CHINA'S DIGITAL CONSTRUCTION AND GREEN TECHNOLOGY INNOVATION: THE TRIPLE MODERATING EFFECT OF SCIENTIFIC RESEARCH, EDUCATION AND INDUSTRY

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Abstract. Advancing a new type of infrastructure construction, represented by digital infrastructure, can significantly impact urban green innovation and offer opportunities for transformational growth, while the "industry–academia–research" triad can play a catalytic role in innovation commercialization. Taking the implementation of the "Broadband China" strategy as a quasi-natural experiment and using panel data for 254 cities from 2006 to2022, this paper examines the impact and mechanisms of urban digital construction on green innovation from the perspectives of scientific research, education, and industry. The empirical results show that (1) digital infrastructure construction exerts a significant enabling effect on regional green technology innovation and promotes the coordinated development of green innovation and economic growth, but shows a preference for quantity over quality, which constrains substantive innovation; (2) increased research investment, higher educational human capital, and optimized industrial structure each positively moderate the relationship between digital construction and urban green innovation; (3) heterogeneity analysis reveals that the green technology innovation effect of digital infrastructure construction is significantly stronger in eastern regions, resource-based cities, and cities with stringent environmental regulation. Moreover, mechanism tests indicate that the financial development and public environmental concern are important channels through which digital infrastructure influences urban green innovation. Therefore, while promoting urban digital development, coordinated efforts within the "industry–academia–research" triad should be used to effectively foster green technology innovation.
Keywords: *digital infrastructure construction, green development, innovation-driven growth, government research investment, educational human capital, industrial upgrading*

Introduction

Achieving the "carbon peak" and "carbon neutrality" (hereinafter referred to as the "dual-carbon" targets) is not only the central goal for countries worldwide in pursuing green and sustainable development, but also a crucial initiative for realizing a beautiful-China. Therefore, to accelerate the coordinated development of China's population, resources, and environment, it is essential to pursue an environmentally friendly, intensive, and sustainable path of green development. Green technology innovation exhibits positive externalities in both innovation output and the environment. As the "green" development concept has been elevated to the level of national strategy, it has become the ultimate solution for attaining carbon neutrality and one of the most important factors influencing future emission-reduction costs (Liu and Xiao, 2022). Cities are the core carriers for promoting the development and application of green technology innovation. In this context, new requirements have been placed on the construction of related infrastructure to achieve green innovative development. As an important component of the new-type infrastructure framework, digital construction builds upon the hardware, software, communication systems, equipment, and database foundations of traditional network information infrastructure, while placing greater emphasis on the digital characteristics, combinability, and dynamism of technologies. It can give rise to a multitude of innovative applications and industrial forms, not only providing the

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necessary carriers for the digital economy and strategic emerging industries, but also creating the essential conditions for knowledge spillovers and technological empowerment in frontier technology development (Baiyere et al., 2023). Research by Wu and Liu (2012), Yang et al. (2021), and Tu et al. (2023) indicates that scientific research investment, educational human capital, and industrial upgrading each drive enhancements in autonomous innovation capacity. Therefore, the triad of "industry–academia–research" constitutes the key pathway for coordinating regional digital construction and green innovation.

Currently, the digital economy, which is based on new-generation information and communication technologies such as artificial intelligence, big data, cloud computing, and the Internet of Things, has become the core engine driving China's high-quality economic development. According to the *China Digital Economy Development Report*, the scale of China's digital economy reached RMB 50.2 trillion in 2022, a nominal year-on-year increase of 10.3%; its share of GDP rose to 41.5%, approaching the proportion contributed by the secondary industry. Concurrently, in order to implement the top-level design of "establishing a green, low-carbon development economic system and promoting a comprehensive green transformation of economic and social development," nine ministries and commissions including the Ministry of Science and Technology jointly issued the *Implementation Plan for Science and Technology Support for Carbon Peak and Carbon Neutrality* in August 2022, reaffirming the need to build a green technology innovation system aligned with the dual-carbon targets. Therefore, China's emphasis on green technology innovation has reached an unprecedented level.

However, digital construction, through its transformative processes and models, can rectify urban resource misallocation and provide solid support for the efficient commercialization of green technology innovations. Moreover, digital construction serves as a medium for information exchange; the digital technologies derived from this construction can integrate dispersed knowledge effectively and thereby reduce innovation risks and technical barriers in green research and development (R&D) activities (Liu et al., 2022). Nevertheless, existing literature has not systematically revealed whether, under the dual-carbon target constraint, a significant relationship exists between regional digital construction and urban green technology innovation, or what the direction of that relationship might be. Clarifying this issue is a necessary prerequisite for delineating the policy-effect boundaries and transmission pathways through which digital infrastructure influences urban green innovation. Building on this foundation, it is essential to examine how key factors such as R&D investment intensity, educational attainment, and industrial structure moderate the strength and nature of this relationship, and to identify the specific mechanisms by which urban digital construction drives green technology innovation. Such an analysis is crucial for a deep understanding of the complex process through which digitalization empowers urban green transformation. This study will focus on these core questions in order to elucidate the intrinsic mechanisms of digital-driven green innovation and to offer theoretical insights and practical recommendations for promoting high-quality, sustainable economic and social development.

In summary, this study uses city-level data on digital infrastructure construction and green technology innovation in China and employs a multi-period difference-in-differences (DID) model with the "Broadband China" strategy as an exogenous policy shock to systematically examine the mechanisms through which urban digital construction affects regional green technology innovation. We focus on how key factors such as research investment, educational human capital and industrial structure moderate

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the relationship between urban digital construction and green technology innovation. At the same time, we analyze regional heterogeneity and transmission channels to uncover the internal logic by which digital construction empowers green innovation. We also assess the quantity versus quality bias in different types of green technology innovation and explore the economic consequences of digital construction for green innovation to provide empirical support for policymaking. The remainder of this paper is organized as follows. Section 2 reviews literature and develops theoretical hypotheses. Section 3 introduces the model and variable definitions. Section 4 presents baseline regression results, moderating-effect analyses, heterogeneity exploration and mechanism tests. Section 5 offers further discussion. Section 6 concludes and provides policy recommendations. Section 7 discusses the study's limitations and suggests avenues for future research.

Literature review and theoretical analysis

Literature review

The economic consequences of urban digital construction are multidimensional and composite. Madden and Savage (2000) find a significant positive relationship between digital construction and economic development in developing countries. On the one hand, digital construction substantially promotes the development of producer services and high-end services, thereby driving the structural upgrading of China's service sector (Yuan and Xia, 2022). On the other hand, digital construction enhances firms' total factor productivity, accelerates corporate digital transformation, and expedites the diffusion of technological knowledge within firms (Li et al., 2021). Existing studies remain divided on the environmental effects of digital construction. Avom et al. (2020) observe that the manufacture and use of digital infrastructure consume large amounts of energy, aggravating regional dependence on fossil fuels and increasing carbon emissions. Conversely, some scholars argue that digital infrastructure, by facilitating industrial structure upgrading, achieves energy savings and emission reductions, thereby reducing urban environmental pollution and ultimately improving urban ecological environments (Shi et al., 2018). The majority of researchers, however, concur that digital construction generates significant innovation-related positive externalities, leading to urban innovation effects and promoting regional innovative development. Audretsch et al. (2015) demonstrate that digital construction significantly fosters innovation activities. Nambisan et al. (2019) emphasize that the integrated use of various digital technologies and digital infrastructure is even more conducive to innovation. Han et al. (2019) contend that digital infrastructure optimizes resource allocation and can serve as a new driver for enhancing regional innovation efficiency.

