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Digital Transformation, Innovation Ecosystem Coordination, And Urban Low-carbon Innovation: Evidence from China

Mengyu Shi[1], Liming Chen[2,*]

[1]Nanjing Tech University Pu Jiang Institute, Li Xue Road, Lishui District, Nanjing, JS, China

[2]Nanjing University of Finance & Economics, Wen Yuan Road, Nanjing, JS, China

[*] Corresponding author

Abstract

Climate challenges, exemplified by global warming, necessitate deeper low-carbon innovation in urban areas, wherein digital transformation emerges as a pivotal enabler. In this context, this study reveals how digitalization intrinsically shapes urban low-carbon innovation from the perspective of innovation ecosystem coordination. It constructs a theoretical framework with innovation ecosystem coordination as the mediating variable and environmental regulatory intensity and public environmental concern as the moderating variables. Empirical analysis of panel data covering 273 Chinese cities (2011–2021) substantiates the hypotheses. Results demonstrate that digitalization significantly fosters urban low-carbon innovation, with ecosystem coordination fully mediating this relationship. Environmental regulation attenuates digitalization's positive effect on innovation ecosystem coordination, which is more robust in cities with higher public environmental concerns; however, innovation ecosystem coordination contributes less to low-carbon innovation in cities with strict environmental regulations or high public environmental concerns. These findings furnish novel empirical support for digitalization's catalytic role in low-carbon innovation while illuminating the underlying nexus between digital transformation and urban sustainability based on the innovation ecosystem perspective, which is important for harmonizing digitalization and decarbonization trajectories in China.

Keywords

Digital transformation, innovation ecosystem coordination, low-carbon innovation, environmental regulation, public environmental concern.

1. INTRODUCTION

Global warming poses severe risks to public health and long-term socioeconomic sustainability [1-2]. Carbon emissions constitute the primary driver of global temperature rise [3-4]. As the world's most populous emerging economy, China bears significant responsibility in international decarbonization efforts [5]. The nation has pledged to reach CO_2 emission maxima by 2030 and attain net-zero carbon status by 2060 [6]. Consequently, curbing domestic carbon emissions represents an urgent policy imperative.

For China, the long-term difficulty lies in achieving carbon reduction targets simply and systematically. As hubs of population, industry, transportation, and infrastructure, cities constitute the primary loci for decarbonization initiatives. While innovation functions as the fundamental impetus underlying urban development, its specific ramifications for carbon emissions remain empirically contested [7]. Consequently, scholarly discourse distinguishes between conventional and low-carbon innovation paradigms. Among them, low-carbon

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innovation, which aims to save energy and reduce emissions, is seen as a more practical approach to mitigating carbon emissions [8]. Nevertheless, strategies to enhance urban low-carbon innovation capacity represent an underexplored frontier in current scholarship.

Concurrently, the integration of big data, cloud computing, and artificial intelligence has catalyzed China's progressive transition toward digitalization. Despite a late start in digital development, China has emerged as the most extensive testing ground for global digital transformation, driven by the collision of digital innovation and the application scenarios of massive super users and industrial powers. Digital embedding plays an undeniable and essential role in developing urban low-carbon innovation. Digital transformation has become crucial for reorganizing factor resources and reshaping the competitive global landscape. The contemporary imperative in China's socioeconomic progression centers on harnessing the catalytic and structuring potentials of digital technological shifts to amplify urban low-carbon innovation capacities.

Extant literature has elucidated the implications of low-carbon innovation for carbon emissions [9], atmospheric pollution [10], and urban green development [11-12]. Some studies have focused on R&D [13], FDI [11-,13], international trade [13], environmental regulation [14] and carbon emissions [15] about low-carbon innovation in cities. Scant research, however, has examined digitalization's influence upon urban innovation capacity [16] and urban low-carbon development [17-19]. The interplay between digital transformation and urban low-carbon innovation remains inadequately conceptualized, with these domains traditionally examined in isolation.

