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RESEARCH ARTICLE

Exploring the path of digital governance of urban industrial pollution: empirical evidence from 280 cities in China

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Abstract
Urban industrial pollution plays a dominant role in environmental pollution in China. Exploring the digital governance path of urban industrial pollution can provide strong support for improving environmental quality. This article empirically investigates the role and path of digitalization in the governance of urban industrial pollution from three dimensions: economic scale, structural scale, and technological scale. The results show that there is an inverted "U"-shaped relationship between digitalization and urban industrial pollution, with initial promotion followed by suppression. Among them, economic scale, industrial transformation and upgrading, and green innovation are the paths for digital governance of urban industrial pollution. In addition, there is a chain path of "green innovation-industrial transformation and upgrading" between the two. Through spatial Durbin model and regional heterogeneity analysis, it is found that digitalization has a spatial spillover effect on urban industrial pollution control, and eastern regions, regions with high economic development level and industrialized cities benefit more from digital urban industrial pollution control. The research conclusions of this article provide references for the Chinese government to formulate relevant policies, deepen the integration of digitalization and urban industrial pollution, and promote digital governance of urban industrial pollution.

Keywords Digitization · Urban industrial pollutant · Nonlinear relation · Economic scale · Industrial transformation and upgrading · Green innovation

Introduction

China is the world's largest carbon emitter, and in the Paris Agreement, China proposed to achieve carbon peak by 2023 and carbon neutrality by 2060. In China, approximately 70% of carbon dioxide emissions originate from industrial production activities (Liu 2023). Based on this, China has implemented a series of policies aimed at reducing urban industrial pollution and promoting low-carbon development in urban industries. For instance, the policy initiative introduced by China titled "Opinions on Accelerating the Establishment of a Policy System for Green Production and Consumption" underscores the pivotal role of clean production methods within industries, accompanied by enforcement measures mandating the implementation of clean production audits across major sectors. While such environmental policies may to some extent alleviate urban industrial pollution, reliance solely on policy formulation may not fundamentally resolve industrial pollution issues. Moreover, the implementation of policies may trigger certain adverse effects. Therefore, alongside policy implementation, complementary measures need to be integrated. Similarly, Castillo-Díaz et al. (2023) pointed out that environmental policies may impact the stability of agricultural systems by reducing their profitability. This highlights that policies solely focused on improving production processes may not comprehensively eradicate industrial pollution and could potentially yield other adverse consequences. To effectively mitigate additional unfavorable impacts, supplementary efforts may be required to harmonize urban industrial governance and development (Li et al. 2022).

Meanwhile, in 2022, China promulgated a significant policy titled "Several Policies on Promoting the Stable Development of the Industrial Economy." This policy places emphasis on supporting industrial enterprises, particularly

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those in the manufacturing sector, in their digital transformation, and upgrading efforts. This indicates that China is demonstrating its commitment to achieving stable industrial growth and reducing urban industrial pollution by prioritizing the impacts of digital policies, rather than solely relying on restrictions on industrial production processes (Geng et al. 2023). The digitalization strategies of enterprises have triggered a paradigm shift in technology, enhancing their ability to identify opportunities for geographical indications and to transform dynamic capabilities in green management. Information technology-driven digital empowerment optimizes green processes and reduces trial-and-error costs (Wang et al. 2024). Hence, digitalization may serve as a beneficial complementary measure for reducing industrial pollution emissions.

Digitalization refers to the systematic and comprehensive transformation of operational methods and business models of various organizations, including governments and enterprises, through the utilization of digital technologies. The rapid development of digitalization has garnered extensive attention from various sectors of society (Cui et al. 2023). In recent years, the advancement of new models and formats such as the internet, artificial intelligence, and blockchain has accelerated the transformation and upgrading of traditional industries (Lei et al. 2023; Carlsson 2004). With the integration and development of the global industrial sector and the digital economy, digital transformation is gradually emerging as a new pathway for the sustainable development of the industrial economy (Wen et al. 2021). Given the continued decline in environmental quality in industrialized nations (Yuan et al. 2020), coupled with the sustained acceleration of digital development, recent scholarly attention has focused on how to leverage digitalization to improve the environment, particularly in addressing urban industrial pollution (Piscicelli 2023; Li et al. 2022).

Currently, some scholars argue that the digital economy exacerbates pollution emissions through information technology (Sun et al. 2022). The pollution effect of digitalization-driven economic growth outweighs its emission reduction effect, thereby causing environmental pollution to a certain extent (Asif and Wu 2022; Halkos and Polemis 2018). Conversely, other scholars suggest that digitalization can effectively control urban industrial pollution, thus improving environmental quality (Hosan et al. 2022). Overall, the impact of digitalization on urban industrial pollution can be summarized at both micro and macro levels. At the microlevel, emerging technologies such as big data, the internet, and cloud computing can create an economic environment of economies of scope, long-tail effects, and economies of scale (Wang et al. 2022a, b). Building upon this, digitalization provides favorable conditions for industrial technological innovation and transformation, resulting in greener technologies and industrial structures, effectively achieving urban industrial pollution control. At the macrolevel, digitalization technologies can construct an entire industrial chain encompassing production, transportation, consumption, and recycling, thereby enhancing the operational efficiency of resource utilization (Wang et al. 2022a, b) and reducing environmental pollution emissions (Sun et al. 2022). Similarly, Xu and Li (2024) discovered through Tobit hierarchical regression that there exists a positive linear relationship between digital finance and industrial carbon unlocking efficiency, indicating that digital finance promotes the improvement of industrial carbon unlocking efficiency. In similar circumstances, Lei et al. (2024) also found a positive linear relationship between digital inclusive finance and carbon emissions reduction. In summary, current research on the impact of digitalization on industrial pollutant emissions has not reached a consensus. This could be attributed to the fact that existing studies mostly approach the relationship between digitalization and industrial pollution from a linear perspective (Bai et al. 2022), without exploring the potential nonlinear relationship between digitalization and industrial pollutant emissions.

So, is there a non-linear relationship between digitalization and urban industrial pollution control? Currently, the academic community has not reached a consensus on the impact and effectiveness of digitalization on industrial pollution emissions. Could this lack of consensus be due to the fact that existing research predominantly focuses on linear relationships? Furthermore, in the pathway of digitalization aiding urban industrial pollution control, are there interactive effects between technological scale and structural scale? Is there a chain-path effect of “green technology innovation-industrial structural transformation” between digitalization and urban industrial pollution control? What are the regional heterogeneity and spatial patterns of the impact of digitalization on urban industrial pollution control? Currently, there is no research discussing the aforementioned questions. This indicates that the influence of digitalization on urban industrial pollution control is widespread. This limited scope leaves ample room for further exploration, particularly in the context of the objectives of this paper.

In light of this, the present study delves into the nonlinear relationship between digitization and industrial pollutant emissions, aiming to address the research gap regarding the interaction between digitization and industrial pollutant emissions. Initially, leveraging a fixed effects model, this paper examines the impact of digitization on industrial pollutant emissions and innovatively introduces the square term of digitization to reveal potential nonlinear associations between digitization and industrial pollution discharge. Subsequently, it further explores the pathways through which economic scale, industrial structure, green technological innovation, and the “green technological innovation - industrial structural transformation” influence the relationship between digitization and industrial pollutant emissions. Lastly, this paper delves into the heterogeneous effects of digitization on industrial pollutant emissions and analyzes its spatial heterogeneity characteristics, aiming to provide theoretical support for enhancing the precision and effectiveness of industrial pollution prevention and control measures.

The present study makes several contributions to the existing literature:

Firstly, while previous literature primarily examines the impact of industrial digitization on urban pollution in a linear manner (Lei et al. 2024; Xu and Li 2024), this study takes a more comprehensive approach by considering the intricate processes through which digitization affects urban industrial pollution. By building upon previous research, this study explores the non-linear interaction between digitization and urban industrial pollution, shedding light on the specific mechanisms through which digitization influences urban industrial pollution. This deeper understanding of the effects of digitization on urban industrial pollution provides a solid foundation for the development of targeted policies.

Secondly, existing literature often focuses on the individual roles of economic scale, technological scale, and structural scale in the digitalization of urban industrial pollution, without exploring the potential interactions between these pathways. It is important to recognize that green technological innovation can influence the transformation of industrial structure, which in turn affects the path effects exerted by both factors. However, the chain pathway of “green technological innovation-industrial structure transformation” is often overlooked. This paper aims to address this gap by delving into the interactions between economic scale, technological scale, and structural scale, and discussing this chain pathway in detail. By doing so, this paper seeks to contribute to the enrichment and deepening of research in this field.

Literature and research hypotheses

Studies have shown that environmental pollution has three significant effects: scale effect, technical effect, and structural effect (Zheng et al. 2022). In addition to its direct impact on urban industrial pollution through its essential characteristics (Bai et al. 2022), it can also have an indirect impact on urban industrial pollution control by influencing economic scale (Zheng et al. 2022), technological scale (Zheng et al. 2022), and structural scale (Bai et al. 2022). Therefore, based on the research of Zheng and other scholars on the impact of digital finance on environmental pollution, this paper discusses the direct impact of digitalization on urban industrial pollution. The transmission mechanism of digitalization to urban industrial pollution control was discussed from three approaches: expanding the scale of social economy, improving the level of green innovation and promoting industrial transformation and upgrading (Zheng et al. 2022). The intermediary role of the chain between “green innovation and industrial transformation and upgrading” is discussed, and the corresponding research hypothesis is proposed (Zheng et al. 2022).

Digitization and urban industrial pollution

Currently, the academic community has not reached a consensus regarding the impact of digitization on industrial pollutant emissions. Some scholars argue that the development of digitization may exacerbate industrial pollutant emissions, primarily based on analyses of its influence on economic scale. However, another group of scholars holds contrary views, suggesting that the advancement of digitization will drive optimization in industrial production processes and enhance energy utilization efficiency, thereby reducing the emissions of industrial pollutants. The divergence between these two perspectives reflects the complexity and uncertainty inherent in the relationship between digitization and industrial pollutant emissions.