In summary, existing literature on digital construction and green technology innovation has not reached a consensus, and most studies focus on their direct linkage, while analyses from the coordinated perspectives of scientific research, education, and industry remain scarce; yet the "industry–academia–research" nexus is a critical stage in the technological innovation process, as it not only absorbs knowledge spillovers and technological empowerment generated by digital construction but also determines the efficiency and effectiveness of knowledge commercialization. Although China has implemented numerous infrastructure projects featuring digital development, the "Broadband China" strategy—released relatively early, with limited interference from subsequent policies and encompassing a broad scope—is particularly well suited for

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evaluating the real effects of digital construction on urban green innovation. Accordingly, this paper treats the implementation of the "Broadband China" strategy as a quasi-natural experiment in urban digital construction, using panel data from 254 prefecture-level cities in China from 2006 to 2022 and adopting the triple perspectives of scientific research, education, and industry to construct a staggered difference-in-differences model to examine the impact of digital construction on urban green technology innovation.

The potential marginal contributions of this study are threefold: first, focusing on the green technology innovation–enabling effects of digital construction, we explore the causal linkage and underlying mechanisms between the two, thereby enriching the positive-externality framework of digital infrastructure; second, whereas existing studies largely concentrate on the environmental effects of digital development, this paper adopts a triple-helix perspective—scientific research, education, and industry—to uncover how these dimensions jointly moderate the impact of digital construction on green innovation, thus extending the boundaries of technology-empowerment research in digital transformation; third, by employing a multi-period difference-in-differences approach to evaluate policy effects, we effectively mitigate estimation bias arising from measurement error and more precisely identify the net effect of digital construction on urban green technology innovation.

Direct impact of digital construction on green technology innovation

Green technology innovation typically spans multiple domains, including energy technology, materials technology, and biotechnology. These areas are highly complex and challenging, requiring not only advanced research capabilities and substantial financial investment but also coordinated cooperation among many stakeholders, which greatly increases implementation complexity and difficulty. Urban digital construction can help overcome these barriers by integrating digital technologies such as 5G, big data, and cloud computing into production processes and various value-chain stages, covering every node of the industrial system. In addition, the knowledge-mining capabilities and enhanced information transparency provided by digital infrastructure and its derivative digital technologies reduce technical challenges and lower transaction costs throughout the innovation process. First, the scale and diffusion effects manifested in digital infrastructure construction also drive improvements in green technology innovation; relying on novel production technologies and business models, digital infrastructure generates technological spillovers to the traditional economy, thereby accelerating urban green technology innovation (Zhu et al., 2022). Second, digital infrastructure, through its information connectivity, directly enhances urban green technology innovation. Under the impetus of the digital economy, the agglomeration of innovation actors—government, universities, and enterprises—reduces information asymmetry in the science and technology market, enabling effective allocation of green innovation resources, breaking the spatiotemporal barriers to technological innovation, and promoting higher levels of green technology innovation. Third, digital infrastructure serves as the carrier of digital-technology empowerment and can effectively compensate for the government's informational disadvantages. Through digital technologies, the government can monitor urban pollution behaviors, improve regulatory efficiency and transparency, and thus advance refined urban environmental management. If an enterprise's compensatory gains are lower than the mandatory penalty costs incurred by non-compliance with environmental standards, the enterprise will be more inclined to enhance green technology innovation (Song et al., 2021). Therefore, digital infrastructure can exert a positive influence on urban green technology

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innovation by leveraging its positive externalities. Moreover, enterprises use digital infrastructure as a bridge to organically integrate production, exchange, and consumption, which reduces transaction costs and information search costs. By simulating production processes online, they avoid unnecessary energy consumption and pollutant emissions, becoming a key driver of improved green innovation efficiency. Based on the above analysis, this study proposes Hypothesis 1.

Hypothesis 1: Urban digital construction can improve the level of urban green innovation.

The moderating effect of digital construction on green technology innovation

Innovative R&D activities cannot proceed without research funding. For public-good-type goods such as digital infrastructure construction and green technology innovation, government subsidies are required to mitigate market failures. Moreover, the development of advanced technologies in modern digital infrastructure demands substantial R&D inputs and other basic innovation elements. The shock of digital infrastructure construction compresses firms' growth space, indirectly constraining their green-technology investment and innovation activities, so the government's "leverage effect" on green innovation gradually emerges. At the same time, government R&D investment generates a "demonstration effect" in the market by strengthening the city's technological foundation, supplying vital resources for energy saving, carbon reduction, pollution control, and sustainable development, thereby promoting green innovation (Cao, 2020). Government science and technology R&D investment provides important material support by sharing the burden of green-innovation funding and attracting talent and intelligent equipment.

The knowledge-spillover and technology-empowerment roles of digital technologies depend on the proactive application of talent and the transformation of knowledge outcomes. Human capital comprises the economically valuable knowledge, skills, and abilities embodied in workers, among which educational attainment is a key determinant of human-capital formation. Talent is the main driver and decisive factor of green technology innovation: the entire process of R&D activities, application of innovation outcomes, and industrialization relies on strong support from high-level human capital (Yin et al., 2018). The higher the level of human capital and the greater the share of highly skilled personnel, the more active R&D investment becomes and the more conducive it is to improve the level of technological innovation (Luan and Ouyang, 2012). Existing research consistently finds a significant positive impact of human capital on green technology innovation, with positive spillover effects (Zhao and Ma, 2018) and increasing the stock of high-tech skilled human capital—leveraging proficient equipment operation and advanced technical application abilities—promotes applied innovation output and enhances firms' technological innovation capacity (Sun and Hou, 2019).

The service and manufacturing sectors exhibit high integration with digital transformation, whereas agriculture's digital integration lags behind and faces many challenges (Ji, 2023). Thus, a region's industrial structure affects its digital transformation process and, in turn, the effectiveness of digital transformation on green innovation. Industrial upgrading—through optimization and reallocation of production factors—attracts more capital and talent to the green-innovation field, driving the R&D and application of green technologies (Wang et al., 2022). Upgrading the industrial structure also promotes a service-oriented economic transformation, especially fostering knowledge-intensive, capital-intensive, and eco-friendly enterprises (Li et al., 2016).

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Because these enterprises tend to emphasize innovation and environmental protection, their development not only transforms the mode of economic growth but also advances and applies green technologies, mitigating the negative externalities of environmental pollution. By promoting the rise of green industries and environmentally friendly firms, industrial upgrading helps improve environmental quality, thereby fostering green innovation. Industrial upgrading also facilitates industrial agglomeration, whereby specific regions may experience clustering effects in green innovation, further promoting green innovation. Based on the above analysis, this paper proposes:

Hypothesis 2: Increased research investment intensity strengthened educational human-capital levels, and optimized industrial structure will enhance the enabling effect of digital construction on urban green innovation.

