, columns 3–4). The synergy effect is significant in high-skill cities but not in low-skill ones—likely because in cities with agglomerated high-skill labor, high-quality workers absorb and convert intelligent technologies and undertake technology spillovers more effectively, whereas in low-skill cities a shortage of specialized talent prevents advanced intelligent equipment from translating into actual abatement.

Table 11
Heterogeneity by factor endowment

INT	(1) Non-resource-based	(2) Resource-based	(3) High-skill	(4) Low-skill
	-2.5680***	-0.1824	-1.6078*	-1.1329
	(-3.1145)	(-0.0675)	(-1.7911)	(-1.2412)
Controls	Yes	Yes	Yes	Yes
Constant	2.9860	14.4613***	3.6445	14.1656***
	(0.6176)	(5.2756)	(0.7140)	(5.2625)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1956	1308	1427	1837
Inter-group difference	2.75***	2.75***	4.87***	4.87***
Adjusted R2	0.730	0.730	0.793	0.793

5. Conclusions and Policy Implications

5.1 Conclusions

Using panel data for 272 Chinese prefecture-level cities over 2011–2022, this study empirically examines the effect of industrial intelligentization on the synergistic reduction of urban pollution and carbon emissions and its underlying mechanisms. Three conclusions emerge. First, industrial intelligentization significantly promotes the urban pollution–carbon synergy, and this result holds after a series of robustness checks and endogeneity tests. Second, mechanism analysis shows that at the macro level industrial intelligentization promotes the synergy by raising urban green innovation, upgrading the industrial structure, and strengthening public environmental awareness, whereas at the micro level it does so by reinforcing corporate environmental responsibility and easing firm-level information asymmetry. Third, heterogeneity analysis shows that the promoting effect differs markedly across groups, being more pronounced in eastern and provincial-capital cities, in cities with higher economic development or lower industrialization, in cities with stronger environmental regulation or greater fiscal decentralization, and in non-resource-based and high-skill cities.

5.2 Policy implications

(1) Improve institutional constraints and guide high-emission industries to upgrade first. Because the coordinated-abatement effect of industrial intelligentization stems from its real-time monitoring and process optimization of energy- and pollution-intensive stages, energy-intensive industries should be

guided to undertake intelligent transformation first and be incorporated into the performance evaluation of pollution-discharge permits for key emitters. Support such as fiscal interest subsidies, tax incentives, and green credit should be linked to actual reductions in energy consumption and emission intensity per unit of output—based on emission performance rather than equipment counts. At the same time, potential energy rebound and low-level redundant retrofitting should be guarded against, with assessment and exit mechanisms oriented toward environmental performance.

(2) Strengthen the multiple transmission pathways and use environmental-information transparency to incentivize coordinated abatement. For green innovation, guide the integration of intelligent technologies with green R&D, incorporate green patents and energy-consumption reductions into the evaluation of intelligent-manufacturing demonstration projects, and grant additional R&D tax deductions. For the industrial structure, promote the process retrofitting of traditional energy-intensive industries and cultivate emerging industries such as intelligent equipment and the industrial internet to replace high-emission capacity. For social oversight, broaden the dissemination of emission information through environmental-information disclosure platforms so that public attention translates into traceable social oversight. On this basis—given that both stronger corporate environmental responsibility and eased information asymmetry presuppose credible and accessible environmental information—the online monitoring systems of key emitters' pollution sources should be networked for direct reporting, compressing the space for information asymmetry and principal–agent problems; corporate environmental credit and ESG ratings should be linked to green credit, government procurement, and emission-rights trading so that fulfilling responsibility yields quantifiable returns, turning environmental responsibility from an external constraint into voluntary behavior, while data-authenticity verification is strengthened to prevent greenwashing.

(3) Adapt to differences in urban conditions and implement differentiated policy guidance. Because the coordinated-abatement effect is stronger in eastern and provincial-capital cities, high-economic/low-industrialization cities, strong-regulation/high-decentralization cities, and non-resource-based and high-skill cities, a uniform policy cannot fit all, and measures should be tailored to binding constraints. For cities with strong stock lock-in, high-industrialization cities should break the technology lock-in and exit barriers of heavy and chemical industries, while resource-based cities should advance intelligent transformation alongside the cultivation of successor and alternative industries. For cities with insufficient factor and institutional supply, low-skill cities should close talent gaps through industry–education integration, while cities with weak economic foundations and fiscal decentralization should ease constraints through regional cooperation and fiscal transfer payments, maintaining the stability and continuity of environmental regulation.

Declarations

Author contributions

Xiaoyun Zhang: Conceptualization, Methodology, Funding acquisition, Supervision, Writing–review and editing. Yuanyuan Wang: Methodology, Software, Data curation, Validation, Visualization, Writing–original draft, Writing–review and editing. Mengting Liu: Methodology, Validation, Visualization, Writing–review and editing. Yilan Yang: Validation, Visualization, Supervision.

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Data availability statement

The authors will provide research data on request

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