Some scholars believe that digitization exacerbates industrial pollution in urban areas. Digitization will drive economic growth, increase human social activities, and industrial production activities, thereby increasing pollutant emissions (Asif and Wu 2022). Some scholars argue that the pollution effects resulting from digitization-driven economic growth outweigh its emission reduction effects; thus, digitization will to some extent cause environmental pollution (Yu et al. 2023). There are also scholars who believe that digitization emphasizes low thresholds, low costs, and easy access, which can improve the convenience of payments, thereby increasing residents’ consumption, especially among residents in areas with lower levels of economic development and low-income groups (Liu et al. 2023; Sui and Rejeski 2002). Residents in areas with lower levels of economic development and low-income groups, due to their limited wealth and payment ability, often focus more on the “quantity” rather than the “quality” of consumer products. This consumption growth will lead to the development of low-end production, further solidifying an extensive growth model characterized by resource increase and scale expansion, resulting in increased energy consumption and pollution emissions (Udomkun et al. 2018).

Other scholars believe that digitalization can effectively control urban industrial pollution and improve environmental quality. Digitization provides new impetus for controlling urban industrial pollution and improving environmental quality, manifested in three aspects (Hosan et al. 2022). Firstly, digitization enables green consumption and promotes the green development of enterprises. Mobile payment methods such as WeChat and Alipay reduce the energy consumption of cash transactions, providing convenience for the public to adopt green travel modes such as public transportation, and promoting the development of the green consumption ecosystem (Zheng et al. 2022). Secondly, digitization has brought significant changes to the development of the environmental protection industry. Internet platforms, relying on their own advantages, facilitate industrial enterprises in carrying out green product innovation, exploring clean production methods, and creating opportunities for high-quality development. By accelerating the greening of industries, digitization promotes the structural adjustment of industrial enterprises (Liu et al. 2023). Thirdly, digitization can provide convenient conditions for public participation in environmental governance (Liu et al. 2023). Digitization can lower the threshold for the public to access environmental information and participate in environmental protection. The public can learn about environmental protection knowledge and understand the achievements of environmental governance through the Internet, mobile terminals, and other platforms. At the same time, the public can assist environmental monitoring departments in regulating industries, thereby forcing the industry to innovate in green technology and reduce pollutant emissions. In a similar situation, Sun et al. (2022) proposed that digitization contributes to the control of urban industrial pollution and the improvement of environmental quality.

Based on this, this paper posits the possibility of a nonlinear relationship between digitization and urban industrial pollution control, characterized by an initial promotion followed by subsequent reduction. Firstly, during the early stages of digitization, there exists a phenomenon termed "green blindness" (Ma et al. 2023), exacerbating urban industrial pollution. Digitization, driving economic development, leads to high consumption and heavy pollution, posing risks to resources and the environment (Asif and Wu 2022). Concurrently, the "rebound effect" of digitization increases output, energy consumption, and pollution emissions (Fisher-vanden and Wing 2008). Digitization enhances industrial resource allocation capability, supporting industrial economic development and continuously promoting economic growth. Secondly, with further digitization, when it surpasses a certain threshold, the green economic growth brought about by digitization will outweigh the pollution effects of economic scale growth. In similar circumstances, Ma et al. (2023) indicate that a specific threshold represents the extent of digital technology development, beyond which digitization has the capacity to reduce pollution. In summary, this paper proposes the following hypothesis, denoted as H1.

H1: The digitization will effectively regulate urban industrial pollution. Its functioning process involves initially exacerbating urban industrial pollution, followed by the further development of digitization, which will lead to the governance of urban industrial pollution.

The role of economic scale in the digital treatment of urban industrial pollution

The economic scale generally refers to the total economic volume, which refers to the total amount of social wealth, that is, the total amount of social value. Theoretically, economic scale can be linked to two aspects: digitization and urban industrial pollution control.

Firstly, the expansion of economic scale exacerbates urban industrial pollution. Research indicates that rapid economic growth inevitably brings negative externalities such as environmental pollution, with environmental pollution being a by-product of rapid economic growth (Yu et al. 2023; Feng et al. 2023). On the one hand, as the economic scale expands, the demand for resources increases, leading to an increase in the by-products of economic activities, namely, the emission of more pollutants, thereby deteriorating environmental quality. This represents the negative impact of economic scale effects on the environment (Yu et al. 2023). On the other hand, with economic development, the national economy will shift from being predominantly agricultural to predominantly industrial (Mhlanga 2020; Myovella et al. 2020). With the acceleration of industrialization, an increasing amount of resources will be exploited and utilized, causing the rate of resource consumption to exceed the rate of resource regeneration and environmental carrying capacity, resulting in an increase in industrial pollutant emissions and exacerbating environmental pollution (Quito et al. 2022). Hence, it can be inferred that the current expansion of economic scale will intensify environmental pollution (Shi et al. 2019). In similar contexts, Shi et al. (2024) pointed out that the impact of rural multifunctional community development on agricultural green total factor productivity varies with different economic levels. Based on this, we believe that at the current level of economic development, the expansion of economic scale will increase the emission of urban industrial pollutants, exacerbating urban industrial pollution.

Secondly, digitization has expanded the economic scale. Existing research indicates that digitization can promote economic development and expand the economic scale (Peng et al. 2023). The development of digital forms such as the internet, digital economy, and cloud computing can enhance the level of social productivity, expand the scale and scope of economic activities, and explore a wider range of economic value, thus expanding the economic scale (Peng et al. 2023). The linkage between digitization and the expansion of economic scale is mainly reflected in three aspects. Firstly, digital technology is an element input that can actively promote technological innovation in social and economic development (Li et al. 2023). Secondly, the digital economy itself can form an industry, transforming the digital economy from an industry into economic growth, thereby expanding the economic scale. Lastly, the integration of digital technology with various industries, namely industrial digitization. Industrial digitization can adjust the industrial structure, affect factor productivity, and expand the economic scale (Tan et al. 2023). Based on this, hypothesis H2 is proposed in this study.

H2: Economic scale plays a negative role in digital control of urban industrial pollution.

The role of industrial transformation and upgrading in the digital control of urban industrial pollution

Industrial transformation and upgrading refers to the process of industrial transformation to be more conducive to economic and social development. From the perspective of mechanism, industrial transformation and upgrading can link the two factors of digitalization and urban industrial pollution.

First, industrial transformation and upgrading can effectively address urban industrial pollution. The secondary sector, especially industries, manufacturing, and heavy industries, are the main energy consumers and polluters, and they contribute significantly to environmental pollution (Yu et al. 2023). Industrial transformation and upgrading primarily involve restricting the development of the secondary sector and supporting the growth of the tertiary sector in urban areas to impact the emission of industrial pollutants. On the one hand, industrial transformation and upgrading will limit the development of the secondary sector. Industrial transformation and upgrading refer to the process of shifting industries towards directions that are more conducive to social development, namely, the sequential transfer of the primary, secondary, and tertiary industries (Kang and Liu 2021). As industrial transformation and upgrading take place, the proportion of the secondary sector will decrease, consequently reducing the emission of industrial pollutants (Yu et al. 2023). On the other hand, industrial transformation and upgrading can promote the development of the tertiary sector, high-tech industries, and environmental protection industries. By guiding them appropriately, industrial transformation and upgrading can accelerate the arrival of China's "post-industrial" era. The tertiary sector, such as the service industry, has the characteristics of "low investment, low energy consumption, and low pollution." Therefore, in the process of industrial transformation and upgrading, the development of the tertiary sector, high-tech industries, and environmental protection industries will be emphasized (Zeng and Liu 2023). Consequently, industrial transformation and upgrading will facilitate the "green" adjustment and upgrading of industries, effectively managing urban industrial pollution. In similar circumstances, Zheng and other scholars believe that only by continuously improving the layout of extensive industries can the "structural pollution" predicament in social production be fundamentally resolved (Zheng et al. 2022).

Second, digitalization promotes industrial transformation and upgrading. Digital industrialization is the foundation and leading condition for promoting industrial transformation and upgrading, and industrial digitalization is the endogenous driving force for promoting industrial transformation and upgrading (Ran et al. 2023; Zhang et al. 2022). First, digitalization can optimize resource allocation, improve production efficiency, guide factors to flow into high-productivity industries, and promote industrial transformation and upgrading (Yu et al. 2023). Second, digitalization helps accelerate the development of the digital economy. The popularity of online shopping has become the main consumption channel for residents, and digital economic activities such as online shopping have accelerated the development of productive service industries such as e-commerce, logistics, and transportation, promoting industrial transformation and upgrading (Yu et al. 2023). Finally, digitalization can reduce consumer costs, improve services, and expand coverage. These advantages alleviate the consumption budget constraints of low-income groups, help promote consumption structure upgrading, and further promote industrial transformation and upgrading (Yu et al. 2023). In similar situations, some scholars believe that the development of the Internet can lead to industrial structure upgrading, thereby improving environmental quality (Wang et al. 2022a). Based on this, we propose hypothesis H3.

H3: Industrial transformation and upgrading have actively delivered the role of digitalization in controlling urban industrial pollution.

The mediating effect of green innovation on the digital treatment of urban industrial pollution

Green innovation, also known as ecological innovation, refers to technological innovation and management innovation for the purpose of protecting the environment. Green innovation is an important carrier to promote environmental improvement and a "sharp tool" to reduce industrial pollutant emissions (Gong et al. 2020). Green innovation plays an intermediary role in the digital control of urban industrial pollution (Zhou et al. 2021).

First, green innovation reduces industrial pollutant emissions. Green innovation serves as a crucial driver for sustainable economic development and has the ability to effectively control industrial pollutant emissions (Asif and Wu 2022). Theoretically, green innovation can control industrial pollutant emissions by enhancing resource utilization efficiency, producing green and low-pollution products (Anderson 2001), and promoting the substitution of clean energy for traditional energy sources (Gerlagh 2007), thereby achieving environmental governance (Gong et al. 2020). From the perspective of green innovation, generally speaking, it exhibits characteristics such as low income, high costs, and long cycles in the early stages of development. Therefore, the initial green innovation lacks economies of scale and may have crowding-out effects on other types of innovation, leading to lower resource allocation efficiency. However, from a long-term perspective, green innovation can improve industrial productivity, enhance the competitiveness of industrial products, and reduce production costs for industrial enterprises, thereby gaining a favorable position in market competition and continuously reducing industrial pollutant emissions (Jie 2021). Therefore, we believe that green innovation can reduce urban industrial pollutant emissions and effectively govern industrial pollution in cities.