In addition, innovative activities in the context of digitization increase ecological characteristics of complexity, dynamism, and adaptability. By fostering context-specific value co-creation, the innovation ecosystem subverts the linear logic of the traditional innovation paradigm and directly affects the level of urban low-carbon innovation. Simultaneously, digital technology has blurred the boundaries between online and offline, reshaped the interaction between innovation entities, and enabled effective collaboration through digital “empathy” and “decentralization”. Hence, the intrinsic nature of innovative endeavors coupled with the contemporary digital landscape calls for systematic inquiry into how urban low-carbon innovation responds to digital transformation through the lens of innovation ecosystem coordination. Existing literature has predominantly examined the impact mechanisms of digital transformation on urban innovation and urban low-carbon development, involving urban characteristics [20], industrial upgrading [18], and innovation factor flow [18]. However, there is a lack of clarity on whether innovation ecosystem coordination mediates the relationship between digital transformation and urban low-carbon innovation.

It is worth noting that existing research on the coordination of innovation ecosystems mainly focuses on evaluating the coordination degree of the industrial innovation ecosystem and describing its role in technological innovation and green transformation [7,21]. Nevertheless, there is a scarcity of studies that assess the coordination of urban innovation ecosystems, and only a few studies have explored the relationship between innovation ecosystems and regional sustainable development [7, 22].

Digital transformation represents the direction of a new round of technological change, and low-carbon innovation serves as the endogenous driving force for urban low-carbon development under dual-carbon constraints. As an essential development strategy, the two will coexist for the foreseeable future, and understanding their relationship has become a significant practical concern. Digital embedding has triggered profound changes in the innovation ecosystem, and innovation ecosystem coordination is a crucial mechanism affecting urban low-carbon innovation. Therefore, this study seeks to demystify the nexus between digitalization and urban low-carbon innovation through the lens of innovation ecosystem coordination. This understanding holds both theoretical and practical value in harnessing digitalization opportunities to strengthen China's low-carbon innovation capabilities and forge competitive edges in urban low-carbon development.

This study addresses these gaps by empirically validating innovation ecosystem coordination as a mediator linking digital transformation to urban low-carbon innovation. Should this mediating effect be confirmed, it would theoretically elucidate the mechanisms through which digital transformation fosters urban low-carbon innovation. To examine this hypothesis, we employ panel data spanning 273 Chinese municipalities over the period 2011–2021. Digital transformation, innovative ecosystem coordination, and urban low-carbon innovation are integrated into a unified analytical framework. Finally, this research furnishes actionable policy guidance and robust empirical support for cities seeking to foster low-carbon innovation via digital transformation initiatives.

This study advances the literature through three principal contributions. First, it systematically analyzes how digital transformation influences low-carbon innovation in urban contexts through the lens of ecosystem coordination. Second, empirical evidence confirms that coordinated innovation ecosystems serve as a mediating mechanism linking digitalization to sustainable urban outcomes. Finally, it explores the moderating effect of environmental pressures (including environmental regulation and public environmental concern) on the relationship between digital transformation and urban low-carbon innovation.

The remainder of this paper is organized as follows. Section 2 presents theoretical analysis and research hypotheses. Section 3 introduces the data, discusses the construction of the variables of interest, and describes the empirical model. Primary findings are documented in Sections 4 and 5. Finally, the study synthesizes the principal conclusions and discusses their broader implications.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1. Digital Transformation Can Promote Urban Low-carbon Innovation

Digital transformation can help foster urban low-carbon innovation. Digital technologies and their application in infrastructure offer new opportunities for low-carbon innovation, which can be analyzed in digital governance, economy, and life.

First, digital governance can promote urban low-carbon innovation. Digital governance leverages the latest technologies to establish a digital public service platform and strengthen business sharing and data collaboration among government departments [23]. It has a twofold effect on urban low-carbon innovation. Primarily, it facilitates the clustering of innovation factors, establishing enabling conditions for advancing low-carbon technological innovation [24]. Secondly, it enhances the effectiveness of carbon emission monitoring regarding energy- and carbon-intensive enterprises, thereby driving these entities to adopt low-carbon production technologies while curtailing energy consumption and carbon emissions throughout manufacturing operations [25].