Indirect impact of digital construction on green technology innovation

Urban digital construction can reduce information asymmetry between lenders and borrowers in financial markets and increase financing channels, thereby enhancing urban financial development and expanding financing scale. Through this financial development effect, urban digital infrastructure construction can supply ample funds for green innovation R&D activities, firmly guaranteeing the capital investment necessary for green innovation. By integrating its digital, intelligent, and low-carbon information technologies with traditional financial services, digital infrastructure can meet the needs of green economic development (Liu et al., 2022). Reasonable support from the financial sector can to some extent alleviate firms' financing difficulties and bears the important responsibility of financing large-scale green infrastructure. The "financial advantages" released by digital finance not only resolve corporate financing constraints but also play a key role in lowering corporate leverage ratios and balancing financial receipts and expenditures (Tang et al., 2020). Cities with higher levels of financial development possess multi-tiered, multi-channel financing methods that can address the funding needs of green technology innovation.

With the vigorous rise of new-generation digital technologies, big data, artificial intelligence, cloud computing—digitalization has become deeply embedded in the evolution of traditional governance models. Digital governance, as a novel mode of state and social governance, must adhere to the core value of "people-centered" regardless of technological evolution or governance transformation. The openness and sharing inherent in the digital economy greatly lower the cost and threshold for public participation in social governance, and public enthusiasm for engaging in environmental governance via Internet and big-data technologies is steadily increasing. Enhanced public environmental concern manifests in the product market as increased demand for products from environmental-governance firms, thereby incentivizing firms to invest more in green environmental technologies. In capital markets, according to stakeholder theory, increased public environmental concern can strengthen the "voting with money" incentive or punitive response toward firms, thereby stimulating firms to undertake green innovations and other environmental measures that align with stakeholder demands. Higher public environmental concern can also suppress collusion between local governments and firms by reducing information asymmetry, thereby limiting one-sided "greenwashing" or compliance-only green innovation driven by government, and in turn prompting governments to increase investment in environmental technologies and elevate green innovation output. Based on the above analysis, this paper proposes:

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Hypothesis 3: Urban digital construction promotes urban green innovation levels through financial development effects and public environmental-concern effects.

Materials and methods

Model specification

First, this study aims to examine whether urban digital construction centered on the "Broadband China" strategy can enhance regional green innovation capacity. The DID approach is a widely used causal-inference method for evaluating the effect of policy interventions. Its main advantage lies in mitigating endogeneity arising from omitted confounders and thereby reducing bias in coefficient estimates, while also quantifying the policy's contribution to the outcome of interest. The "Broadband China" pilot began in 2014 and was extended in successive waves in 2015 and 2016, making it well suited to a DID framework for identifying the causal impact of digital infrastructure on urban green innovation. Accordingly, we specify a multi-period DID model with city fixed effects and year fixed effects as follows:

$$Y_{it+1} = \alpha_1 + \beta_1 Broadband_{it} + X_{it}\gamma_1 + \mu_i + \delta_t + \varepsilon_{it} \qquad \text{(Eq.1)}$$

where i indexes city and t indexes year. The dependent variable Y_{it} denotes the level of green innovation. The key independent variable $Broadband_{it}$ is a dummy equal to 1 if city i is covered by the "Broadband China" pilot in year t, and 0 otherwise; its coefficient β_1 captures the impact of digital construction on urban green innovation. X_{it} is a vector of control variables. We include year fixed effects δ_t and city fixed effects μ_i to net out time trends and other unobserved factors. ε_{it} is the idiosyncratic error term.

Second, to test the moderating effects of research investment intensity, educational human capital, and industrial structure optimization, we follow Zheng et al. (2024) in specifying the following interaction-term model. Where V_{ct} denotes the moderating variable, which primarily comprises indicators from the dimensions of scientific research investment, educational human capital, and industrial structure.

$$Y_{it+1} = \alpha_2 + \beta_2 Broadband_{it} + c_1 V_{ct} \times Broadband_{it} + X_{it}\gamma_2 + \mu_i + \delta_t + \varepsilon_{it} \qquad \text{(Eq.2)}$$

Third, based on the theoretical analysis of the mechanisms through which urban digital construction affects green technology innovation, this paper follows Baron and Kenny (1986), we construct the following model for mediation testing. In this specification, M_{it} represents the mediating variable through which urban digital construction influences green innovation. All other variables are defined as in *Equation 1*.

$$M_{it} = \alpha_3 + \beta_3 Broadband_{it} + X_{it}\gamma_3 + \mu_i + \delta_t + \varepsilon_{it} \qquad \text{(Eq.3)}$$

$$Y_{it+1} = \alpha_4 + \beta_4 Broadband_{it} + \lambda_1 M_{it} + X_{it}\gamma_4 + \mu_i + \delta_t + \varepsilon_{it} \qquad \text{(Eq.4)}$$

Variable selection

Dependent variable

The dependent variable is the level of green innovation in each prefecture-level city, measured by green patent applications per ten thousand population (*GT*), following Song

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et al. (2023). To obtain city-level green patent data, we follow Zhou and Shen (2020) by screening each city's annual patent applications for those matching the WIPO "International Patent Classification Green Inventory," thus capturing green patent grants and applications. To account for technological advancement and the lag in patent grants, we lag the dependent variable by one period. Moreover, to ensure the robustness of our analysis, we replace the dependent variable in *Equation 1* with the one-period-lagged green patent grants per ten thousand population (*GTG*) for each city when conducting the robustness test.

Independent variable

The core independent variable in this study is the dummy variable *Broadband*. It takes the value one in the year a city first enters the "Broadband China" pilot list and in every year thereafter, and zero otherwise. *Table 1* shows the three batches of pilot cities in 2014, 2015 and 2016. Since some counties were listed separately, aggregating entries to the city level can create duplicates. To address this, each city is assigned the year of its first inclusion on the pilot list. Because of data availability and completeness constraints, our analysis focuses on the 98 pilot cities, including Shanghai, Shenzhen and Guangzhou, which account for 82% of the total 120 cities on the official lists. This approach ensures the validity of our empirical analysis.

Table 1. *List of "broadband China" pilot cities*

Batch	Year	List of cities
First batch	2014	Beijing, Tianjin, Shanghai, Changsha-Zhuzhou-Xiangtan City Cluster, Shijiazhuang, Dalian, Benxi, Yanbian, Harbin, Daqing, Nanjing, Suzhou, Zhenjiang, Kunshan, Jinhua, Wuhu, Anqing, Fuzhou, Xiamen, Quanzhou, Nanchang, Shangrao, Qingdao, Zibo, Weihai, Linyi, Zhengzhou, Luoyang, Wuhan, Guangzhou, Shenzhen, Zhongshan, Chengdu, Panzhihua, Aba, Guiyang, Yinchuan, Wuzhong, Alaer
Second batch	2015	Taiyuan, Hohhot, Ordos, Anshan, Panjin, Baishan, Yangzhou, Jiaxing, Hefei, Tongling, Putian, Xinyu, Ganzhou, Dongying, Jining, Dezhou, Xinxiang, Yongcheng, Huangshi, Xiangyang, Yichang, Shiyan, Suizhou, Yueyang, Shantou, Meizhou, Dongguan, Chongqing, Mianyang, Neijiang, Yibin, Dazhou, Yuxi, Lanzhou, Zhangye, Guyuan, Zhongwei, Karamay
Third batch	2016	Yangquan, Jinzhong, Wuhai, Baotou, Tongliao, Shenyang, Mudanjiang, Wuxi, Taizhou, Nantong, Hangzhou, Suzhou, Huangshan, Ma'anshan, Ji'an, Yantai, Zaozhuang, Shangqiu, Jiaozuo, Nanyang, Ezhou, Hengyang, Yiyang, Yulin, Haikou, Ya'an, Luzhou, Nanchong, Zunyi, Wenshan, Lhasa, Nyingchi, Weinan, Wuwei, Jiuquan, Tianshui, Xining

Control variables

To control for other factors affecting regional green innovation, we include: population density (*Density*), economic development level (*Econ*), government intervention (*Gov*), consumption level (*Consume*), environmental regulation (*Envi*), innovation atmosphere (*RD*), and labor cost (*Wage*).