Second, digitalization drives green innovation. Digitalization can lower the threshold for enterprises to acquire knowledge, thus creating convenient conditions for them to obtain knowledge and skills related to green production, thereby enhancing the level of industrial green innovation (Fisher-Vanden and Wing 2008). In the era of data explosion, the widespread use of the internet has accelerated the dissemination of ideas and information, promoting the application of innovative technologies and increasing innovative activities (Audretsch et al. 2015). The theory of economic growth holds that knowledge is a core element of technological innovation. The deep integration of digital technology and traditional manufacturing has promoted the intelligent transformation of low-end manufacturing, increased the proportion of technological factors in its overall factors, and facilitated the transformation of some low-end manufacturing industries into technology-intensive manufacturing industries. Furthermore, the development of the digital economy can not only directly promote industrial green innovation but also indirectly promote it by effectively integrating regional economies into the global value chain (Fisher-Vanden and Wing 2008). Based on this, this paper proposes the following research hypotheses.

> H4: Green innovation plays a positive role in the digital control of urban industrial pollution.

The transmission role of "green innovation—industrial transformation and upgrading" in the digital treatment of urban industrial pollution

Green innovation can promote industrial transformation and upgrading. On the one hand, the starting point of green innovation is to take into account environmental benefits and economic benefits, while pursuing technological innovation, environmental protection and economic development. Green innovation creates a strong driving force for the research and development and innovation of advanced technologies, thus driving industrial development and accelerating industrial transformation and upgrading. On the other hand, green innovation is conducive to improving the production efficiency of the industrial industry, so that the industrial industry with high energy consumption and high pollution can transform to low energy consumption and low pollution, to achieve industrial transformation and upgrading. In a similar context, Verbano and Crema (2016) believe that innovation can promote the optimization and upgrading of industrial structure by improving industrial productivity. Therefore, this paper believes that green innovation has a positive impact on industrial transformation and upgrading.

By summarizing the existing literature, it is found that digitization can promote industrial green innovation by lowering the threshold for enterprises to acquire knowledge (Fisher-Vanden and Wing 2008). Green innovation can promote industrial transformation and upgrade by improving industrial productivity (Asif and Wu 2022). Industrial transformation and upgrading will promote the development of "double-high" industries to "double-low" industries (Yu et al. 2023), thus reducing the emission of industrial pollutants. Based on the above analysis, this paper proposes the following hypothesis 5.

> H5: "Green innovation–industrial transformation and upgrading" plays a chain intermediary role in the digital reduction of industrial pollutant emissions.

Based on the above analysis, the research framework of this paper is constructed, as shown in Figure 1.

Research design

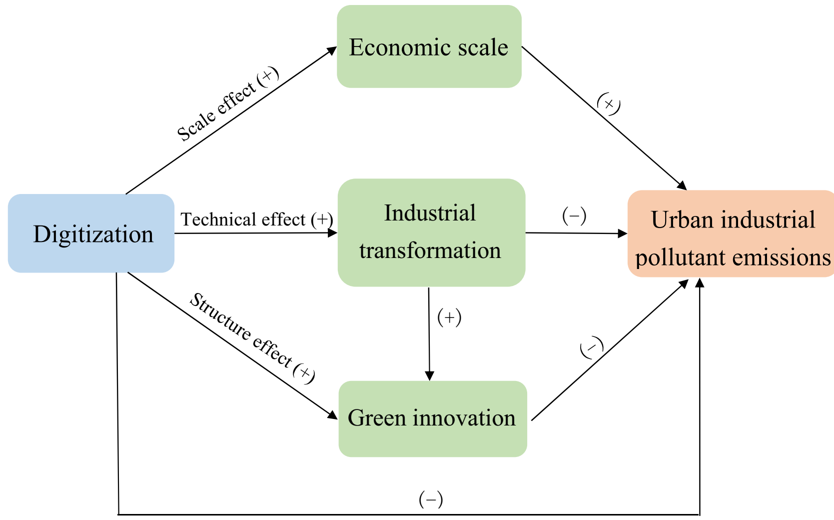
Model construction

First, to test the previous research hypothesis, this paper first constructs the following basic model for the direct conduction mechanism of digitalization affecting urban industrial pollutant emission:

$$\mathrm{Ln}Poll_{it} = \alpha_0 + \alpha_1 \mathrm{Ln}Dige_{it} + \alpha_c \mathrm{Ln}Z + \mu_i + \delta_i + \varepsilon_{it} \tag{1}$$

In model (1), $\mathrm{Ln}Poll_{it}$ is the urban industrial pollutant emission level of the city i in year t (including industrial sulfur dioxide emissions, industrial wastewater emissions,

Fig. 1 Research framework



and industrial smoke and dust emissions), $\mathrm{Ln}Dige_{it}$ is the digital level of the city i in year t, and LnZ represents the control variables (including infrastructure, population size, urban greening, education level, social consumption, and foreign investment), μ_i represents the regional fixed effect, δ_i represents the time fixed effect, and ε_{it} represents the random disturbance term.

Second, to test hypotheses 2, 3, 4, and 5, we construct a model of intermediary effects. Specific test steps are as follows: based on the significant coefficient in the linear regression model (1) of the digital index for industrial pollutant emission, first of all, the linear regression equation of the digital index for the intermediary variables (including economic scale, industrial transformation and upgrading, and green innovation) is constructed. Secondly, the regression equation of digitalization and intermediary variables (including economic scale, industrial transformation and upgrading, and green innovation) on industrial pollutant emissions is constructed. Finally, the regression equation of green innovation on industrial transformation and upgrading is constructed to test the chain mediating effect of green innovation and industrial transformation and upgrading. The specific form of the above regression model is set as follows:

$$\mathrm{Ln}M_{it} = \beta_0 + \beta_1 \mathrm{Ln}Dige_{it} + \beta_c \mathrm{LnZ} + \mu_i + \delta_i + \varepsilon_{it} \tag{2}$$

$$\mathrm{Ln}Poll_{it} = \gamma_0 + \gamma_1 \mathrm{Ln}Dige_{it} + \gamma_2 \mathrm{Ln}M_{it} + \gamma_c \mathrm{LnZ} + \mu_i + \delta_i + \varepsilon_{it} \tag{3}$$

$$\mathrm{Ln}Ts_{it} = \theta_0 + \theta_1 \mathrm{Ln}Tep_{it} + \theta_c \mathrm{LnZ} + \mu_i + \delta_i + \varepsilon_{it} \tag{4}$$

In models (2) to (4), $\mathrm{Ln}M_{it}$ represents the intermediary variables (including economic scale, industrial transformation and upgrading, and green innovation), $\mathrm{Ln}Ts_{it}$ is the industrial transformation and upgrading the level of the city i in year t, and $\mathrm{Ln}Tep_{it}$ is the green innovation level of the city i in year t. The significant performance of regression coefficients such as β_1, γ_1, γ_2, and θ_1 can determine whether the intermediary effect exists.

Third, to test the spatial spillover effect of digitalization on urban industrial pollutant emissions, we construct a spatial Durbin model for testing. The setting of the spatial Durbin model is as follows:

$$\begin{aligned}\mathrm{Ln}Poll_{it} = {} & \partial_0 + \pi W\mathrm{Ln}Poll_{it} + \varphi_1 W\mathrm{Ln}Dige_{it} + \partial_1 \mathrm{Ln}Dige_{it} \\ & + \varphi_c W\mathrm{LnZ}_{it} + \partial_c \mathrm{LnZ}_{it} + \mu_i + \delta_i + \varepsilon_{it}\end{aligned} \tag{5}$$

In model (5), π represents the spatial autoregressive coefficient, and W is the spatial weight matrix. The level of digitization and the degree of urban industrial pollutant emission are closely related to the level of economic development, so we choose the economic weight matrix for testing. φ_1 and φ_c are the elastic coefficients of the spatial interaction terms of the core explanatory variable and the control variable respectively.

Measurement and description of variables

Explained variable

The explained variable of this paper is urban industrial pollutant emission. The comprehensive index of environmental pollution fully considers the diversity of pollutants, but more reflects on the relative emission degree of pollutants than the absolute emission scale, and the weighting of different pollutant emissions is too subjective and one-sided. Therefore, it is more reasonable to use a single pollutant index to evaluate industrial pollutant emissions. Considering the availability and accuracy of data, drawing on the practice of scholars such as Zheng et al., three indicators of industrial sulfur dioxide emissions ($\mathrm{LnSO_2}$), industrial wastewater emissions (LnWater), and industrial smoke and dust emissions (LnDust) were used to reflect industrial pollutant emissions at the level of prefectural cities in China (Zheng et al. 2022).

Core explanatory variable

The core explanatory variable of this paper is the digitization level, which is measured by the development level of the digital economy (Nathan et al. 2013). This paper measures the digital economy development index from two aspects: Internet development and digital finance development. First, in terms of Internet development, the development level of the Internet is measured from four aspects: Internet penetration rate, relevant employees, relevant output, and Internet penetration rate. The specific corresponding contents of the above four indicators are shown in Figure 2. Second, the development of digital finance. The level of digital financial development in China is measured by the "Peking University Digital Financial Inclusion Index" at the prefecture-level city level, which is jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Group. We standardized the corresponding indicators to form quantitative indicators, and finally obtained the index by dimensionless method, which has certain reliability and representativeness.

Intermediate variable

According to the theoretical model above, this paper selects economic scale, industrial transformation and upgrading, and green innovation as the intermediary variables of digitalization affecting urban industrial pollutant emission.

(1) Economic size (LnPGDP). GDP per capita can effectively remove the effect of population size, so we use GDP per capita to measure the size of the economy.

