Digital Technology Empowering Urban Environmental Governance: Energy Conservation, Emission Reduction, and Efficiency Enhancement

Yixuan Ma
(School of Business, Nanjing University, Nanjing 210093, China)

Abstract: Using panel data for 282 prefecture-level and above cities in China from 2011–2020, this study empirically examines whether digital technology contributes to urban environmental governance through three channels—energy conservation, emission reduction, and efficiency enhancement. The results show that digital technology significantly reduces energy consumption and pollutant emissions while improving energy efficiency; these findings remain robust after endogeneity and robustness checks. Heterogeneity analyses indicate that the effects are more pronounced in cities with lower economic development, higher marketization, non-resource-based characteristics, and in core cities. Mechanism tests suggest that digital technology promotes energy conservation, emission reduction, and efficiency enhancement by stimulating green technological innovation, upgrading industrial structure, and improving human capital. Moderation tests show that environmental regulation strengthens these effects, whereas capital-factor and labor-factor distortions weaken them. Spatial econometric results further reveal positive spillover effects of digital technology on neighboring cities' energy conservation, emission reduction, and efficiency enhancement. Accordingly, policies should steadily advance digital technology development, foster green innovation, industrial upgrading, and human-capital accumulation, strengthen environmental regulation, reduce factor-market distortions, and promote coordinated regional development.

Keywords: digital technology; environmental governance; energy conservation; emission reduction; efficiency enhancement

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1 Introduction

Since China's reform and opening-up, rapid urbanization and industrialization have accelerated economic growth, but an extensive, factor-driven development pattern has also consumed large amounts of energy and increased emissions of gaseous, liquid, and solid pollutants, resulting in serious environmental pressure. In response, governments have strengthened environmental laws and regulations, increased pollution-control efforts, and promoted the transformation of the growth model, achieving certain progress but not fundamentally resolving the tension among resource utilization, environmental protection, and economic development. Coordinating economic growth with ecological protection has therefore become a key task for high-quality development. The Report to the 20th National Congress of the Communist Party of China emphasizes prioritizing ecology, practicing conservation and intensive use, advancing green and low-carbon development, accelerating the green transition of development models, and steadily promoting carbon peaking and carbon neutrality.

Against this background, identifying tools and approaches that can enhance urban environmental governance remains a major focus in both policy and research. Digital technology is driving the emergence of new industries and business models and features strong penetration, integration, openness, substitutability, and synergy. It can influence low-carbon transition, sustainable development, and reductions in energy intensity, reshaping production, lifestyles, and governance modes. By enabling rapid processing of environmental big data, digital technology can endow environmental governance with capabilities such as sensing, memory, and learning, alleviate mismatches in governance resources, improve decision-making efficiency, optimize governance procedures, and support low-carbon regional transition—making it an increasingly important instrument for environmental governance.

Existing studies mainly focus on measuring digital technology and assessing its environmental impacts. Measurement approaches include direct accounting and indicator-system methods, often constrained by data availability and accounting limitations. Prior work suggests that digital technology can enhance green innovation, facilitate industrial upgrading, optimize capital allocation, improve energy performance, and raise green total factor productivity. Research has examined firm-level digital embedding and cost reduction, industry-level resource allocation and structural green transition, and regulatory-level improvements in data connectivity, scientific decision-making, and refined governance, as well as enhanced public participation and collaborative governance via digital platforms. However, the literature has not reached consensus, and few studies systematically unpack the internal mechanisms or jointly examine energy conservation, emission reduction, and efficiency enhancement. Using panel data for 282 Chinese prefecture-level and above cities during 2011–2020, this paper empirically tests the effects of digital technology on the three dimensions and investigates the mechanisms and spatial spillovers. The contributions are fourfold: (1) a systematic review and empirical test of the threefold effects; (2) heterogeneity analyses by economic development, marketization, resource endowment, and administrative level; (3) identification and testing of mechanism pathways; and (4) examination of spatial spillover effects.

2 Literature Review and Hypotheses

2.1 Digital Technology and Urban Environmental Governance

Digital technology can influence urban environmental governance primarily through energy conservation, emission reduction, and efficiency enhancement. For energy conservation, digital technology promotes technological upgrading, process optimization, and equipment renewal; it also provides real-time monitoring tools to optimize energy scheduling, adjust production status promptly, improve production efficiency, and avoid unnecessary energy use. It can improve the type and structure of production factors, raise allocation efficiency, facilitate industrial transformation and upgrading, and improve energy utilization efficiency, thereby reducing energy consumption. Moreover, by accelerating the diffusion of advanced technologies and knowledge sharing, it fosters greener industrial transformation.