Furthermore, digital economies foster low-carbon innovation within urban contexts. Such economies expedite the creation, circulation, and aggregation of innovative elements, thereby furnishing enterprises with conducive environments for pursuing low-carbon innovation. Concurrently, enhanced capabilities in information analytics and processing contribute to elevated levels of low-carbon innovation performance. From a theoretical perspective, the deployment of digital technologies to optimize production and managerial workflows generates positive effects on low-carbon innovation [26]. Schumpeterian theory posits that innovation fundamentally constitutes the recombination of innovative elements. Digitalization accelerates the development of contemporary information and communication infrastructures. Given that

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data, knowledge, and information constitute pivotal innovative resources, these are swiftly diffused and utilized via network technologies, rendering it more accessible for enterprises to acquire diverse innovative inputs and establish knowledge interconnections [27]. Moreover, extensive digital technology adoption facilitates the movement of innovative elements across both internal and external organizational boundaries, thereby dismantling intangible barriers to innovation [28]. Digital transformation not only catalyzes the circulation but also engenders additional innovative resources. Technologies such as big data analytics and cloud computing enable systematic storage and analysis of data, knowledge, and information, whereas the stockpiling of these innovation resources establishes foundational prerequisites for low-carbon innovation. Conversely, leveraging digital technologies coupled with comprehensive data availability enables enterprises to monitor real-time energy usage and pollutant discharges throughout various production phases. Organizations can thereby achieve conservation in energy utilization and reductions in emissions via process reengineering and the optimization of energy consumption structures [29]. Additionally, firms often exhibit reluctance toward green innovation attributable to complexities associated with processing and integrating data derived from legacy manufacturing systems when pursuing environmental upgrades. Enhancing information processing capability increases enterprises' willingness to engage in green innovation [30], thus indirectly improving their low-carbon innovation level.

Finally, digital life can promote urban low-carbon innovation. Digital life encourages the formation of low-carbon lifestyles of urban residents [31]. Additionally, it creates market demand for low-carbon products and social application scenarios for low-carbon technologies. This guides enterprise innovations towards low-carbon orientation and provides niche markets for enterprise low-carbon innovations, promoting urban low-carbon innovation.

Therefore, we propose the following hypothesis:

H1: Digital transformation can promote urban low-carbon innovation.

2.2. The Mediating Role of Innovation Ecosystem Coordination

An innovation ecosystem constitutes an organic framework where entities engage with one another and their surrounding environment via resource exchange and capability building to generate value. In terms of connotation, its components include innovation communities and habitats. Innovation ecosystem coordination is essential for digital transformation to promote low-carbon innovation.

On the one hand, digital transformation reshapes the interactive behaviors and factor structure of innovation entities in the innovation ecosystem, resulting in a more integrated and coordinated system. The innovation ecosystem can be regarded as a complex network of heterogeneous innovation factors. Digital transformation realizes the coordination of the innovation ecosystem by integrating technology, knowledge, and social networks. Digital technology significantly reduces coordination and transaction costs, improves the efficiency of resource integration and matching, and enhances cooperation among innovation actors [32]. In addition, digital technology substantially strengthens linkages among heterogeneous knowledge bases and participants, transcending traditional boundaries of knowledge transfer and enabling extensive circulation of knowledge assets throughout the innovation ecosystem, thus fostering a dynamic environment conducive to knowledge exchange [33].

Simultaneously, digital transformation promotes the coordination of intercity innovation ecosystems. Digitalization, based on digital technology, has robust connectivity. It transcends geographical constraints, bridging distant resources and enabling innovation assets, information flows, and energy to overcome spatial barriers, broadening the breadth and depth of knowledge overflow from innovation entities between different cities [33]. Consequently, digital transformation facilitates knowledge exchange and collaborative innovation among

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cities, supports resource concertation and values co-creation, and is conducive to coordinating intercity innovation ecosystems.

On the other hand, innovation ecosystem coordination can foster low-carbon innovation in cities. Serving as the primary drivers of innovation activities, research communities can convert their professional knowledge and expertise into research results or applications for addressing carbon emissions [7]. Ecosystem-level coordination can satisfy the cooperation needs of diverse functional innovation actors, lower the cost of low-carbon innovation, and achieve economies of scale. The higher the degree of coordination within the innovation ecosystem, the more influential the interaction among enterprises, universities, and research institutions, which contributes to enhancing the speed and success rate of low-carbon innovation and advancing low-carbon innovation [34]. Meanwhile, low-carbon innovation activities require greater resource allocation [35]. Nevertheless, no organization can possess all the necessary resources, thus making it essential to acquire scarce resources from other actors in the innovation ecosystem and facilitate the free flow of innovation resources [22]. As a result, innovation ecosystem coordination can advance low-carbon innovation and thus effectively control emissions.