(2) Industrial transformation and upgrading (LnTs). The industrial structure level index is used to represent industrial transformation and upgrading. The larger the index, the higher the degree of regional industrial transformation and upgrading. The formula for calculating the industrial structure level index is as follows:

$$Ts_{it} = \frac{Y_1}{Y} \times 1 + \frac{Y_2}{Y} \times 2 + \frac{Y_3}{Y} \times 3 \tag{6}$$

Where Ts_{it} represents the industrial transformation and upgrading degree of region i in the t year, Y_n represents the output value of the nth industry, Y represents the total output value, and $n = 3$ represents the three major industries.

(3) Green innovation (LnTep). This paper uses the number of green patent applications to measure the level of

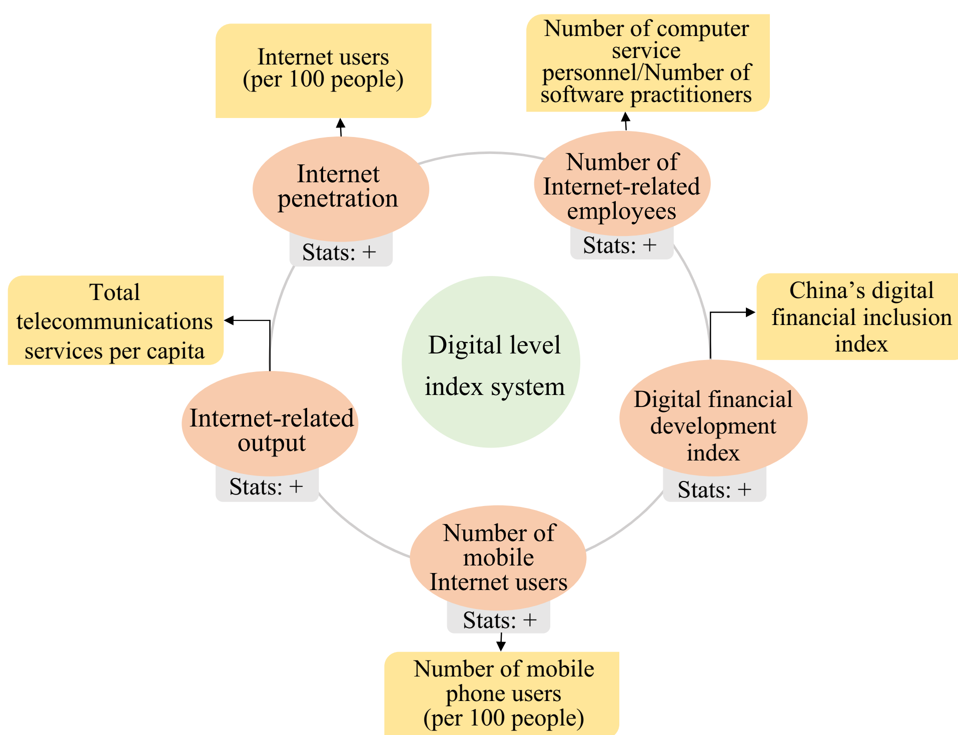


Fig. 2 Digital level index system

green innovation. According to the classification number of the Green List of International Patent Classification issued by WIPO, we searched the green patent applications of each region in the incoPat patent database, and finally obtained the number of green patent applications of each region in each year to measure the level of green innovation in each region in each year.

Control variable

Based on existing studies, the following variables that may affect environmental quality are controlled: (1) Infrastructure (LnCar). The number of buses per 10,000 people is used to measure the indicator. (2) Population size (LnPop). The total population of the region at the end of the year was represented. (3) Urban greening (LnGreen). Improving the urban green coverage rate can effectively improve environmental pollution. We use the urban green coverage rate to represent urban green. (4) Education level (LnStu). The educational level is represented by the number of college students per 10,000 people in the city. (5) Social consumption (LnCons). The level of social consumption is represented by the total retail sales of urban commodities. (6) Foreign Investment (LnFDI). Foreign investment is expressed using actual foreign direct investment.

Data sources and descriptive statistics

In this paper, 280 cities at the prefecture level and above in China were studied from 2011 to 2019 (except Tibet, Hong Kong, Macao, Taiwan Sansha, and other special samples), and an equilibrium panel observation of 2520 city-years was formed. In addition to the digital financial index, the data used in this study are all from the China City Statistical Yearbook, some prefecture-level city statistical Annual reports, the EPS database, and the Wind database. For missing values, the interpolation method is used to fill in. From the perspective of control variables, there are obvious differences in infrastructure (LnCar), population size (LnPop), urban greening (LnGreen), education level (LnStu), social consumption (LnCons), and foreign investment (LnFDI) among different cities. The results of descriptive statistical analysis are shown in Table 1.

Empirical analysis

Hypothesis testing

Benchmark regression test

Table 2 presents the baseline estimates of the impact of digitization on urban industrial pollution. The results of the fixed-effects models in columns (1), (3), and (5) show that the estimated coefficients of the digitization indicators are significantly negative, indicating that digitization can effectively reduce the emissions of industrial sulfur dioxide, industrial wastewater, and industrial particulate matter, thus achieving a certain level of industrial pollutant reduction. As for columns (2), (4), and (6), the negative squared coefficients of the digitization level suggest an inverted U-shaped

Table 1 Descriptive analysis of variables

Variable type	Variable name	Variable	Sample size	Mean value	Variance	Minimum value	Maximum value
Explained variable	Industrial sulfur dioxide emissions	$LnSO_2$	2520	10.017	1.234	0.693	13.183
	Industrial wastewater discharge	LnWater	2520	8.167	1.125	1.946	11.477
	Industrial smoke and dust emissions	LnDust	2520	9.692	1.186	3.466	15.458
Core explanatory variable	Digitization index	LnDige	2520	8.614	0.939	5.801	12.803
Intermediate variable	Economic scale	LnPGDP	2520	10.701	0.574	8.773	13.056
	Industrial transformation and upgrading	LnTs	2520	5.433	0.062	5.210	5.646
	Green innovation	LnTep	2520	4.309	1.755	0.000	10.182
Control variable	Infrastructure	LnCar	2520	6.516	0.881	1.099	11.624
	Population size	LnPop	2520	5.883	0.701	2.970	8.136
	Urban greening	LnGreen	2520	8.265	0.289	4.078	10.536
	Educational level	LnStu	2520	10.532	1.382	5.416	13.910
	Social consumption	LnCons	2520	15.443	1.460	5.333	20.909
	Foreign investment	LnFDI	2520	9.969	1.978	1.099	14.152

Variables are in the form of natural logarithms

Table 2 Test results of the effect of digitization on industrial pollutants

Variable	$LnSO_2$		LnWater		LnDust	
	(1)	(2)	(3)	(4)	(5)	(6)
LnDige	−0.106** (0.045)	1.508*** (0.254)	−0.286*** (0.033)	0.685*** (0.207)	−0.271*** (0.051)	1.191*** (0.277)
$LnDige^2$		−0.089*** (0.014)		−0.035*** (0.011)		−0.075*** (0.015)
LnCar	0.130*** (0.025)	0.126*** (0.025)	−0.052* (0.019)	0.076*** (0.021)	−0.034 (0.030)	0.131*** (0.027)
LnPop	0.245*** (0.041)	0.167*** (0.042)	0.168 (0.201)	0.253*** (0.035)	−0.511* (0.310)	0.122*** (0.046)
LnGreen	0.223*** (0.072)	0.170** (0.071)	−0.282*** (0.044)	0.156*** (0.058)	−0.206*** (0.068)	0.122 (0.078)
LnStu	0.015 (0.024)	0.012 (0.024)	−0.261*** (0.036)	−0.018 (0.019)	−0.330** (0.055)	0.074*** (0.026)
LnCons	0.206*** (0.027)	0.229*** (0.027)	−0.210*** (0.021)	0.272 (0.022)	−0.217*** (0.033)	0.158*** (0.029)
LnFDI	−0.041*** (0.014)	−0.046*** (0.014)	−0.021 (0.014)	0.105*** (0.012)	−0.019 (0.021)	−0.000 (0.016)
Constant	4.602*** (0.614)	−1.954* (1.184)	22.193*** (1.534)	−2.938*** (0.068)	27.562*** (2.362)	−0.254 (1.293)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	No	No	No	No
Regional fixation	No	No	Yes	Yes	Yes	Yes
F	103.620	101.320	48.030	165.140	18.350	43.210
P	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.379	0.389	0.842	0.510	0.663	0.211

The content reported in brackets in the table is robust standard error. *, **, and *** indicate significant at the significance level of 10%, 5%, and 1%, respectively

relationship between digitization and the emissions of industrial sulfur dioxide, industrial wastewater, and industrial particulate matter. In other words, in the early stages of digitization, it promotes the emissions of these industrial pollutants. However, as digitization further develops, it leads to a reduction in the emissions of industrial sulfur dioxide, industrial wastewater, and industrial particulate matter, thus achieving effective control of urban industrial pollution. Hypothesis H1 is supported by the findings.

The internal reason may be that the relationship between digitalization and industrial pollutant discharge meets the classical environmental Kuznets hypothesis, that is, in the initial stage of digitalization, when the level of digitalization is low, the industrial pollutant discharge increases from low to high with the development of digitalization, and the industrial pollutant emissions increase with the development of digitalization. After digitalization reaches a certain level, that is, after crossing the critical value, with the further development of digitalization, the emission level of industrial pollutants will turn from high to low, the emission degree of industrial pollutants will gradually decrease, and the environmental quality will gradually improve. In terms of control variables, the results in columns (1) to (6) show that the influence of control variables on the emission of different pollutants is heterogeneous. Mainly because there are differences in the current level of industrial pollutant emissions, and there are deviations in the level of industrial technology.

Robustness test

In order to further verify the robustness of the empirical results, this paper adopts three methods of replacing the explained variables, excluding the municipalities directly under the central government and excluding the provincial capital city to carry out the robustness test.

First, replace the explained variable. To avoid the estimation bias caused by the selection of explained variables, this paper uses the emission intensity of industrial pollutants, that is, the ratio of industrial pollutant emissions to actual GDP, as the explained variable and carries out the estimation test again. Among them, the estimated coefficients of digitization level are significantly negative, which is consistent with the previous empirical results, and further proves the robustness of the empirical results in this paper.