For emission reduction, digital technology can support cleaner production by upgrading equipment and processes, introducing advanced and environmentally friendly technologies and end-of-pipe treatment facilities, and reducing pollutant emissions. It helps integrate information in firms' production decisions, reduces fragmentation and information asymmetry, and facilitates the adoption of clean energy. At the same time, it enables real-time monitoring and dynamic evaluation by governments, enhances early warning and sensing of pollution sources, improves the precision and effectiveness of regulation, and reduces emissions. For efficiency enhancement, digital technology improves the diffusion of energy-use technologies, matches supply and demand more effectively, reduces transaction costs, and thus increases energy efficiency. By building environmental information-sharing platforms and improving disclosure, it can guide green investment and consumption, and further enhance efficiency. Accordingly, we propose:

H1: Digital technology has measurable effects on energy conservation, emission reduction, and efficiency enhancement.

2.2 Digital Technology, Mediating Mechanisms, and Urban Environmental Governance

First, green technological innovation. Digital technology makes it easier for firms to acquire information about green products and green consumption, providing abundant innovation resources and clearer directions for green innovation, thereby reducing innovation risk and increasing outputs. It expands the breadth and depth of knowledge search inside and outside the firm, improves technology transformation capability, helps evaluate profit potential and market prospects, reduces the cost of green innovation, and supports financing by alleviating information asymmetry between firms and investors. Through spillovers and intensified market competition, digital technology can foster a virtuous innovation cycle, improving green innovation. Green innovation then upgrades equipment and processes, improves resource allocation, accelerates commercialization, increases the share of green industries, and achieves energy conservation, emission reduction, and efficiency enhancement from the source.

Second, industrial structure upgrading. Digital technology improves digital infrastructure and information transmission efficiency, reducing search, transaction, and matching costs and mitigating potential supply–demand information asymmetry. Digitalized production is more standardized and features high cleanliness, replicability, and low-cost transmission, strengthening coordination across sectors. With digital industrialization and industrial digitalization, industry shifts toward knowledge- and technology-intensive activities, optimizing production processes and increasing resource efficiency while raising the share of green and low-carbon industries. Digital technology also intensifies market competition, expands the scope of resource allocation, and promotes the flow of resources to more productive sectors. By reducing barriers to factor mobility and improving the allocation of capital, labor, and technology, it helps the regional industrial structure evolve toward high-tech and low-energy-consumption directions. Structural upgrading, in turn, drives the transformation of high-pollution and high-energy-consuming industries and reduces pollution and resource waste.

Third, human capital improvement. Digital technology encourages new business forms and creates employment opportunities, while requiring workers to learn new technologies through learning-by-doing, vocational training, and continuing education. It stimulates investment in human capital—especially in digital talent—and strengthens links among digital knowledge, skills, and interdisciplinary capabilities. Digital education tools (search engines, online learning, AI, real-time translation, etc.) broaden knowledge access and raise workforce skill levels. Higher human capital supports the innovation, application, and diffusion of energy-saving and emission-reducing technologies, and can be associated with stricter regulation. Given increasing returns to human capital, it can substitute for material inputs and promote green, low-carbon development.

H2: Digital technology promotes energy conservation, emission reduction, and efficiency enhancement through green technological innovation, industrial structure upgrading, and improved human capital.

2.3 Digital Technology, Moderating Mechanisms, and Urban Environmental Governance

First, environmental regulation. Environmental regulation is a key policy instrument for promoting firms' green transition and achieving the "dual-carbon" goals. It works by forcing or incentivizing firms to increase R&D input and pollution-control capability, improving environmental quality. When regulation is weak, pollution-intensive industries may dominate and overall support for digital technology may be limited; scarce funds may be diverted due to short-sighted behavior, weakening the governance effect of digital technology. Stronger regulation can create pressure and incentives for innovation in energy utilization and pollution-control technologies, facilitating green progress and structural upgrading, improving resource allocation, and phasing out inefficient, high-energy, and high-pollution industries. Therefore, environmental regulation is expected to positively moderate the effect of digital technology.

Second, factor distortions. Digital technology can reduce information asymmetry among economic agents and enable more financial resources to support green innovation and services, improving factor allocation and optimizing supply and value chains. However, the effectiveness of digital technology depends on the degree of factor-market distortions—mainly capital and labor distortions—where resource allocation deviates from welfare-maximizing outcomes. Financial frictions are a key driver of capital distortions, raising credit thresholds, while labor-market segmentation and information asymmetry contribute to labor distortions. Distortions hinder free factor mobility and allocation efficiency, reduce incentives for green upgrading under low factor prices, and may lock regions into low-efficiency, low-technology equilibria, exacerbating pollution. Hence, factor distortions are expected to weaken the governance effects of digital technology.

H3: Environmental regulation strengthens, while capital- and labor-factor distortions weaken, the mechanism through which digital technology promotes energy conservation, emission reduction, and efficiency enhancement.