Moderating variables

(1) Research investment intensity. Following Guo and Wang (2024), we measure city research investment by the natural log of the ratio of government science expenditure to total fiscal expenditure (*Scipay*).

(2) Educational human capital. We measure this via regional educational attainment (*Edu1*) and human-capital level (*Edu2*). Regional educational attainment follows Chen et al. (2023) and is expressed as *Edu1* = (illiterate population × 1 + primary-educated population × 6 + junior-secondary-educated population × 9 + senior-secondary and vocational-educated population × 12 + tertiary-educated population × 16) divided by the population aged six and above. The reason for using the population aged six and above as the denominator for educational attainment is that countries such as the United States, France, Japan, and Germany set the starting age for formal education at six, and China likewise defines six as the statutory age at which individuals acquire the right and obligation to receive compulsory education. Therefore, this study uses the total population aged six and above as the denominator when calculating the regional educational-attainment ratio. Due to data availability, this indicator spans 2006-2020. Regional human-capital level is measured as the proportion of full-time university students to the total population of the region.

(3) Industrial structure optimization. Industrial structure optimization is measured following Gan et al. (2011) by two dimensions: industrial upgrading (*Ind1*) and industrial advancement (*Ind2*). Industrial upgrading is measured as: $Ind1 = \Sigma q_i \times I = q_1 \times 1 + q_2 \times 2 + q_3 \times 3$ (q_i is the value-added share of sector i). Industrial advancement is measured as: $Ind2 = q_3/q_2$ (q_i is the value-added of sector i).

Mechanism variables

(1) Financial development effect (*Fin*). Following Zhang et al. (2012), we measure financial development by the ratio of loans by city financial institutions to city GDP.

(2) Public environmental concern (*Focus*). Following Dong and Wang (2021), we use the Baidu search index for the keyword “environmental pollution,” logged. Due to data availability, this indicator spans 2011-2022.

To avoid the influence of scale differences, outliers and heteroskedasticity on our regression results, we apply a logarithmic transformation to all non-dummy, non-percentage dependent and control variables. Because data for certain variables, such as municipal sulfur dioxide emissions, R&D personnel counts and average annual employee wages, are difficult to obtain, we compiled a balanced panel of 254 prefecture-level cities covering 2006 to 2022 to ensure data completeness and model robustness. The treatment group comprises 98 pilot cities including Shanghai, Shenzhen and Guangzhou, while the control group comprises 156 non-pilot cities such as Tangshan, Heze and Handan. *Table 2* summarizes each variable’s name, symbol, definition and data source. Any remaining missing values were filled using linear fitting or interpolation.

Results

Baseline regression results

The regression results of digital construction’s impact on urban green technology innovation are reported in *Table 3*. By sequentially adding control variables and then controlling for city and year fixed effects, we find in column (1) that, without any controls, the estimated coefficient on regional digital construction is significantly positive, indicating that digital infrastructure construction facilitates improvements in a city’s green technology innovation. Columns (2)-(4) show that, regardless of whether control variables and city and year fixed effects are included, digital construction consistently exerts an empowering

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effect on green innovation. This confirms that digital infrastructure construction greatly promotes the frequent flow of urban innovation factors and injects new vitality into urban green technology innovation, thereby supporting Hypothesis 1.

Robustness tests

Parallel-trend test

When establishing pilot cities, the state takes regional differences into account, which may cause inherent divergent trends between pilot and non-pilot cities. Therefore, a parallel-trend test is necessary to verify whether there were systematic differences among cities prior to policy implementation. The pilot-policy effect may exhibit lag due to policy intensity and baseline conditions. Following Beck et al. (2016), we employ a dynamic DID model to test the policy's dynamic effects. As shown in *Figure 1*, the significance of the estimated coefficients before and after the policy shock differs markedly, indicating that the pilot policy satisfies the parallel-trend assumption.

Table 2. *Variable names, symbols, definitions, and data sources*

Variable type	Variables name	Symbol	Definition	Data source
Dependent variable	City green technology innovation	*GT*	Log of green patent applications per ten thousand population	Incopat database
	City green technology innovation quantity	*GTG*	Log of green patent grants per ten thousand population	
Independent variable	City digital construction	*Broadband*		Ministry of Industry and Information Technology
Control variables	Population density	*Density*	Log of population per unit area	EPS database CEIC database China City Statistical Yearbook
	Economic development level	*Econ*	Log of per-capita GDP	
	Government intervention	*Gov*	Ratio of fiscal expenditure to GDP	
	Consumption level	*Consume*	Ratio of total retail sales of consumer goods to GDP	
	Environmental regulation	*Envi*	Log of (1 – industrial SO_2 emissions / industrial value-added)	
	Innovation atmosphere	*RD*	Ratio of R&D personnel to local population	
	Labor cost	*Wage*	Log of average wage of on-the-job workers	
Mechanism variables	Financial development effect	*Fin*	Log of financial institutions' loan balance / city GDP	EPS database
	Public environmental concern	*Focus*	Log of Baidu search index for keyword "environmental pollution"	Baidu Search Index
Moderating variables	Research investment intensity	*Scipay*	Log of (government science expenditure / total fiscal expenditure)	EPS database CEIC database China's Fifth, Sixth, and Seventh National Population Censuses
	Educational human capital	*Edu1*	Log of [(illiterates × 1 + primary × 6 + junior × 9 + senior × 12 + tertiary × 16) / population aged ≥ 6]	
		Edu2	Ratio of full-time university students to total population	
	Industrial structure optimization	*Ind1*	Log of ($q_1 \times 1 + q_2 \times 2 + q_3 \times 3$), where q_i is the value-added share of sector *i*	
		Ind2	Log of (q_3 / q_2), where q_i is the value-added of sector *i*	

(1) Incopat database url: https://www.incopat.com/advancedSearch/simpleInit; (2) EPS database url: https://www.epsnet.com.cn/index.html#/Index; (3) CEIC database url: https://www.ceicdata.com/en; (4) China City Statistical Yearbook url: https://data.cnki.net/yearBook/single?nav=%E7%BB%9F%E8%AE%A1%E5%B9%B4%E9%89%B4&id=N2025020156&pinyinCode=YZGCA; (5) Baidu Search Index url: https://index.baidu.com/v2/index.html#/

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Table 3. *Direct impact analysis of digital construction on green technology innovation*