Second, eliminate the variable. This paper excludes the individual value impact of the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing on the overall sample due to their special status in administrative divisions, removes the data of the four regions of Beijing, Tianjin, Shanghai, and Chongqing, and conducts a re-estimation test on the samples after the exclusion of these four municipalities (Zheng et al. 2022). In the empirical results, the estimated coefficients of digitalization on industrial sulfur dioxide emissions, industrial wastewater emissions, and industrial smoke and dust emissions are still significantly negative, indicating that the above empirical results are relatively robust.

Third, exclude the particularity of the provincial capital city. Chinese capital cities generally gather the most administrative resources, educational resources, medical resources and financial resources in the province. Therefore, in order to exclude the influence of provincial capital cities on the individual value of the whole sample, this paper conducted a re-estimation test on the sample after eliminating the data of provincial capital cities. In the empirical results, the estimated coefficients of digitalization on industrial sulfur dioxide emissions, industrial wastewater emissions, and industrial soot emissions are still significantly negative, indicating that the empirical results in this paper have strong robustness.

Endogeneity test

In order to further test the endogeneity of empirical results, this paper conducts endogeneity test by introducing first-order lag terms of explanatory variables and second-order lag terms of explanatory variables and instrumental variables.

First, in order to further reduce the possible mutual causal influence between the explanatory variable and the explained variable, this paper further changed the explanatory variable to the $t-1$ and $t-2$ phase digitization index. In the empirical results, the estimated coefficients of digitalization on industrial sulfur dioxide emissions, industrial wastewater emissions, and industrial soot emissions are still significantly negative, and the test results are consistent with the baseline regression results. It can be seen that the regression result of introducing the lag term of explanatory variables further solves the endogeneity problem and supports the research conclusion of this paper.

Second, this paper uses the number of posts and telecommunications per 10,000 people in each city in 1984 and the number of Internet users in the previous year to construct a cross-multiply term, which is used as the instrumental variable (Z) of the digitalization index for testing (Nunn and Qian 2014), so as to alleviate the possible reverse causality problem. Among them, after considering the endogeneity, the effect of digital inhibition of industrial pollutant emissions is still valid, and the results are significant at 1% level. In addition, under the weak instrumental variable test, the Cragg-Donald Wald F statistic is greater than the critical value of 10% bias under the Stock-Yogo weak instrumental variable test, indicating that there is no weak instrumental variable problem. In the unidentifiable test, the p-value of the LM statistic is less than 0.001, indicating that there is no problem of insufficient identification of instrumental variables. The above tests demonstrate the rationality of the selection of instrumental variables in this paper. Therefore, the regression results of instrumental variables further solve the endogeneity problem and support the research conclusions of this paper.

Due to space constraints, the specific results of the robustness test are not presented in detail.

Mediation effect analysis

First, in terms of economic scale, the aforementioned theoretical analysis demonstrates the transmission role of economic scale in digitally governing industrial pollution in urban areas. To verify the hypothesis of this mechanism, this paper takes the economic scale as the mediating variable and makes an empirical analysis. As can be seen from the model (1) in Table 3, the coefficient of digitalization is 0.096, and the significance test at the 1% level indicates that digitalization can expand the scale of the economy. From model (2) to model (4), it can be seen that when digitalization and economic scale are introduced at the same time, the coefficient of economic scale is significantly positive. In model (2), the coefficient of economic scale is 0.791, and through the 1% level significance test, it indicates that industrial sulfur dioxide emissions will increase by 79.1% with each unit of economic scale expansion. In model (3), the economic scale coefficient is 0.826, and the 1% level significance test is passed, indicating that the industrial wastewater discharge will increase by 82.6% when the economic scale increases by one unit. In model (4), the digitalization coefficient is 0.641, and the 1% level significance test shows that the industrial smoke and dust emissions will increase by 64.1% for every 1% increase in economic scale.

From models (2) to (4), it can be observed that economic scale increases the emission of urban industrial pollutants, with the strongest promotion effect on industrial wastewater discharge, followed by industrial sulfur dioxide and industrial particulate matter. This may be attributed to the fact that the expansion of economic scale leads to an increase in the demand for resources, thereby resulting in an increase in the by-products of economic activities, namely the emission of more pollutants, consequently deteriorating environmental quality. Furthermore, with economic development, the national economy shifts from being primarily agricultural to

Table 3 Economic scale, industrial transformation, and upgrading mechanism test results

Explanatory variable	The mediating effect of economic size				The intermediary effect of industrial transformation and upgrading			
	(1)LnPGDP	(2)$LnSO_2$	(3)LnWater	(4)LnDust	(5)LnIS	(6)$LnSO_2$	(7)LnWater	(8)LnDust
LnDige	0.096*** (0.013)	−0.181*** (0.044)	−0.026 (0.035)	−0.242*** (0.048)	0.023*** (0.002)	0.076* (0.045)	−0.086 (0.057)	0.016 (0.047)
LnPGDP		0.791*** (0.065)	0.826*** (0.052)	0.641*** (0.072)				
LnIS						−19.389*** (0.509)	−5.456*** (0.780)	−12.708*** (0.530)
Constant	7.906*** (0.098)	−0.024 (0.607)	−5.730*** (0.484)	1.640** (0.670)	4.469*** (0.084)	135.711*** (3.043)	48.147*** (5.910)	84.361*** (3.170)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	Yes	Yes	No	Yes	No	No
Regional fixation	No	No	No	No	Yes	No	Yes	Yes
Observed value	2520	2520	2520	2520	2520	2520	2520	2520
F	495.260	111.930	196.170	47.460	47.920	30.700	46.570	24.990
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.746	0.413	0.554	0.228	0.842	0.772	0.850	0.732

The content reported in brackets in the table is robust standard error. *, **, and *** indicate significant at the significance level of 10%, 5%, and 1% respectively

primarily industrial (Mhlanga 2020; Myovella et al. 2020). With the acceleration of industrialization, an increasing number of resources are exploited, leading to a consumption rate surpassing the rate of resource regeneration and environmental carrying capacity, thus increasing the emission of industrial pollutants. Therefore, Hypothesis 2 is supported.

Second, industrial transformation and upgrading. From the perspective of industrial transformation and upgrading, the transmission mechanism of digital reduction of urban industrial pollutant emissions is theoretically analyzed. To verify the hypothesis of the mechanism of action, this paper takes the industrial transformation and upgrading as the intermediary variable and analyzes the intermediary effect. As can be seen from the model (5) in Table 3, the digitalization index coefficient is 0.023 and passes the significance test at the 1% level, indicating that digitalization will promote industrial transformation and upgrading.

From models (6) to (8), it can be seen that industrial transformation and upgrading can reduce the emission of urban industrial pollutants, and industrial transformation and upgrading is the transmission path of digitally empowered industrial pollutant emission reduction. The reason may be that digitalization can promote industrial transformation and upgrade by optimizing the allocation of credit funds, promoting the development of the digital economy, and lowering the consumption threshold of residents, while industrial transformation and upgrading can reduce the emission of industrial pollutants by limiting the secondary industry and supporting the tertiary industry. Therefore, hypothesis H3 is tested. In model (6), the digitalization index coefficient is significantly positive, and the industrial transformation and upgrading coefficient is significantly negative, indicating that digitalization will directly promote industrial sulfur dioxide emissions, but it will indirectly reduce industrial sulfur dioxide emissions through the transmission path of industrial transformation and upgrading, and the indirect effect is stronger than the direct effect. In models (7) and (8), the digitalization coefficient is not significant, and the industrial transformation and upgrading coefficient is significantly negative, indicating that the reduction effect of digitalization on industrial sulfur dioxide and industrial smoke dust emissions mainly plays a role through the intermediary transmission path of industrial transformation and upgrading.

Third, green innovation. The previous theoretical analysis has explained the transmission role of green innovation between digitization and industrial pollutant emission reduction. This paper further verifies the intermediary role of green innovation from the empirical aspect. As can be seen from model (1) in Table 5, the coefficient of digitalization index is 0.431, and the significance test at 1% level indicates that digitalization will promote green innovation, and the level of green innovation will increase by 43.1% for each unit of digitalization development. As can be seen from the model (2), the coefficient of digital economy is

Table 4 The mechanism test results of the mediating role of green innovation and the chain mediating role of green innovation-industrial transformation and upgrading

Explanatory variable	The intermediary effect of green innovation				Chain mediation			
	(1)LnTep	(2)$LnSO_2$	(3)LnWater	(4)LnDust	(5)LnIS	(6)$LnSO_2$	(7)LnWater	(8)LnDust
LnDige	0.497*** (0.047)	−0.048 (0.049)	−0.123*** (0.030)	−0.074 (0.048)	0.011*** (0.001)	0.121*** (0.044)	−0.040 (0.028)	0.041 (0.046)
LnTep		−0.632*** (0.021)	−0.328*** (0.013)	−0.398*** (0.021)	0.023*** (0.001)	−0.292*** (0.024)	−0.161*** (0.015)	−0.166*** (0.025)
LnIS						−14.943*** (0.609)	−7.354*** (0.393)	−10.185*** (0.650)
Constant	−29.390*** (2.128)	28.924*** (2.247)	11.010*** (1.385)	14.773*** (2.298)	5.208*** (0.069)	106.742*** (3.747)	49.309*** (2.419)	67.814*** (3.996)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	No	No	No	No	No	No	No	No
Regional fixation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	2520	2520	2520	2520	2520	2520	2520	2520
F	59.750	24.140	63.200	22.310	77.190	33.220	7.040	25.530
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.870	0.726	0.876	0.708	0.897	0.787	0.893	0.737

The content reported in brackets in the table is robust standard error. *, **, and *** indicate significant at the significance level of 10%, 5%, and 1%, respectively

not significant, while the coefficient of green innovation is significantly negative, indicating that the effect of digitalization on the reduction of industrial sulfur dioxide emissions is mainly through the intermediary path of green innovation. As can be seen from the model (3), the digitalization level coefficient is -0.121 and passes the significance test at 1% level, and the green innovation coefficient is -0.319 and passes the significance test at 1% level. The results show that the effect of digitization on industrial wastewater discharge through green innovation is stronger than that of digitization on industrial wastewater discharge directly. It can be seen from the model (4) that the digitalization coefficient is not significant, while the green innovation coefficient is significantly negative, indicating that the effect of digitalization on industrial smoke dust mainly plays a role through the intermediary path of green technology innovation, and the effect is similar to that of the model (2).