2.4 Digital Technology, Spatial Spillovers, and Urban Environmental Governance

Digital technology changes factor mobility and connectivity, compressing the spatiotemporal distance of governance resources and allowing governance benefits to spill over through digital networks. On the one hand, it lowers factor mobility costs and supports cross-regional integration and collaboration of labor, capital, and technology, promoting the sharing of information, knowledge, and other resources. It can improve production layout and energy-use efficiency, facilitate joint prevention and control of pollution through data sharing, and diffuse successful governance experiences to nearby regions, generating positive spillovers. On the other hand, competition for resources and digital divides may cause talent and funding to flow to better-performing regions; moreover, high-input and high-pollution firms may be relocated to neighboring regions with weaker governance, potentially worsening outcomes there. Thus, the net spillover effect is theoretically ambiguous. We propose:

H4: Digital technology generates spatial spillover effects on neighboring cities' energy conservation, emission reduction, and efficiency enhancement.

3 Research Design

3.1 Sample Selection and Data Sources

The study uses panel data for 282 prefecture-level and above cities in China (excluding Tibet as well as Hong Kong, Macao, and Taiwan) from 2011–2020. The period is chosen because (i) the Ministry of Environmental Protection revised the statistical indicator system, survey methods, and technical standards starting in 2011, and (ii) data availability and continuity are stronger for this span. Data sources include the Digital Inclusive Finance Index from the Institute of Digital Finance at Peking University; patent data from the National Intellectual Property Administration; the marketization index from the "China Marketization Index" report; and other indicators from the China City Statistical Yearbook, China Energy Statistical Yearbook, China Regional Economic Statistical Yearbook, China Statistical Yearbook, local government websites, CSMAR, and Wind. Missing values are imputed using interpolation; continuous variables are winsorized at the 1% level at both tails.

3.2 Variable Definitions

3.2.1 Dependent Variables

Environmental governance (*Env*) is measured from three perspectives: (1) Energy consumption (*Elc)*: following Lü Qian and Liu Haibin (2020), we construct a calibrated measure by merging DMSP-OLS stable nightlight data with NPP-VIIRS nightlight data. (2) Pollution emissions (*Plu)*: following Li et al. (2013), we combine industrial SO_2 emissions, industrial wastewater discharge, and industrial smoke/dust emissions using the entropy method. (3) Energy efficiency (*Efc*): following Wang Qingxi et al. (2022), we compute a Super SBM-DEA model with undesirable outputs. Energy input is electricity consumption; non-energy inputs include labor (number of employees) and capital (measured by the perpetual inventory method for total fixed-asset investment with a 10.96% depreciation rate). Undesirable outputs include industrial SO_2, wastewater, and smoke/dust emissions.

3.2.2 Explanatory Variable

Digital technology (*Dt)* is measured by constructing an evaluation index system and applying the entropy method, following Fu Zhihua and Mei Huiyang (2023). The first-level index is digital technology, with three second-level dimensions: digital infrastructure, digital application, and digital innovation. Digital infrastructure is proxied by internet penetration rate, length of long-distance optical cable, and the number of internet access ports. Digital application includes the number of internet domain names, per-capita telecom services, the share of employment in software and IT services, and the Digital Inclusive Finance Index. Digital innovation is proxied by the number of R&D personnel and internal R&D expenditure of industrial firms above designated size, and the number of authorized patent applications.

3.2.3 Mediating Variables

Mediators include: (1) Green technology innovation (*Gti*), measured as the natural logarithm of the number of green invention patent applications in a city-year, following Wang Hai et al. (2023); (2) Industrial structure (*Is*), $Is = \sum_{v=1}^{3} h_v v / \mathrm{GDP}$ measured by an industrial structure hierarchy index, following Zheng Wanteng et al. (2022); and (3) Human capital (*Hc*), measured by the ratio of the number of students in regular higher-education institutions to the resident population.

3.2.4 Moderating Variables

Moderators include: (1) Environmental regulation intensity (*Er*), constructed as the natural logarithm of the frequency of environment-related terms in government work reports, following Zhang Jianpeng and Chen Shiyi (2021). (2) Capital-factor distortion (*Dcf*) and labor-factor distortion (*Dlf*): following Bai Junhong and Bian Yuanchao (2016), we estimate a translog production function and compute Dcf = MPK/r and Dlf = MPL/d, where MPK and MPL are the marginal products of capital and labor; r is the actual price of capital (proxied by the annual average statutory loan interest rate), and d is the actual price of labor (proxied by the average wage of urban employees deflated to 2011 as the base year).

3.2.5 Control Variables

Following Deng Rongrong and Zhang Aoxiang (2021) and Zhu Xian and Ma Yingge (2022), we control for: urbanization level (*Ul,* urban population/resident population), population density (*Pd*, population per km²), fiscal expenditure (*Fe*, fiscal expenditure/real GDP), foreign direct investment (*Fdi*, utilized FDI/real GDP), financial development (*Fdl*, year-end deposits and loans of financial institutions/real GDP), and road area (*Ra*, urban road area/urban built-up area). Table 1 reports descriptive statistics.