Variable name	Model (1)	Model (2)	Model (3)	Model (4)
Broadband	0.0777** (0.0339)	0.3571*** (0.0385)	0.3011*** (0.0335)	0.0912*** (0.0335)
Density		0.3365 (0.2206)	0.2469*** (0.0269)	0.0364 (0.1877)
Econ		0.8811*** (0.1378)	1.5312*** (0.0972)	0.2486*** (0.0827)
Gov		1.9648** (0.7788)	1.5850*** (0.4394)	0.1534 (0.4058)
Consume		1.0142*** (0.1954)	1.1573*** (0.1594)	-0.1105 (0.1698)
Envi		0.1889*** (0.0236)	0.0634*** (0.0235)	0.0952*** (0.0311)
RD		3.6431*** (1.2810)	23.0938*** (5.0710)	4.1454*** (1.1151)
Wage		0.5775*** (0.1554)	0.5514*** (0.1498)	0.0564 (0.0432)
Constant	-1.3951*** (0.0095)	-17.9745*** (1.0926)	-24.0735*** (1.2867)	-5.1897*** (1.1404)
Time FE	YES	NO	YES	YES
City FE	YES	YES	NO	YES
$Adj\text{-}R^2$	0.8670	0.8534	0.7741	0.8700
N	4064	4064	4064	4064

***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses. The same as below

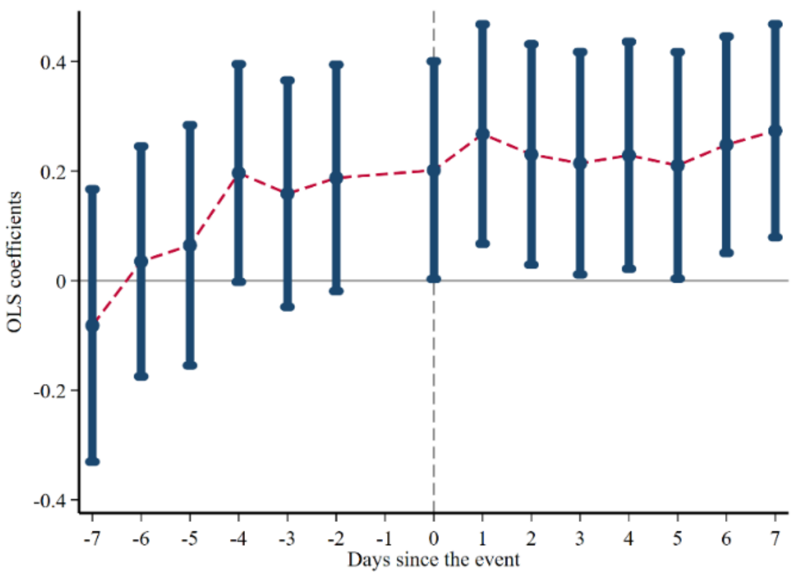

Figure 1. *Parallel trend test*

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Placebo test

The statistical significance of the policy effect may stem from latent random factors. To address this, we conduct an indirect placebo test by randomly generating pseudo-treatment-group dummies and pseudo-policy-shock dummies. We assign random implementation years and, in each draw, randomly select 98 cities as the treatment group, yielding 500 sets of the pseudo-variable $Broadband_{random}$. *Figure 2* displays the kernel density of the 500 estimates β_{random} and their p-value distribution. We observe that the β_{random} estimates concentrate near zero and that most p-values exceed 0.1, consistent with the expectations of a placebo test.

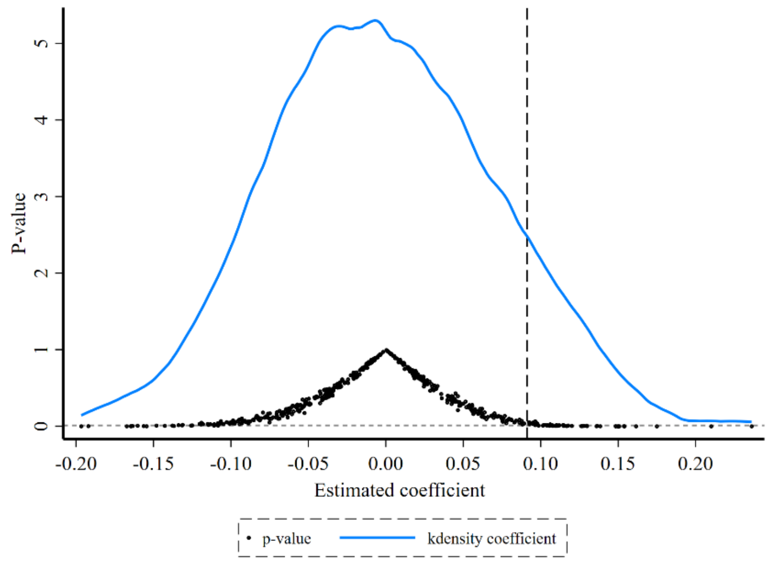

Figure 2. *Placebo test*

Goodman-Bacon decomposition

The overall coefficient from a multi-period DID is a weighted average of the treatment-control estimates across groups; large negative weights can introduce severe bias. To address this, we apply the Goodman and Bacon (2021) method to decompose the average treatment effect of the multi-period DID (as shown in *Table 4*). The sum of the products of weights and group-specific estimates equals 0.0912 (computed as $0.0625 \times 0.1218 + 0.0423 \times 0.2936 + 0.8952 \times 0.0795$), matching the result in column (4) of *Table 3*. The weight on comparisons using never-treated cities as the control group is 89.52%, indicating that the positive effect of the pilot policy on green technology innovation is robust.

Table 4. *Goodman-Bacon results*

DD comparison	Avg DD Est	Weight
Timing_groups	0.1218	0.0625
Within	0.2936	0.0423
Never_v_timing	0.0795	0.8952
Diff-in-diff estimate	0.0912** (0.0396)	

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PSM-DID

To avoid endogeneity caused by selection bias, this paper uses the PSM-DID method to further control for other factors that may affect whether a city is included in the pilot list, thereby testing the impact of digital infrastructure construction on urban green innovation. For matching, we apply year-by-year cross-sectional one-to-four nearest-neighbor matching, radius matching, and kernel matching to find suitable control samples for the treatment-group cities, using all control variables as matching covariates. We then perform balance tests on the selected covariates to ensure their validity (balance tests were conducted for all three matching methods; due to space constraints, we report only the one-to-four nearest-neighbor results here, with the others available upon request). As shown in *Table 5* and *Figure 3*, all variables are widely dispersed before matching and concentrate around zero after matching; post-matching biases are all below 10% and p-values are not significant, indicating that PSM effectively mitigates sample self-selection bias.