From models (1) to (4), it can be seen that green innovation positively conducts the effect of digitalization on reducing urban industrial pollutant emissions. The reason for this phenomenon may be that digital technology can accelerate green innovation, and green innovation can continue to promote the reduction of urban industrial pollutants by improving the production efficiency of industrial enterprises, enhancing the competitiveness of industrial products, and reducing their production costs. Therefore, hypothesis H4 is tested.

Fourth, is chain mediation. The above theoretical analysis shows that "green innovation–industrial transformation and upgrading" is an intermediary channel for the digital reduction of urban industrial pollutant emissions. The coefficient of green innovation in column (5) of Table 4 is 0.023 and is significant at the 1% level, indicating that green innovation can effectively promote industrial transformation and upgrading. On this basis, combined with column (1) of Table 5 and column (6) to column (8) of Table 4, it can be seen that in the process of digitalization reducing urban industrial pollutant emissions, the chain intermediary role of "green innovation–industrial transformation and upgrading" is established, and the chain intermediary can positively conduct the role of digitalization reducing urban industrial pollutant emissions, and hypothesis H5 is verified.

Fifth, look at the whole. The effect of digitalization on industrial sulfur dioxide emission by economic scale is 0.076 (0.096×0.791), the effect value of industrial transformation and upgrading is −0.446 (0.023×-19.389), and the effect value of green innovation is −0.314 (0.497×-0.632). The effect size through the chain mediation was −0.171 ($0.497 \times 0.023 \times -14.943$). The effect value of digitalization on industrial wastewater discharge through economic scale is 0.079 (0.096×0.826), that through industrial transformation and upgrading is −0.125 (0.023×-5.456), and that through green innovation is −0.163 (0.497×-0.328). The effect size through the chain

Table 5 The mediation effect test of Bootstrap

Panel A						
Explanatory variable	The mediating effect of economic size			The intermediary effect of industrial transformation and upgrading		
	(1)$LnSO_2$	(2)LnWater	(3)LnDust	(4)$LnSO_2$	(5)LnWater	(6)LnDust
Indirect effect $x \rightarrow M \rightarrow y$	0.076*** (0.020)	0.079*** (0.021)	0.061*** (0.016)	−0.169*** (0.029)	−0.083*** (0.016)	−0.115*** (0.021)
Direct effect $x \rightarrow y$	−0.177*** (0.054)	0.048 (0.037)	−0.240*** (0.064)	0.121** (0.051)	−0.040 (0.031)	0.041 (0.052)
Total effect	−10.1%	12.7%	−17.9%	−4.8%	−12.3%	−7.4%
Upper 95% confidence interval for indirect effects	0.036	0.038	0.031	−0.225	−0.114	−0.156
Lower 95% confidence interval for indirect effects	0.115	0.119	0.092	−0.113	−0.052	−0.074
Upper 95% confidence interval for direct effects	−0.282	−0.024	−0.366	0.021	−0.102	−0.060
Lower 95% confidence interval for direct effects	−0.071	0.120	−0.113	0.221	0.022	0.143
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	Yes	No	No	No
Regional fixation	No	No	No	Yes	Yes	Yes
Observed value	2520	2520	2520	2520	2520	2520
Panel B						
Explanatory variable	The intermediary effect of green innovation(M_1)			The intermediary effect of "green innovation(M_1)—industrial transformation and upgrading(M_2)"		
	(1)$LnSO_2$	(2)LnWater	(3)LnDust	(4)$LnSO_2$	(5)LnWater	(6)LnDust
Indirect effect $x \rightarrow M_1 \rightarrow y$	−0.145*** (0.022)	−0.080*** (0.013)	−0.082*** (0.017)	−0.145*** (0.022)	−0.080*** (0.013)	−0.082*** (0.017)
Indirect effect $x \rightarrow M_1 \rightarrow M_2 \rightarrow y$				−0.169*** (0.022)	−0.083*** (0.013)	−0.115*** (0.018)
Direct effect $x \rightarrow y$	0.121** (0.051)	−0.040 (0.031)	0.041 (0.052)	0.121** (0.051)	−0.040 (0.031)	0.041 (0.052)
Total effect	−2.4%	−12%	−12.3%	−19.3%	16.3%	−19.7%
Upper 95% confidence interval for indirect effects	−0.188	−0.106	−0.115	−0.188	−0.106	−0.115
Lower 95% confidence interval for indirect effects	−0.102	−0.054	−0.050	−0.102	−0.054	−0.050
Upper 95% confidence interval for direct effects	0.021	−0.102	−0.060	0.021	−0.102	−0.060
Lower 95% confidence interval for direct effects	0.221	0.022	0.143	0.221	0.022	0.143
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	No	No	No	No	No	No
Regional fixation	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	2520	2520	2520	2520	2520	2520

The content reported in brackets in the table is robust standard error. **, and *** indicate significant at the significance level of 5% and 1%, respectively mediation was 0.084 (0.497 × 0.023 × −7.354). The effect value of digitalization on industrial smoke and dust emission through economic scale is 0.062 (0.096 × 0.641), that through industrial transformation and upgrading is −0.292 (0.023 × −12.708), and that through green innovation is −0.034 (0.431 × −0.380). The size of the action through the chain intermediary is −0.115 (0.497 × 0.023 × −10.185).

It can be seen that economic scale negatively conducts the effect of digitalization on the reduction of urban industrial pollutant emissions, while green innovation and industrial transformation and upgrading both positively conduct the effect of digitalization on the reduction of urban industrial pollutants, and "green innovation–industrial transformation and upgrading" has a chain intermediary effect of positive conduction between digitalization and urban industrial pollutant emission reduction.

For robustness considerations, this study employs Bootstrap tests to validate the mediating effects of economic scale, industrial structural transformation, green technology innovation, and the mediating effect of "green technology innovation–industrial structural transformation." Based on the original dataset ($N = 2520$), 500 Bootstrap samples are randomly drawn through repeated random sampling. The mediating effect estimates generated from the 500 samples are sorted in ascending order, and a 95% confidence interval for the mediating effects is obtained. If the 95% confidence interval of the mediating effects does not include 0, it indicates a significant mediating effect, as detailed in Table 5.

In terms of economic scale, as indicated from models (1) to (3) in Panel A of Table 5, it is observed that the 95% confidence intervals of the indirect effect coefficients of economic scale do not include zero, suggesting the presence of a mediating effect of economic scale. In model (1), the mediating effect of economic scale is estimated to be 7.6%; in model (2), it is 7.9%; and in model (3), it is 6.1%.

Regarding industrial structural transformation, based on models (4) to (6) in Panel A of Table 5, it is evident that the 95% confidence intervals of the indirect effect coefficients of industrial structural transformation do not include zero. This suggests the existence of a mediating effect of industrial structural transformation. In model (4), the mediating effect of industrial structural transformation is estimated to be −16.9%; in model (5), it is −8.3%; and in model (6), it is −11.5%.

In the realm of green technology innovation, as evident from models (1) to (3) in Panel B of Table 5, it is observed that the 95% confidence intervals of the indirect effect coefficients of green technology innovation do not encompass zero, indicating the existence of a mediating effect of green technology innovation. In model (4), the mediating effect of green technology innovation is estimated to be -14.5%; in model (5), it is −8%; and in model (6), it is −8.2%.

In the context of "green technology innovation–industrial structural transformation," as deduced from models (4) to (6) in Panel B of Table 5, it is apparent that the 95% confidence intervals of the indirect effect coefficients of "green technology innovation–industrial structural transformation" do not include zero, indicating the presence of a chained mediating effect. In model (4), the chained mediating effect of "green technology innovation–industrial structural transformation" is estimated to be −16.9%; in model (5), it is −8.3%; and in model (6), it is −11.5%.

The results indicate that the mediated effects, validated through Bootstrap testing, remain robust, thus further affirming the robustness of the mediation effects proposed in this study.

Further analysis

Study on regional heterogeneity

In fact, due to different resource endowments and stages of development, there is significant heterogeneity in regional distribution, whether it is the level of digitization, economic scale, or industrial pollutant emissions. Therefore, the effect of digitalization on urban industrial pollution control may also be heterogeneous in regional distribution, and it is necessary to further explore this issue. We divided 280 prefecture-level cities into three regions, east, middle, and west, according to the division criteria of the National Bureau of Statistics, and carried out regional heterogeneity analysis. Before the test of classification regression, the differences in digitization level, economic scale, and industrial pollutant emission in different regions are described. Table 6 reveals a sequential decline in the digitalization level, economic scale, and industrial pollutant discharge (excluding industrial sulfur dioxide) across the eastern, central, and western regions. This observation establishes a fundamental platform for examining the regional variations in digitization's impact on controlling industrial pollution in urban areas.

First, industrial sulfur dioxide emissions. It can be seen from Table 7 (1) to (3) that digitalization in eastern, central, and western regions can significantly reduce industrial sulfur dioxide emissions. The digitalization coefficient in the eastern region is −0.575, and the significance test at the 1% level shows that the industrial sulfur dioxide emissions in the eastern region will decrease by 57.5% when the digitalization development level increases by 1%. The digitalization coefficient in the central region was −0.519, and passed the significance test at the 1% level, indicating that every 1% development of digitalization in the central region would reduce the industrial sulfur dioxide emissions in the central region by 51.9%. The digitalization coefficient in the western region is −0.256, and it passes the significance test at the 1% level, indicating that every 1% increase in the digital

Table 6 Differences in digitization, economic scale, and pollutant emission in various cities

City classification	Sample size	Mean value	Median	Standard deviation	Mean value	Median	Standard deviation	Mean value	Median	Standard deviation
		Industrial sulfur dioxide emissions (LnSO_2)			Industrial wastewater discharge (LnWater)			Industrial smoke and dust emissions (LnDust)		
Eastern region	900	10.190	5.985	1.272	8.741	1.087	5.969	9.840	6.460	1.196
Central region	1080	9.915	6.708	1.160	8.028	5.802	0.892	9.723	6.463	1.177
Western region	540	9.932	7.225	1.281	7.487	4.870	1.140	9.383	7.155	1.130
		Digitization index (Ln*Dige*)			Economic scale index (Ln*GDP*)					
Eastern region	900	9.088	7.293	0.937	17.099	15.380	0.900			
Central region	1080	8.418	6.955	0.711	16.396	14.756	0.711			
Western region	540	8.214	6.226	1.001	16.056	14.441	0.921			

Variables are in the form of natural logarithms

development level in the western region will reduce industrial sulfur dioxide emissions by 25.6%.