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	P25	Median	P75	Max
Elc	3384	0.391	0.902	0.011	0.083	0.178	0.397	0.798
Plu	3384	0.086	0.071	0.004	0.038	0.068	0.109	0.345
Efc	3384	0.389	0.081	0.297	0.352	0.367	0.395	1.048
Dt	3384	0.095	0.041	0.022	0.076	0.088	0.105	0.255
Gti	3384	2.312	0.147	1.973	2.235	2.916	2.397	2.672
Is	3384	2.322	0.152	1.967	2.317	2.317	2.414	2.920
Hc	3384	0.019	0.208	0.002	0.006	0.012	0.182	0.191
Er	3384	8.616	0.223	6.466	8.496	8.634	8.757	9.280
Dcf	3384	0.961	1.932	0.005	0.086	0.152	0.292	0.887
Dlf	3384	0.110	0.047	0.032	0.759	0.103	0.141	0.267
Ul	3384	0.551	1.043	0.009	0.347	0.381	0.757	0.892
Pd	3384	4.552	3.334	0.025	1.901	3.675	6.655	15.112
Fe	3384	0.213	0.144	0.085	0.143	0.204	0.245	0.676
Fdi	3384	0.232	0.242	0.002	0.126	0.278	0.376	1.298
Fdl	3384	0.999	0.537	0.301	0.645	0.839	1.157	3.675
Ra	3384	1.324	0.830	0.153	0.743	1.324	1.433	4.443

3.3 Model Specification

Based on the theoretical framework and Hypothesis H1, we estimate the following baseline model (Equation 1).

$$Env(Elc、Plu、Efc)_{it} = a_0 + a_1 Dt_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad （1）$$

To test mediating mechanisms, we extend the baseline to mediation models (Equations 2–3).

$$U(Gti、Is、Hc)_{it} = b_0 + b_1 Dt_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad (2)$$

$$Env(Elc、Plu、Efc)_{it} = c_0 + c_1 Dt_{it} + c_2 U(Gti、Is、Hc)_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad (3)$$

To test moderation, we introduce interaction terms to obtain the moderation models (Equations 4–6).

$$Env(Elc、Plu、Efc)_{it} = d_0 + d_1 Dt_{it} + d_2 Er_{it} + d_3 Dt_{it} \times Er_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad (4)$$

$$Env(Elc、Plu、Efc)_{it} = e_0 + e_1 Dt_{it} + e_2 Dcf_{it} + e_3 Dt_{it} \times Dcf_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad (5)$$

$$Env(Elc、Plu、Efc)_{it} = f_0 + f_1 Dt_{it} + f_2 Dlf_{it} + e_3 Dt_{it} \times Dlf_{it} + \gamma Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \quad (6)$$

To test spatial spillovers, after the Hausman test, spatial-model diagnostics (LM test) and two-way fixed-effects tests (LR test), we estimate a two-way fixed-effects Spatial Durbin Model (SDM) (Equation 7).

$$\begin{aligned} Env(Elc、Plu、Efc)_{it} = {} & g_0 + \rho W Env(Elc、Plu、Efc)_{it} + g_1 Dt_{it} + g_2 W Dt_{it} + g_3 Controls_{it} \\ & + g W Controls_{it} + \varepsilon_i + \mu_t + \varphi_{it} \end{aligned} \quad (7)$$

Here, Control denotes control variables; i indexes cities and t indexes years; province and time fixed effects are included; ρ is the spatial autoregressive coefficient; and W is the spatial weight matrix. We consider three matrices: contiguity ($W1$), geographic distance ($W2$), and an economic–geographic matrix ($W3$) constructed from squared geographic distances and city-level averages of real GDP and GDP growth.

4 Empirical Results and Analysis

4.1 Baseline Regression Results

Table 2 reports the baseline regression results. Columns (1), (3), and (5) present random-effects (RE) estimates, while columns (2), (4), and (6) present fixed-effects (FE) estimates. For energy consumption (Elc), the coefficient of digital technology is significantly negative, indicating an energy-conservation effect. For pollution emissions (Plu), the coefficient is also significantly negative, implying an emission-reduction effect. For energy efficiency (Efc), the coefficient is significantly positive, implying an efficiency-enhancement effect. Hausman and F tests suggest that the fixed-effects specification is preferred.

Table 2. Baseline regression results

Variable	（1）	（2）	（3）
	Elc	*Plu*	*Efc*
Dt	-3.360***	-0.378***	0.661***
	（-5.35）	（-20.97）	(11.34)
Ul	-0.006	0.002*	0.017***
	（-0.18）	（2.34）	(5.66)
Pd	-0.034	-0.008***	0.034***
	（-0.99）	（-7.54）	(10.84)
Fe	-0.366*	-0.032***	-0.015
	（-2.20）	（-6.68）	(-0.64)
Fdi	9.492	1.027***	-1.930***
	（1.39）	（5.14）	(-3.47)
Fdl	-0.014	0.003**	0.003
	（-0.25）	（3.16）	(0.83)
Ra	0.542	0.009	-0.015