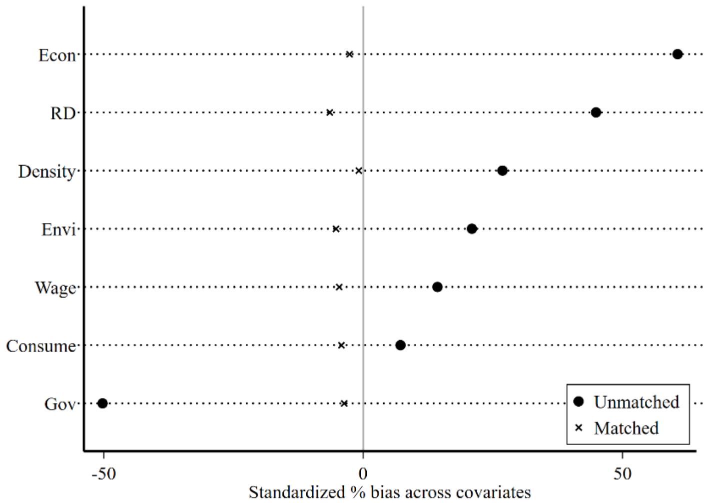

Figure 3. *PSM-DID standardized bias*

Table 5. *Balance test*

Variable name		Mean		Bias	Reduct bias	t	t-test (p > t)
		Treated	**Control**				
Density	Unmatched	-3.179	-3.402	26.9	96.8	8.89	0.000
	Matched	-3.179	-3.172	-0.9		-0.26	0.799
Econ	Unmatched	10.807	10.379	60.6	95.6	19.56	0.000
	Matched	10.807	10.825	-2.6		-0.76	0.448
Gov	Unmatched	0.150	0.190	-50.2	92.7	-15.60	0.000
	Matched	0.150	0.153	-3.7		-1.18	0.237
Consume	Unmatched	0.377	0.369	7.2	41.7	2.30	0.022
	Matched	0.377	0.381	-4.2		-1.25	0.211
Envi	Unmatched	7.087	6.716	21.0	75.0	6.74	0.000
	Matched	7.087	7.180	-5.2		-1.55	0.122
RD	Unmatched	0.008	0.003	44.9	85.7	14.74	0.000
	Matched	0.008	0.008	-6.4		-1.17	0.242
Wage	Unmatched	10.785	10.701	14.3	67.7	4.58	0.000
	Matched	10.785	10.812	-4.6		-1.30	0.193

The relevant regression results in models (1)-(3) of *Table 6* indicate that the “Broadband China” strategy has indeed increased the green innovation level of pilot cities, and that the baseline regression results are robust, implying that digital construction has a significant enabling effect on urban green innovation.

Table 6. *PSM-DID test of digital construction’s impact on green technology innovation*

Variable name	**Nearest neighbor matching (1:4)**	**Radius matching**	**Kernel matching**
	Model (1)	**Model (2)**	**Model (3)**
Broadband	0.0537* (0.0315)	0.0866*** (0.0321)	0.0982*** (0.0333)
Density	0.5742** (0.2247)	0.3902** (0.1943)	0.0489 (0.1882)
Econ	0.5542*** (0.0740)	0.4488*** (0.0748)	0.3105*** (0.0826)
Gov	0.2102 (0.2878)	0.1375 (0.3496)	0.2670 (0.4183)
Consume	-0.0620 (0.1547)	-0.2033 (0.1503)	-0.0871 (0.1683)
Envi	-0.0161 (0.0130)	-0.0176 (0.0193)	0.0938*** (0.0313)
RD	-4.8719* (2.9154)	2.8378 (2.4222)	3.9683*** (1.0905)
Wage	0.0337 (0.0314)	0.0642 (0.0841)	0.0514 (0.0419)
Constant	-5.6180*** (1.2015)	-5.3966*** (1.4208)	-5.7708*** (1.1304)
Time FE	YES	YES	YES
City FE	YES	YES	YES
Adj-R^2	0.9015	0.8852	0.8701
N	3440	3995	4062

Adjust sample structure

To further validate the robustness of the finding that urban digital construction generates a green-innovation effect, we reexamine the results under alternative sample structures. First, we replace the dependent variable. Recognizing that patent applications may not fully reflect true technological advancement, we substitute the one-period-lagged green patent grants per ten thousand population (*GTG*) for the dependent variable in *Equation 1* and re-estimate, results appear in column (1) of *Table 7*. Second, we exclude interference from other policies. During our study period, staggered pilot policies for low-carbon cities (*Low*), new-energy demonstration cities (*Newenergy*), carbon-emissions-trading pilot cities (*ETS*), and national independent-innovation demonstration zones (*Innov*) may confound our estimates. We therefore include these policy dummies as additional controls; results appear in column (2) of *Table 7*. Third, we

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remove the impact of the COVID-19 pandemic and exclude provincial capitals and sub-provincial cities. Because the 2020–2022 pandemic shock may distort our sample and because local governments differ substantially in behavior and resource endowments, we restrict the sample to 2006–2019 and drop provincial-capital and sub-provincial cities, retaining only ordinary prefecture-level cities; results are shown in column (3). Fourth, we allow for city-specific time trends. Given heterogeneous historical, geographic, and resource endowments across cities, inter-city differences may evolve over time; we therefore add city × time trend interactions to the baseline specification (1) and re-estimate, with results in column (4). Across all these checks, the incentivizing effect of urban digital construction on regional green technology innovation remains robust, further confirming the reliability and rigor of our empirical findings.

Table 7. *Robustness tests of digital construction's impact on green technology innovation based on altered sample structure*

Variable name	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Broadband	0.1529*** (0.0427)	0.0764** (0.0316)	0.1407*** (0.0416)	0.0594* (0.0320)
Low		-0.0669 (0.0527)		
Newenergy		-0.0365 (0.0438)		
ETS		0.0989** (0.0426)		
Innov		0.1227*** (0.0377)		
Density	-0.1497 (0.2109)	0.0234 (0.1893)	0.4264 (0.4004)	-0.3178 (0.2142)
Econ	-0.0282 (0.0892)	0.2619*** (0.0831)	0.0667 (0.0921)	0.2977*** (0.0842)
Gov	-0.7886 (0.5137)	0.1922 (0.4200)	-0.3757 (0.4352)	0.3665 (0.4282)
Consume	0.3419 (0.2228)	-0.0890 (0.1704)	-0.1988 (0.2698)	-0.0594 (0.1712)
Envi	0.1127*** (0.0340)	0.0938*** (0.0312)	0.1889*** (0.0412)	0.0890*** (0.0310)
RD	3.7427** (1.5364)	3.8311*** (1.1005)	4.6574*** (1.4820)	2.8164** (1.1414)
Wage	0.0990* (0.0535)	0.0592 (0.0438)	0.0968 (0.1459)	0.0543 (0.0449)
Constant	-3.9312*** (1.2669)	-5.4255*** (1.1589)	-3.3398 (2.2829)	-6.6836*** (1.1951)
Time FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
City × time trend	NO	NO	NO	YES
Adj-R^2	0.8005	0.8702	0.7983	0.8707
N	4064	4064	2860	4064

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Moderating effect analysis

(1) Research investment intensity. Based on the moderating-effect model specified in *Equation 2*, we include the interaction term *Broadband* × *Scipay* in *Equation 2* to test how research investment intensity moderates the enabling effect of digital construction on green technology innovation. The results in column (1) of *Table 8* show that the coefficient on *Broadband* × *Scipay* is significantly positive, indicating that higher city research investment further amplifies the enabling effect of digital infrastructure construction on green innovation. This occurs because increased research funding fosters a supportive R&D environment, strengthens individual incentives for innovation, and leverages the government's demonstration effect to spur enterprises and other actors to invest more in R&D, thereby boosting green technology innovation output.