The reason may be that at present, all parts of China pay more attention to industrial sulfur dioxide emission reduction, and the effect of industrial sulfur dioxide pollution brought by digital economic growth is higher than its emission reduction effect, so digital development can significantly help industrial sulfur dioxide emission reduction in various regions.

Second, in terms of industrial wastewater discharge. From Table 7 (4) to (6), it can be seen that digitalization in the eastern region can effectively reduce the discharge of industrial wastewater, while digitalization in the central region has no significant effect on the discharge of industrial wastewater, while digitalization in the western region will significantly promote the discharge of industrial wastewater. In column (4), the digitalization coefficient is −0.128, and passes the significance test at the 5% level, indicating that for each 1% development of digitalization in the eastern region, industrial wastewater discharge will decrease by 12.8%; The digitalization index in column (5) is not significant, indicating that digitalization has no obvious effect on industrial wastewater discharge in the central region; In column (6), the digitalization index coefficient is 0.236, and it is significant at the 1% level, indicating that for each unit of digitalization development in the western region, industrial wastewater discharge will increase by 23.6%.

The reason may be that the level of economic development and digital-based society in the eastern region is the highest, while the western region is the lowest. Therefore, digital development in the eastern region can significantly reduce the discharge of industrial wastewater, the effect of digitalization in the central region is not obvious, and the improvement of digitalization in the western region will bring about a “rebound effect,” which will increase energy consumption and pollution emissions.

Third, in terms of industrial smoke and dust emissions. From Table 7 (7) to (9), it can be seen that digitalization in the eastern and central regions can significantly reduce industrial smoke dust emissions, while that in the western region can significantly promote industrial smoke dust emissions. The digitalization coefficient in the eastern region is -0.708 and passes the significance test at the 1% level. Every 1% increase in the digitalization level in the eastern region will reduce the industrial smoke and dust emissions in the eastern region by 70.8%. The digitalization coefficient in the central region is −0.345 and passes the significance test at the 1% level. Every 1% increase in digitalization in the central region will reduce the industrial smoke and dust emissions in the central region by 34.5%; the digitalization coefficient in the western region is −0.173, and every 1% increase in the digitalization level in the western region passes the significance test at the 10% level. This would increase dust

Table 7 Analysis of regional heterogeneity

Explanatory variable	$LnSO_2$			LnWater			LnDust		
	(1) Eastern region	(2) Central region	(3) Western region	(4) Eastern region	(5) Central region	(6) Western region	(7) Eastern region	(8) Central region	(9) Western region
LnDige	−0.575*** (0.072)	−0.519*** (0.091)	−0.256*** (0.085)	−0.128** (0.054)	−0.075 (0.056)	0.236*** (0.080)	−0.708*** (0.078)	−0.345*** (0.093)	0.173* (0.090)
Constant	−0.936 (1.493)	38.502*** (2.982)	33.922*** (6.473)	24.338*** (2.533)	1.562* (0.867)	3.273*** (0.800)	4.953*** (1.626)	22.057*** (3.059)	5.312*** (0.898)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	Yes	No	No	No	No	No	No
Regional fixation	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	900	1080	540	900	1080	540	900	1080	540
F	54.320	12.990	21.560	65.870	55.460	26.920	25.530	12.560	13.170
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.471	0.583	0.716	0.884	0.431	0.419	0.290	0.575	0.253

The content reported in brackets in the table is robust standard error. *, **, and *** indicate significant at the significance level of 10%, 5%, and 1%, respectively

emissions in the western region by 17.3%. The digitalization index in eastern and central regions is significantly negative, indicating that digitalization in eastern and central regions can effectively control industrial smoke and dust emissions. The digital and economic development level in the western region is low, and the digital will promote the emission of industrial smoke and dust. To comprehensively improve environmental quality, we should pay attention to the digital and economic development of the Western region, formulate more policies for the introduction of talent for the Western region, and continue to increase financial investment in the Western region.

Fourth, compare. In the eastern region, the effect of digitalization on industrial pollutants is reduced. In the central region, the effect of digitization on industrial sulfur dioxide and industrial smoke dust is reduced, but the effect on industrial wastewater discharge is not significant. In the western region, digitalization will significantly promote the discharge of industrial wastewater and industrial smoke and dust but will reduce the discharge of industrial wastewater. Compared with the central and western regions, digitalization in the eastern region has a more obvious effect on reducing industrial pollutant emissions. This may be because the level of economic development and digitalization in the eastern, central, and western regions of China are showing a decreasing trend in turn, and the eastern region has a superior digital foundation compared with the central and western regions, and the release of digital dividends is more adequate, showing an obvious “icing on the brocade” effect on the control of industrial pollutant emissions. In addition, compared with industrial wastewater and smoke dust, digitalization has a stronger effect on reducing industrial sulfur dioxide. To effectively improve environmental quality, it is necessary to strengthen the control of industrial wastewater and smoke dust emissions in central and western regions and formulate relevant policies for the emission reduction of digitally empowered industrial wastewater and industrial smoke dust in central and western regions.

Study on the heterogeneity of economic development stage

Existing studies have shown that regions at different stages of economic development have different levels of digitalization and industrial pollutant emission, so the impact of digitalization on industrial pollutant emission in regions at different stages of economic development may also be heterogeneous. According to the average economic development level of 280 cities in China, 280 prefecture-level cities in China are divided into high-economic-level areas and low-economic-level areas.

First, areas with high levels of economic development. It can be seen from columns (1), (3), and (5) of Table 8 that digitization has significantly reduced the emission of industrial sulfur dioxide, industrial wastewater, and industrial smoke dust. The effect coefficient of digitalization on industrial sulfur dioxide emissions is −0.618. Through the significance test at the 1% level, it shows that every 1% increase in digitalization will reduce industrial sulfur dioxide emissions by 61.8%; The effect coefficient of digitalization on industrial wastewater discharge was −0.157, and passed the significance test at the 5% level, indicating that

Table 8 Heterogeneity analysis of economic development level

Explanatory variable	$LnSO_2$		LnWater		LnDust	
	(1) High level	(2) Low level	(3) High level	(4) Low level	(5) High level	(6) Low level
LnDige	−0.618*** (0.075)	−0.308*** (0.060)	−0.157** (0.066)	0.055 (0.046)	−0.510*** (0.092)	0.042 (0.061)
Constant	5.716*** (1.918)	30.147*** (2.440)	24.861 (2.290)	0.120 (0.552)	6.556*** (2.342)	5.204*** (0.721)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	No	No	No	No
Regional fixation	No	No	Yes	Yes	Yes	Yes
Observed value	657	1863	657	1863	657	1863
F	50.490	14.830	41.590	75.110	17.230	29.840
P	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.531	0.613	0.830	0.374	0.271	0.189

The content reported in brackets in the table is robust standard error. *** indicate significant at the significance level of 1%, respectively

each unit developed by digitalization would reduce industrial wastewater discharge by 15.7%. The effect coefficient of digitalization on industrial smoke dust was −0.51, and passed the significance test at the 1% level, indicating that each unit of digitalization development would reduce industrial smoke dust emissions by 51%.

Second, areas with low levels of economic development. It can be seen from columns (2), (4), and (6) of Table 8 that digitization has a significant effect on industrial sulfur dioxide emissions, while it has no significant effect on industrial wastewater and industrial smoke and dust emissions. In the model of the effect of digitalization on industrial sulfur dioxide, the digitalization index coefficient is −0.308, and it passes the significance test at the 1% level, indicating that each unit of digitalization development in low-level economic development areas will reduce industrial sulfur dioxide emissions by 30.8%. This phenomenon is similar to the conclusion in the previous study on regional heterogeneity, that is, compared with industrial wastewater and smoke dust, digitization has a stronger effect on the reduction of industrial sulfur dioxide.

Third, compare. We found the following: First, in various stages of economic development, compared with industrial wastewater and industrial smoke and dust emissions, digitization has a more obvious effect on reducing industrial sulfur dioxide emissions. Second, in areas with high levels of economic development, digitalization can significantly reduce the emission of industrial pollutants. In areas with low levels of economic development, digitization can only reduce industrial sulfur dioxide emissions and has no significant effect on industrial wastewater and industrial smoke and dust emissions. This may be because regions with a higher level of economic development have a correspondingly higher level of infrastructure and technology, which are more conducive to digitalization and can release more digital dividends (Zheng et al. 2022).

Study on the heterogeneity of industrialized and deindustrialized cities

Research findings indicate variations in the levels of industrial pollutant emissions between industrial and non-industrial cities, suggesting potential heterogeneity in the impact of digitization on industrial pollutant emissions across these regions. Guided by the "National Old Industrial Base Adjustment and Reconstruction Plan (2013–2022)," the study sample is stratified into industrial and non-industrial cities accordingly.

First, industrial cities. In the context of the industrial city, an analysis of columns (1), (3), and (5) in Table 9 reveals a profound impact of digitization on various industrial pollutants. Specifically, digitization has significantly mitigated the emissions of industrial sulfur dioxide, industrial wastewater, and industrial soot. The influence coefficient pertaining to industrial sulfur dioxide emissions stands at −0.561, which, upon undergoing a significance test at the 1% level, indicates a reduction of 56.1% in emissions for every 1% increase in digitization. Similarly, for industrial wastewater discharge, the digitization influence coefficient of −0.31 suggests a 31% decrease in emissions for every 1% rise in digitization, also validated by the significance test at the 1% level. Finally, with regard to industrial soot, the digitization influence coefficient of −0.341 indicates that every incremental unit of digitization contributes to a reduction of 34.1% in soot emissions, a finding that is further corroborated by the significance test at the 1% level.