	(0.45)	(0.27)	(-0.15)
Constant	0.942***	0.153***	0.163***
	(5.36)	(31.04)	(10.23)
City/Year	Yes	Yes	Yes
F	18.57***	170.25***	17.99***
Hausman	16.73***	154.65***	17.58***
R^2	0.45	0.39	0.37
N	3384	3384	3384

Notes: t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.2 Endogeneity and Robustness Tests

4.2.1 Endogeneity Tests

First, to account for possible lagged effects of digital technology, we re-estimate the models using one- and two-period lags for all variables except Dt. The signs and significance of Dt remain consistent with the baseline results, supporting robustness. Second, to mitigate potential reverse causality, we follow Huang et al. (2019) and Nunn & Qian and construct an instrumental variable by interacting the national number of internet users in the previous year with the number of telephones per 10,000 people in each province in 1984. Two-stage least squares (2SLS) results indicate that the instruments are relevant (Kleibergen–Paap statistics) and the estimated effects of Dt remain consistent.

Table 3. Endogeneity tests

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lagged-effects tes						Instrumental variables		
	Lag 1			Lag 2					
	Elc	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*
Dt	-3.152***	-0.406***	0.551***	-3.226***	-0.451***	0.449***	-9.568***	-0.269*	0.939***
	(-4.49)	(-20.91)	(10.84)	(-4.02)	(-21.55)	(8.70)	(-6.67)	(-1.81)	(3.99)
Constant	1.007***	0.164***	0.141***	1.175***	0.183***	0.132***	-0.296**	0.135***	0.319***
	(4.96)	(29.67)	(9.60)	(4.81)	(28.94)	(8.12)	(-2.78)	(10.95)	(18.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM							[83.62]	[85.64]	[85.71]
K-P rk Wald F							{18.65}	{17.76}	{16.38}
City/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.67	0.57	0.43	0.78	0.54	0.57	0.45	0.35	0.29
N	3102	3102	3102	2820	2820	2820	3384	3384	3384

Notes: Values in [ ] are p-values of the corresponding statistics; values in { } are the 10% critical values from the Stock–Yogo test.

4.2.2 Robustness Checks

We conduct several robustness checks. First, we replace Dt with an alternative proxy (Tel), constructed as the interaction between per-capita telecom services and per-capita GDP; the results remain consistent. Second, we test the policy effect of the "Broadband China" strategy using a difference-in-differences specification, where the policy dummy Plc equals 1 after 2013 and 0 otherwise. The results show stronger effects in pilot cities. Third, we exclude the four municipalities directly under the central government (Beijing, Shanghai, Tianjin, Chongqing) to avoid special-case influence; results are unchanged.

Table 4. Robustness checks

Variable	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）
	Alternative measure of the explanatory variable			Policy effect			Excluding municipalities		
	Elc	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*
Tel	-2.800***	-0.315***	0.606***	-2.843**	-0.455***	0.387***			
	（-5.35）	（-20.97）	（14.01）	(-2.36)	(-15.96)	(6.33)			
Dt							-2.635***	-0.277***	0.690***
							（-7.46）	（-14.20）	（10.65）
Constant	0.634***	0.119***	0.232***	0.923**	0.923**	0.923**	0.820***	0.138***	0.152***
	（3.79）	（25.13）	（15.65）	(2.92)	(2.92)	(2.92)	（7.01）	（21.53）	（6.65）
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.34	0.42	0.41	0.43	0.38	0.41	0.42	0.37	0.36
N	3384	3384	3384	2820	2820	2820	3384	3384	3384

4.3 Heterogeneity Analysis

First, testing for heterogeneity in economic development levels. Considering that the impact of digital technologies on energy conservation, emission reduction, and efficiency gains may vary across cities with differing economic development levels. This study uses per capita GDP as the indicator for economic development. The sample is divided into two groups—high and low economic development levels—based on the median. Regression analyses are conducted, with results presented in columns (1) (2) (7) (8) (13), and (14) of Table 5. The regression findings indicate that the energy-saving, emission-reducing, and efficiency-enhancing effects of digital technologies are more pronounced in cities with higher economic development levels. (1) (2) (7) (8) (13) and (14). The regression results indicate that the energy-saving, emission-reduction, and efficiency-enhancement effects of digital technologies are more pronounced in cities with higher levels of economic development.

Second, heterogeneity testing by resource endowment. Considering that the impact of digital technologies on energy conservation, emission reduction, and efficiency enhancement may vary across cities with different resource endowments, the sample was divided into resource-based and non-resource-based groups based on the classification criteria from the National Sustainable Development Plan for Resource-Based Cities (2013-2020). The regression results are presented in columns (3) (4) (9) (10) (15) and (16) of Table 5. and (16) of Table 5. The regression results indicate that the energy-saving, emission-reduction, and efficiency-enhancement effects of digital technologies are more pronounced in non-resource-based cities.