Table 8. *Analysis of the moderating effects of digital construction on green technology innovation*

Variable name	**Research investment**	**Educational human-capital level**		**Industrial structure optimization**	
	R&D expenditure	**Years of schooling**	**University enrollment**	**Industrial upgrading**	**Industrial advancement**
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Broadband	0.5481*** (0.2062)	0.0646* (0.0338)	0.1277*** (0.0444)	0.1042*** (0.0352)	0.1027*** (0.0344)
Broadband×Scipay	0.0453** (0.0201)				
Broadband×Edu1		1.0501** (0.4395)			
Broadband×Edu2			0.0868* (0.0526)		
Broadband×Ind1				0.9500** (0.4830)	
Broadband×Ind2					0.1648** (0.0724)
Constant	-5.3401*** (1.1555)	-7.3033*** (1.6286)	-5.1050*** (1.1355)	-5.9961*** (1.1564)	-5.2504*** (1.1378)
Control variables	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Adj-R^2	0.8700	0.8971	0.8700	0.8700	0.8700
N	4064	3474	4064	4064	4064

(2) Educational human capital. Regional educational attainment and human-capital level are core to transforming R&D into innovation outcomes, affecting both the practice of knowledge application and the quality of innovation output. Regions with higher educational human capital therefore play a stabilizing and enhancing role in the process by which digital construction empowers urban green innovation. To verify this

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mechanism, we include $Broadband \times Edu1$ and $Broadband \times Edu2$ in *Equation 2*. Columns (2) and (3) of *Table 8* report the results: both interaction coefficients are significantly positive, indicating that higher regional educational human capital further stimulates the green-innovation-enabling effect of digital construction. This is because regions with higher educational human capital enjoy fuller talent mobility and collaboration; the positive externalities and spillovers of human capital are better realized, facilitating knowledge exchange, sharing, and transformation of innovation outcomes, optimizing resource allocation and efficiency, and thus raising green innovation output.

(3) Industrial structure optimization. By reconfiguring production and innovation factors, industrial structure optimization attracts more capital and talent to green innovation, promoting green technology R&D and application. To test this, we add $Broadband \times Ind1$ and $Broadband \times Ind2$ to *Equation 2*. Columns (3) and (4) of *Table 8* show that both interaction coefficients are significantly positive, indicating that industrial upgrading and advancement strengthen the effect of digital construction on green innovation. This is because industrial upgrading fosters industry clustering; under the positive externalities of digital technologies, clustering effects in green innovation emerge, thereby promoting green innovation. Thus, hypothesis 2 is confirmed.

Heterogeneity analysis

(1) Geographic region. One key task of the "Broadband China" strategy is to promote coordinated development of regional broadband networks, with information-technology goals tailored to the developmental stages of the eastern, central, and western regions. Following the National Bureau of Statistics' regional classification (Eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning, Jilin and Heilongjiang. Central and western regions include Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.), we divide sample cities into eastern and central-western regions to examine the policy effect of digital construction. We define a dummy *Region* and, following Wang et al. (2023), replace *Broadband* in *Equation 1* with the interaction $Broadband \times Region$ and re-estimate. Results in columns (1) and (2) of *Table 9* show that digital construction significantly empowers green technology innovation in eastern cities but is not significant in central-western cities. A likely reason is that eastern regions possess inherent advantages in economic development, industrial structure, and talent resources, making it easier for digital infrastructure to optimize resource allocation and enhance the efficiency of innovation factors, thus producing stronger gains in both the quantity and quality of green innovation (Chao et al., 2020).

(2) Degree of resource dependence. Whether resource dependence is a "blessing" or a "curse" for economic growth can be discerned by its impact on technological innovation. Given the uncertainty of natural-resource dependence's effect on innovation (Qin et al., 2023; Wan et al., 2022), we use the State Council's 2013–2020 National Sustainable Development Plan for Resource-Based Cities to classify cities as resource-based or non-resource-based via dummy *City* and re-estimate (as shown in *Table 9*, columns (3) and (4)). The results show a larger enhancement of green technology innovation in highly resource-dependent cities, confirming a "blessing" effect of natural resources on innovation. On one hand, pilot cities have accumulated wealth through resource extraction and utilization, providing ample fiscal support for innovation; on the other hand, resource-based cities face greater environmental-management pressure, so

promoting green technology innovation both alleviates environmental stress and creates new economic growth poles, helping cities tap renewable-energy development potential.

(3) Environmental-regulation intensity. Because cities set different environmental-regulation targets according to their development levels to constrain firms' investment and production behavior and achieve green economic growth, unconstrained local governments might favor high-energy-consumption, high-emission industries for growth, temporarily foregoing long-term innovation. Following Zhang and Chen (2021), we count the frequency of environment-regulation-related keywords in government work reports from 2006 to 2022. We measure regulation intensity as the share of these keyword frequencies in total report word counts, then classify cities by the mean into high- and low-intensity groups via dummy *ER*. Results in columns (5) and (6) of *Table 9* indicate that digital infrastructure construction yields a stronger green-innovation effect in cities with stringent environmental regulation. Under regulatory constraint, firms are compelled to intensify innovation to achieve green transformation, thereby reducing compliance costs and ultimately enhancing green development.

Table 9. *Heterogeneity analysis of the impact of digital construction on green technology innovation based on regional distribution, city resource dependence and environmental regulation intensity*

Variable name	Eastern region	Central/Western region	Resource-based cities	Non-resource-based cities	High	Low
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Broadband×Region	0.1322*** (0.0366)	-0.0299 (0.0355)				
Broadband×City			0.1089** (0.0481)	0.0555 (0.0346)		
Broadband×ER					0.1817*** (0.0392)	-0.0405 (0.0343)
Constant	-4.6614*** (1.1365)	-4.7586*** (1.1125)	-4.8871*** (1.1245)	-4.9915*** (1.1201)	-4.9874*** (1.1155)	-4.6669*** (1.1202)
Control variables	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Adj-R^2	0.8698	0.8701	0.8699	0.8698	0.8702	0.8698
N	4064	4064	4064	4064	4064	4064

Mechanism analysis

Based on the mechanism analysis models in *Equations 3* and *4* for urban digital construction's impact on green technology innovation, this section conducts path analyses of the financial development effect and public environmental concern. (1) Financial development effect. We regress with city financial development level as the mediating variable; results are reported in columns (1)-(2) of *Table 10*. The estimates show that digital construction significantly expands the scale of loans by urban financial institutions, thereby raising regional financial development. Financial development is positively correlated with regional green technology innovation at the 5% significance

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level, because higher financial development secures funding for firms' green innovation activities. Moreover, in column (2) the coefficient on Broadband remains statistically significant at the 1 % level but is smaller in magnitude than in column (4) of *Table 3*, demonstrating that digital construction enhances urban green innovation in part by promoting regional financial development.

(2) Public environmental concern. Columns (3)-(4) of *Table 10* report regressions using public environmental concern as the mediating variable. Urban digital construction markedly increases public environmental concern. As public concern rises, green-innovation actors face both the Porter effect and "voting with money," which indirectly raises firms' pollution costs, deters short-term behavior, and prompts greater investment in environment-friendly technologies, resulting in increased green innovation output. At the same time, heightened public environmental concern reflects a shift in societal environmental awareness, and consumer demand for green products in turn compels firms to pursue green transformation, further boosting green innovation output. This confirms that public environmental concern is an important mechanism through which digital infrastructure construction influences green innovation. Thus, hypothesis 3 is validated.