Second, non-industrial cities. As can be seen from columns (2), (4), and (6) of Table 9, digitization has significantly reduced the emissions of industrial sulfur dioxide, industrial wastewater and industrial soot. The influence coefficient of digitalization on industrial sulfur dioxide emissions is −0.283, and the significance test at 1% level shows

Table 9 Heterogeneity analysis of urban industrialization degree

Explanatory variable	$LnSO_2$		LnWater		LnDust	
	(1) Industrialized city	(2) Deindustrialized city	(3) Industrialized city	(4) Deindustrialized city	(5) Industrialized city	(6) Deindustrialized city
LnDige	−0.561*** (0.119)	−0.283*** (0.061)	−0.310*** (0.072)	−0.269*** (0.036)	−0.341*** (0.114)	−0.237*** (0.055)
Constant	27.765*** (5.871)	52.465*** (2.702)	16.333*** (3.546)	21.913*** (1.583)	15.493*** (5.605)	29.233*** (2.412)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	No	No	No	No	No	No
Regional fixation	Yes	Yes	Yes	Yes	Yes	Yes
F	8.020	19.940	25.820	62.190	10.820	22.040
P	0.000	0.000	0.000	0.000	0.000	0.000
Adj R^2	0.454	0.685	0.746	0.875	0.538	0.707

The content reported in brackets in the table is robust standard error. *** indicate significant at the significance level of 1%, respectively

that if the digitalization level increases by 1%, industrial sulfur dioxide emissions will decrease by 28.3%. The influence coefficient of digitalization on industrial wastewater discharge is −0.269, and the significance test at 1% level shows that every 1% increase in digitalization level will reduce industrial wastewater discharge by 26.9%. The influence coefficient of digitization on industrial soot is −0.237, and the significance test at 1% level shows that digitization can reduce the unit industrial soot emission by 23.7%.

Third, comparison. The study revealed the following key findings: First, regardless of whether in industrial or non-industrial cities, an enhancement in digitization levels significantly reduces industrial pollutant emissions. Second, a comparative analysis between the two city types revealed that in industrial cities, the absolute value of the digitization coefficient for industrial pollutant emissions is notably higher. This indicates that in industrial cities, an increase in digitization is more effective in mitigating industrial pollutant emissions. This phenomenon could be attributed to the fact that industrial cities typically possess a higher baseline of industrial pollutant emissions and a more robust industrial infrastructure. Consequently, with the same level of digitization, industrial cities are able to harness greater digital dividends, thereby achieving a more effective reduction in industrial pollutant emissions.

Discussion on spatial spillover effect

In this paper, the Moran's I method is used to calculate the spatial effects of each year under the economic matrix, as shown in Table 10. As can be seen from Table 10, both the digitalization index and the industrial pollutant emission index from 2011 to 2019 reached a significance level of 1% in the Moran's I index under the economic weight, which indicates that there is a significant spatial autocorrelation between urban digitalization and industrial pollutant emission in China from 2011 to 2019; that is, the spatial distribution of the two is clustered.

Table 10 Characteristics of digitalization and "spread" of industrial pollutant emissions

Year	$LnSO_2$		LnWater		LnDust		LnDige	
	Moran index	Z-value	Moran index	Z-value	Moran index	Z-value	Moran index	Z-value
2011	0.054***	9.305	0.277***	10.051	0.087***	14.285	0.075***	12.385
2012	0.060***	10.287	0.276***	9.996	0.087***	14.353	0.065***	10.692
2013	0.059***	10.138	0.316***	11.455	0.087***	14.239	0.063***	10.436
2014	0.064***	11.071	0.336***	12.154	0.085***	13.929	0.057***	9.450
2015	0.068***	11.290	0.326***	11.793	0.080***	13.200	0.059***	9.865
2016	0.059***	9.868	0.346***	12.533	0.054***	9.086	0.056***	9.352
2017	0.041***	6.935	0.387***	13.983	0.045***	7.580	0.054***	9.086
2018	0.039***	6.708	0.356***	12.880	0.033***	5.693	0.055***	9.231
2019	0.031***	5.361	0.348***	12.572	0.023***	4.180	0.054***	9.116

The content reported in brackets in the table is robust standard error. *** indicate significant at the significance level of 1%, respectively

In order to compare and analyze the influence of digitization in a certain region on industrial pollution control in this region and its neighboring cities, the partial differential explanation of variable change is adopted; that is, the direct effect and indirect effect are used to explain the influence of digitization in a certain region on industrial pollutant emission in this region and other regions. As can be seen from Table 11, both the spatial spillover effect and the total effect of digitalization on industrial pollutant discharge are significantly negative, while the direct effect of digitalization on industrial sulfur dioxide discharge is significantly positive, and the direct effect on industrial wastewater and smoke dust discharge is not significant. It shows the existence of the spatial spillover effect of digitization to reduce industrial pollutant emissions, which is superior to the direct effect and plays a leading role.

Conclusions and recommendations

This paper studies the problem of digital urban industrial pollution control through economic scale, industrial transformation, and upgrading and green innovation. Based on the data from prefecture-level cities in China from 2011 to 2019, this paper uses the fixed effect model, intermediary effect model, and spatial Durbin model to construct digitalization level index and industrial transformation and upgrading. The influence of digitalization on industrial pollutant emission and its internal mechanism was tested by a multi-dimensional empirical study.

The main conclusions are as follows: First, there is a nonlinear relationship between digitalization and urban industrial pollutant discharge, and digitalization has become a "sharp tool" for urban industrial pollution control in the new era. The conclusion is still valid through the robustness test, such as changing the expression of indicators and removing individual values. Second, the two intermediary factors of green innovation and industrial transformation and upgrading can enhance the effect of digitalization on urban industrial pollution control, while the two intermediary factors of economic scale will weaken the effect of digitalization on urban industrial pollution control. "Green innovation–industrial transformation and upgrading" plays a positive intermediary role in the transmission chain between digitalization and urban industrial pollution control. Third, the spatial spillover effect of digitalization on urban industrial pollution control has also been confirmed, indicating that digitalization contributes to the formation of a green economic pattern of industrial pollution control. Fourth, in terms of regional heterogeneity, the eastern region enjoys a greater digital dividend than the central and western regions, the positive impact of digitalization on high-development areas is better than that on low-development areas, and the positive impact of digitalization on industrialized cities is better than that on non-industrialized areas.

In addition to providing a series of empirical evidence for effective digital empowerment of urban industrial pollution control, the conclusions of this paper also have the following policy implications:

First under the context of the increasingly prominent role of digitalization in fostering new momentum for industrial pollutant emission reduction, there is a pressing need to intensify investments in the digital domain to comprehensively propel the construction of Digital China. Specifically, emphasis should be placed on accelerating the development and application of cutting-edge technologies such as digital economy, artificial intelligence, and blockchain. These endeavors are aimed at deepening their integration and utilization in the domain of industrial pollutant emission reduction, thereby further consolidating and expanding the significant dividends and advantages conferred by digitalization. Such measures not only contribute to enhancing the greening and intelligence

Table 11 Estimated results of spatial effect test

Explanatory variable	Explained variable: *LnSO*$_2$			Explained variable: *LnWater*			Explained variable: *LnDust*		
	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect
LnDige	0.104*** (0.039)	−0.763** (0.379)	−0.659* (0.397)	−0042 (0.026)	−0.384*** (0.092)	−0.425*** (0.096)	0.024 (0.044)	−0.481* (0.258)	−0.457* (0.272)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixation	Yes	Yes	Yes	No	No	No	No	No	No
Regional fixation	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	2520	2520	2520	2520	2520	2520	2520	2520	2520

The content reported in brackets in the table is robust standard error. *, **, and *** indicate significant at the significance level of 10%, 5%, and 1%, respectively levels of industrial production but also provide robust support for achieving sustainable development goals.

Secondly, given that the positive impact of digitization on industrial pollution reduction in central and western regions as well as regions with low economic development levels has yet to be fully explored and deepened, this underscores the necessity of implementing differentiated and precision-oriented digitization strategies in these areas. By formulating and implementing targeted digitalization policies, we can more effectively leverage digital technologies as "key tools" for industrial pollutant reduction, thereby achieving more significant emission reduction results in these regions, promoting green transformation of industrial production, and fostering sustainable development.

Thirdly, digitalization facilitates the internal driving force for reducing industrial pollutant emissions by promoting green innovation and industrial transformation and upgrading. This substantiates the notion that the convergence of digitalization, green innovation, and industrial transformation and upgrading can generate novel impetus for green economic development, thereby playing a pivotal role in pollution reduction and environmental enhancement in the contemporary era. In the realm of digitalization, emphasis should be placed on key core technologies, as well as the allocation of data element resources and other related tasks.

Fourthly, given the significant spillover effect of digitization in spatial layout, it is urgent for regions to strengthen cross-regional collaborative development strategies in digitization. The core objective of this strategy is to continuously deepen the process of digitalization construction in various regions, thus fully unleashing the potential power of digitization in spatial optimization. Through this cross-regional collaborative model, we can efficiently promote the reduction of industrial pollutants, laying a solid foundation for building a green and low-carbon industrial development path. This not only helps to improve the environmental protection level of industrial production but also provides strong technical support for achieving sustainable development goals.

Author contribution The author contributed to the study conception and design. Conceptualization, material preparation, data collection, and analysis were performed by SS. The first draft of the manuscript was written by SS including the previous versions of the manuscript. This final manuscript is read and approved by the author.

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval Not applicable as the research is based on secondary data already available in public domain. No human participants are involved.

Consent to participate Not applicable as the research is based on secondary data already available in public domain. No human participants are involved.

Consent for publication Not applicable as the research is based on secondary data already available in public domain. No human participants are involved.

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