Third, heterogeneity testing by administrative tier. Considering that the impact of digital technologies on energy conservation, emission reduction, and efficiency gains may vary across cities of different administrative tiers, the sample was divided into central cities (municipalities directly under the central government and sub-provincial cities) and peripheral cities (general prefecture-level cities) based on administrative tier for regression analysis. The results are presented in columns (5) (6) (11) (12) (17), and (18) of Table 5. The regression results indicate that the energy-saving, emission-reduction, and efficiency-enhancing effects of digital technologies are more pronounced in central cities.

Table 5 Regression Results for Heterogeneity Tests

Variable	（1）	（2）	（3）	（4）	（5）	（6）
	Elc					
	Economic development		Resource		City level	
	High	Low	Based	Non- Based	Core cities	Peripheral cities
Dt	-3.351***	-2.681**	-2.477*	-3.531***	-3.875***	-0.364***
	（-11.90）	（-2.09）	（-1.96）	（-17.80）	（-6.76）	（-3.76）
Constant	0.937***	1.097	0.940	0.891***	1.155	0.186***
	（11.82）	（1.61）	（1.39）	（17.99）	（1.65）	（23.64）

Controls	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.41	0.37	0.40	0.37	0.34	0.43
N	1692	1692	888	2496	420	2964
P	0.001		0.002		0.000	

	（7）	（8）	（9）	（10）	（11）	（12）
	Plu					
Variable	Economic development		Resource		City level	
	High	Low	Based	Non- Based	Core cities	Core cities
Dt	-0.354***	-0.254***	-0.352***	-0.454***	-1.123***	-0.354***
	（-14.43）	（-9.02）	（-14.54）	（-17.54）	（-6.76）	（-3.65）
Constant	0.154***	0.145***	0.181***	0.171***	0.895***	0.286***
	（21.64）	（18.78）	（15.81）	（24.53）	（14.25）	（6.76）
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.35	0.35	0.41	0.37	0.33	0.35
N	1692	1692	888	2496	420	2964
P	0.000		0.002		0.000	

	（13）	（14）	（15）	（16）	（17）	（18）
	Efc					
Variable	Economic development		Resource		City level	
	High	Low	Based	Non- Based	Core cities	Core cities
Dt	1.045***	0.043**	0.234**	1.395***	0.453***	0.142***
	（13.87）	（2.45）	（2.83）	（17.92）	（6.54）	（3.64）
Constant	0.545**	0.354***	0.154***	0.183***	0.161***	0.163***
	（2.86）	（26.73）	（5.56）	（11.86）	（13.64）	（10.54）
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.42	0.45	0.41	0.39	0.34	0.37
N	1692	1692	888	2496	420	2964
P	0.000		0.001		0.002	

Note: The experience P-value indicates whether there is a significant difference in the coefficient of Dt between the regression results of the two sample groups, obtained by repeating the calculation 1000 times using the Bootstrap method. The same applies to the table below.

4.4 Mediation Mechanism Tests

Based on Models (1) to (3), empirical tests were conducted to examine the existence of mediation mechanisms. Table 6 reports the regression results for these mediating effects. Firstly, regarding green technological innovation: in Column (1), the coefficient for digital technology is 2.242, significant at the 1% level. In columns (2) to (4), the coefficients for digital technology are -1.917, -0.158, and 0.654 respectively, significant at the 5%, 1%, and 1% levels; the coefficients for green technology innovation are -0.644, -0.099, and 0.026 respectively, significant at the 5%, 1%, and 5% levels. Second, industrial structure. In column (5), the coefficient for digital technology is 2.670, significant at the 1% level. In columns (6) to (8), the coefficients for digital technology were -2.562, -0.221, and 0.654 respectively, significant at the 5%, 1%, and 1% levels; the coefficients for industrial structure were -0.301, -0.063, and 0.045 respectively, significant at the 5%, 1%, and 5% levels. Thirdly, human capital. In column (9), the coefficient for digital technology is 0.088, significant at the 1% level. In columns (10) to (12), the coefficients for digital technology are -3.225, -0.338, and 0.643 respectively, all significant at the 1% level; while the coefficients for human capital were -1.555, -0.476, and 0.723, respectively, significant at the 5%, 1%, and 5% levels. These findings indicate that digital technology promotes energy conservation, emission reduction, and efficiency gains through green technological innovation, industrial structure optimisation, and human capital enhancement, thereby validating research hypothesis H2.

Considering that the traditional three-step mediation test may suffer from three potential endogeneity issues in the independent, dependent, and mediating variables, the IVMEDIATE model proposed by Dippel et al. [48] was adopted to conduct a causal mediation analysis on the aforementioned mediation model. The lagged value of the mediating variable was employed as the instrumental variable. Results indicate that F-statistics in the first stage exceed 10, passing weak instrumental variable identification. Specifically: - Green technological innovation explains 40.45%, 70.58%, and 43.17% of digital technology's impact on energy conservation, emission reduction, and efficiency enhancement respectively. Optimisation of industrial structure explains 42.78%, 69.27%, and 42.88% of the effects of digital technology on energy conservation, emission reduction, and efficiency enhancement respectively. Human capital explains 58.52%, 78.43%, and 42.37% of these effects respectively. This indicates that the mediating effects remain valid after employing instrumental variables to mitigate endogeneity issues.