Table 10. *Mechanism analysis of digital construction's impact on green technology innovation*

Variable name	Financial development effect		Public environmental concern effect	
	Fin	***GT***	***Focus***	***GT***
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Broadband	0.1099*** (0.0273)	0.0757** (0.0335)	0.1083** (0.0503)	0.0326* (0.0188)
Fin		0.1438*** (0.0360)		
Focus				0.0104* (0.0057)
Constant	3.2063*** (0.8468)	-5.6400*** (1.1841)	8.6389*** (1.6740)	-5.0641*** (0.9836)
Control variables	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Adj-R^2	4318	4064	2987	2987
N	0.6182	0.8710	0.6939	0.9299

Discussion

Substantive innovation or strategic innovation

The empirical results above indicate that the implementation of the "Broadband China" strategy has had a positive impact on urban green innovation, but its effect on the types of green innovation warrants further discussion. In practice, substantive innovation typically requires substantial human, material, and financial investment in technology R&D and more fully reflects the intrinsic value of technological innovation. By contrast, strategic

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green innovation refers to low-quality, non-invention green patents that may be pursued merely to satisfy environmental regulation through patent counts. To examine this, we define green invention patent applications per ten thousand population (*GP*) as a measure of substantive innovation, and green utility-model and design patent applications per ten thousand population (*GPI*) as a measure of strategic innovation. We then re-estimate the baseline specification using *GP* and *GPI*, respectively, as the dependent variable. The results in *Table 11* show that the enabling effect of digital construction on urban green innovation is concentrated in strategic innovation activity, while its effect on substantive innovation is not significant. This indicates that the innovation-enabling benefits of urban digital construction have not yet fostered substantive, breakthrough green development.

Table 11. *Further analysis of digital construction's impact on substantive green technology innovation*

Variable name	Innovation strategies				Economic consequences	
	Substantive innovation: GP		Strategic innovation: GPI		*GTFP*	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Broadband	-0.0259 (0.0291)	0.0022 (0.0302)	0.0483** (0.0245)	0.0846*** (0.0246)	0.0141*** (0.0046)	0.0077* (0.0043)
Constant	-2.3339*** (0.0096)	-4.8856*** (1.1303)	-1.9125*** (0.0077)	-5.0163*** (0.8886)	0.3197*** (0.0015)	0.7223*** (0.1817)
Control variables	NO	YES	NO	YES	NO	YES
Time FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Adj-R^2	0.9179	0.9199	0.9363	0.9384	0.6521	0.6661
N	4064	4064	4064	4064	4016	4016

Analyzing the economic consequences of digital construction on urban green technology innovation

Our earlier results demonstrate that digital construction exerts a positive effect on urban green technology innovation. According to Romer's endogenous growth theory (1986), technological innovation serves as the engine of economic development. Accordingly, it remains to be seen whether the green-innovation impetus provided by digital construction can be transformed into an endogenous driver of regional economic growth and thereby support high-quality economic and social development. Following Sun and Yang (2020), we calculate regional green total factor productivity (*GTFP*), lag it by one period, and substitute it for the dependent variable in *Equation 1* for re-estimation. GTFP reflects high-quality economic and social development under resource and environmental constraints through technological progress, managerial optimization, and institutional innovation. The regression results in *Table 11,* models (5) and (6), show that digital construction not only accelerates regional green innovation growth but also effectively drives green and sustainable economic development. It reduces undesirable outputs while substantially increasing the rate of desired outputs, thus achieving a synergy between green innovation and high-quality economic growth.

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Conclusions

Using a balanced panel of 254 prefecture-level cities from 2006 to 2022, this paper employs the implementation of the "Broadband China" strategy as a quasi-natural experiment and a multi-period DID framework to examine how urban digital construction affects green technology innovation from the triple perspectives of scientific research, education, and industry. The main findings are as follows. First, urban digital construction significantly enhances regional green technology innovation, and this result remains robust across a battery of tests. Second, the intensity of regional research investment, the level of educational human capital, and the optimization of industrial structure each positively moderate the relationship between digital construction and urban green innovation. On the one hand, synergy among industry, academia, and research leverages the resource-allocation benefits of digital infrastructure and innovation-factor agglomeration to accelerate green technology innovation; on the other hand, this synergy fosters an improved innovation environment and raises the efficiency of innovation commercialization, further empowering urban green innovation. Third, heterogeneity analysis shows that the enabling effect of digital construction on green innovation is particularly pronounced in eastern regions, resource-dependent cities, and cities with stringent environmental regulation. Mechanism tests reveal that urban digital construction influences regional green technology innovation via two channels: enhancing regional financial development and elevating public environmental concern. Fourth, a closer look at innovation types uncovers a "quantity-over-quality" preference in green innovation, indicating that digital construction has yet to foster substantive improvements in the quality of urban green innovations. Furthermore, analysis of the economic consequences of digital construction empowering urban green innovation indicates that digital construction not only enhances regional green innovation levels but also effectively drives green and sustainable social and economic development, ultimately strengthening the synergy between green innovation and economic growth.

Policy recommendations

First, continue to advance the Digital China initiative and incubate strategic digital industries to support the development of frontier digital technologies, thereby stimulating urban green technology innovation. Fully leverage the energy-saving, emission-reducing, and green-enabling functions of digital infrastructure by establishing and improving a green low-carbon standards system to guide low-carbon development across industries. Second, further increase government support for science and technology R&D, actively cultivate and attract interdisciplinary talent skilled in both digital and green technologies, establish mechanisms for high-tech talent recruitment, and promote regional industrial upgrading to harness the synergistic empowerment of industry, academia, and research. Third, design and implement differentiated digital-infrastructure development pathways: in central-western regions, non-resource-based cities, and areas with weak environmental regulation, step up investment in AI, big-data centers, and 5G/IoT infrastructure to foster low-consumption, sustainable industrial structures and green innovation systems. Finally, deepen financial-system reforms and enhance supporting financial services: guide financial institutions to expand green credit offerings, and intensify public education on environmental protection and social responsibility by disseminating timely positive and negative case studies that underscore the importance of collective environmental stewardship.

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Research limitations and future direction

Although this study has systematically examined the impact of urban digital construction on green innovation and revealed how research investment, educational human capital, and industrial structure moderate the enabling effect of digital infrastructure, several limitations remain. First, the data cover only 254 prefecture-level cities in China, which may not fully capture the characteristics of digital construction’s impact on green technology innovation in other regions. In addition, we have not explored in depth the specific causes of the observed “quantity-over-quality” bias in green innovation under digital construction. Second, our analysis of moderating effects focuses exclusively on the triad of research, education, and industry, leaving other potential moderating factors underexplored. Future research could extend the analysis to firm-level or cross-country panel data and deepen the framework for evaluating green technology innovation. The author may investigate how digital infrastructure fosters optimized collaboration among industry, academia and research, and examine additional mechanisms such as technological spillovers or institutional environments that shape digital-enabled green innovation. Such work would provide more targeted policy recommendations to overcome the quality bottleneck in green technological advances.

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