Table 7. Mediation mechanism tests

Variable	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）	（10）	（11）	（12）
	Green technology innovation				Industrial structure upgrading				Human capital			
	Gti	*Elc*	*Plu*	*Efc*	*Is*	*Elc*	*Plu*	*Efc*	*Hc*	*Elc*	*Plu*	*Efc*
Dt	2.242***	-1.917**	-0.158***	0.695***	2.670***	-2.562**	-0.211***	0.648***	0.088***	-3.225***	-0.338***	0.678***
	（32.43）	（-2.65）	（-10.01）	（11.33）	(37.54)	(-2.95)	(-9.85)	(12.38)	(16.33)	(-4.90)	(-18.06)	(13.83)
Gti		-0.644**	-0.099***	0.024**								
		（-2.76）	（-18.01）	（2.76）								
Is						-0.301*	-0.063***	0.038**				
						(-2.53)	(-14.58)	（2.44）				
Hc										-1.555**	-0.476***	0.740**
										(-2.68)	(-8.16)	（2.04）
Constant	1.853***	2.254***	0.378***	0.213***	1.800***	1.667***	0.269***	0.163***	0.00434**	0.946***	0.155***	0.146***
	（32.46）	（6.23）	（26.65）	（6.76）	(92.27)	(4.98)	(29.08)	(5.96)	(2.91)	(5.38)	(31.75)	(10.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.35	0.43	0.44	0.42	0.33	0.35	0.33	0.35	0.41	0.34	0.42	0.36
N	3384	3384	3384	3384	3384	3384	3384	3384	3384	3384	3384	3384
mediation effects		1.44	0.22	0.05		0.80	0.17	0.10		0.14	0.04	0.07
Proportion of mediating effect		42.95%	58.20%	7.16%		23.81%	44.44%	13.36%		4.17%	10.58%	9.36%

4.5 Moderation Mechanism Tests

Based on Models (4) to (6), empirical tests were conducted to examine the existence of moderating mechanisms. Table 7 reports the regression results for these moderation tests. First, environmental regulation. In columns (1) to (3), the coefficients for the interaction term between digital technology and environmental regulation (Dt×Er) are -0.713, -0.167, and 0.466 respectively, significant at the 5%, 5%, and 1% levels. The coefficients for digital technology are -3.846, -1.667, and 0.388 respectively, all significant at the 1% level. Second, factor distortion. In columns (4) to (6), the coefficients for the interaction term between digital technology and capital factor distortion (Dt×Dcf) are 1.343, 0.176, and -0.054 respectively, all significant at the 5% level; the coefficients for digital technology are -3.378, -0.476, and 0.656 respectively, all significant at the 1% level. In columns (7) to (9), the coefficients for the interaction term between digital technology and labour factor distortion (Dt×Dlf) are 1.945, 1.776, and -4.148 respectively, significant at the 10%, 1%, and 1% levels; The coefficients for digital technology were -1.873, -0.376, and 0.971 respectively, significant at the 5%, 1%, and 1% levels. These findings indicate that within the mechanism through which digital technology influences energy conservation, emission reduction, and efficiency enhancement, environmental regulations exert a positive moderating effect, while distortions in capital and labour factors exert negative moderating effects, thereby validating research hypothesis H3.

Table 8. Moderation mechanism tests

Variable	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）
	Environmental regulation			Factor distortions					
				Capital distortion			Labor distortion		
	Elc	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*
Dt	-3.625**	-1.349***	3.298***	-3.514***	-0.442***	0.642***	-1.911**	-0.371***	0.949***
	（-2.29）	（-3.59）	（-3.45）	（-3.94）	（-19.05）	（11.00）	（-2.99）	（-13.49）	（13.24）
Er	0.048	0.012**	0.042***						
	（0.30）	（2.64）	（3.74）						
Dt×Er	-0.700**	-0.106**	0.454***						
	（-2.43）	（-2.45）	（4.15）						
Dcf				0.150	0.003	-0.004			
				（1.60）	（1.36）	（-0.63）			
Dt×Dcf				1.268**	0.129**	-0.034**			
				（2.60）	（2.36）	（3.61）			
Dlf							1.396	0.026	-0.389***
							（1.55）	（1.24）	（-6.85）
Dt×Dlf							1.942*	1.373***	-4.052***
							（1.86）	（4.99）	（-5.64）
Constant	0.544	0.260***	0.522***	0.918***	0.158***	0.163***	0.380	0.126***	0.127***
	（0.38）	（6.81）	（5.38）	（3.98）	（25.72）	（10.33）	（1.49）	（19.21）	（7.15）
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.21	0.22	0.20	0.32	0.30	0.31	0.29	0.28	0.29
N	2820	2820	2820	2820	2820	2820	2820	2820	2820

4.6 Spatial Spillover Tests

We first compute Moran's I to assess spatial dependence and find that digital technology exhibits significant positive spatial autocorrelation (Table 9), motivating spatial econometric analysis. We then estimate a two-way fixed-effects SDM and decompose total effects into direct and indirect (spillover) effects using partial derivatives. As shown in Table 10, digital technology significantly reduces both local and neighboring cities' energy consumption and pollutant emissions, and increases both local and neighboring cities' energy efficiency, across the contiguity, geographic distance, and economic–geographic weight matrices. Overall, digital technology produces positive spillovers on neighboring cities' energy conservation, emission reduction, and efficiency enhancement, supporting H4.

Table 9. Moran's I for digital technology and environmental governance

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Dt	0.001	0.006	0.011	0.020	0.022	0.018	0.025	0.016	0.013	0.015
*p-value**	0.008	0.076	0.021	0.000	0.000	0.001	0.000	0.002	0.008	0.003

Table 10. Spatial spillover effects (SDM)

Variable	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）
	Contiguity matrix （W1）			Geographic distance matrix (W2)			Economic–geographic matrix （W3）		
	Elc	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*	*Elc*	*Plu*	*Efc*
Total effect	-6.400***	-1.237**	1.620**	-1.401***	-1.237***	1.620***	-1.311**	-0.273***	0.862***

	（-4.91）	（-2.86）	（5.84）	（-4.91）	（-3.86）	（3.84）	（-2.97）	（-3.45）	（5.40）
Total effect	-5.409***	-1.991**	1.011**	-1.306***	-1.120***	0.608***	-1.007***	-0.202***	0.614***
	（-5.17）	（-2.58）	（2.76）	（-5.17）	（3.15）	（9.75）	（-3.52）	（-3.15）	（9.86）
Indirect effec	-0.991*	-1.121*	0.609***	-0.095**	-0.117**	1.011**	-0.304**	-0.071*	0.248*
	（-2.23）	（-2.14）	（9.75）	（-2.09）	（-2.14）	（1.76）	（2.13）	（-1.81）	（1.99）
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Lik	254.63	5765.45	5653.65	257.38	5602.13	5211.64	286.18	5596.34	5213.89
R^2	0.29	0.26	0.38	0.26	0.29	0.39	0.29	0.25	0.39
N	2820	2820	2820	2820	2820	2820	2820	2820	2820

5 Conclusions and Policy Recommendations

5.1 Conclusions

From the threefold perspective of energy conservation, emission reduction, and efficiency enhancement, this paper investigates how digital technology affects urban environmental governance. Using panel data for 282 Chinese cities during 2011–2020, we conduct baseline estimation, endogeneity and robustness tests, heterogeneity analysis, mediation and moderation tests, and spatial spillover analysis. We find that digital technology significantly promotes energy conservation, emission reduction, and efficiency enhancement, and these results remain robust under various checks. The effects are heterogeneous and are more evident in cities with lower economic development, higher marketization, non-resource-based characteristics, and in core cities. Mechanism analyses show that green technology innovation, industrial structure upgrading, and human-capital improvement are important channels, while environmental regulation positively moderates and factor distortions negatively moderate the effects. Spatial econometric results reveal positive spillovers to neighboring cities.

5.2 Policy Recommendations

(1) Steadily advance digital technology development and improve overall digitalization. Leveraging the momentum of "new infrastructure", governments should systematically plan and invest in digital infrastructure. They should promote the application of digital technology across industries, accelerate the digital transformation of traditional industries, and cultivate the digital sector to enhance efficiency. Digital technology should be integrated into environmental governance through the upgrading of production technologies and management platforms, improved governance procedures, and digital skills training for governance personnel. Examples include intelligent environmental monitoring systems, environmental information-sharing systems, and public communication platforms, which can improve precision and effectiveness. Policies should also account for heterogeneous city conditions and adopt targeted development plans.

(2) Emphasize green innovation, industrial upgrading, and human capital in enabling digital technology to improve governance. Because the threefold effects largely act from the source, policy should strengthen innovation incentives and support R&D in clean production and new energy technologies to reduce pollution at the origin. Industrial policies should facilitate structural upgrading by reducing reliance on heavy industry, phasing out outdated capacity, and expanding low-energy and low-pollution environmental industries. Education and training systems should cultivate interdisciplinary and practice-oriented talent, improve digital literacy and skills, and provide human-capital support for green development.

(3) Strengthen environmental regulation, reduce factor-market distortions, and promote coordinated regional development. Governments should improve the top-level design of regulation, clarify standards, and appropriately increase enforcement intensity. Capital-market reforms should reduce administrative intervention in credit

allocation and rely more on market mechanisms. Population and talent policies should improve education, reduce barriers to labor mobility, and promote efficient allocation of labor across industries. Digitally advanced regions should play a leading role and help diffuse digital dividends to neighboring areas, while cities should strengthen cooperation via digital platforms to realize joint environmental governance and coordinated green development.

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