Therefore, we propose the following hypothesis:

H2: Innovation ecosystem coordination mediates the relationship between digital transformation and urban low-carbon innovation.

2.3. The Moderating Role of Environmental Regulation and Public Environmental Concerns

The intensity of environmental regulation and public environmental awareness may influence the impact of digital transformation on urban low-carbon innovation.

Currently, the intensity of environmental regulation in China is gradually strengthening, and increasingly stringent environmental regulation stimulates the willingness of innovation entities to engage in green research and technological innovation. This thereby intensifies resource investment in related domains, furthering green technology innovation capabilities along with carbon emission reductions [33]. Moreover, environmental regulation implementation promotes low-carbon innovation factor inflow and agglomeration [14]. Such agglomeration accelerates information circulation and knowledge spillovers among innovation entities, consequently mitigating low-carbon innovation uncertainties and elevating its overall level.

Serving as a critical informal governance mechanism, public environmental concern shapes the low-carbon innovation behavior of innovation entities by intensifying external environmental pressures. Public environmental concern fosters low-carbon innovation through two primary channels. First, consumers' environmental concerns drive their choice of environmentally friendly products [36]. Grounded in ethical and social responsibility, people's consumption behavior is influenced by convenience, price, and social norms, creating a trade-off between essential product attributes and the degree of greenness [37]. Environmentally aware consumers increasingly favor low-carbon products, and this trend is expanding [38]. In response to the growing demand for low-carbon products, innovation entities seek low-carbon innovations. Second, as carbon information disclosure progresses globally, public environmental concerns heighten attention to corporate environmental responsibility. When a firm violates environmental ethics, the public can form strong opinions through public media reports on the firm's pollution degree or environmental governance level, thus affecting the firm’s business performance [39]. This pressure obliges firms to reflect on their carbon emission behaviors and adopt innovative activities for their corporate image, thereby motivating more innovation entities to participate in low-carbon innovation [40].

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

Accordingly, we advance the following hypotheses:

H3: Environmental regulation will strengthen the facilitating effect of digital transformation on urban low-carbon innovation.

H4: Public environmental concern will strengthen the facilitating effect of digital transformation on urban low-carbon innovation.

3. EMPIRICAL RESEARCH DESIGN

The validation process consists of three stages. The first stage examines Hypothesis 1, assessing whether digital transformation facilitates low-carbon innovation. The second stage evaluates Hypothesis 2, exploring whether innovation ecosystem coordination functions as a key mediating pathway linking digital transformation to low-carbon innovation. The third stage tests Hypotheses 3 and 4, investigating whether environmental regulation and public environmental concerns moderate digital transformation's effect on low-carbon innovation.

3.1. Variables and Data

3.1.1. Dependent Variables

Low-carbon innovation is essential for transcending resource and environmental bottlenecks and realizing environmental load reduction. Compared with traditional technological innovation, low-carbon innovation has more positive external effects and can benefit enterprises more socially. According to the existing literature on innovation measurement, the quantity of patent applications for low-carbon innovation is chosen to measure low-carbon innovation output [11,15].

3.1.2. Independent Variables

This paper measures digital transformation across digital governance, economy, and life dimensions. It is computed via the entropy method.

Digital governance reflects the government's capacity for digital administration. Considering data availability, this paper employs the occurrence of terms associated with digital technology as well as digital application within prefecture-level city government work reports as a proxy for governance digitalization.

The digital economy encompasses digital information, the Internet alongside technological innovation. Due to city-level data constraints, this study evaluates Internet development in conjunction with digital financial inclusion following the research framework of Liang and Li [41]. The percentage of employees in computer services and software and the total amount of telecommunication services per capita serve as indicators for Internet development. Digital finance is proxied by the Peking University Digital Financial Inclusion Index [42].

Digital life denotes digital technology deployed to improve citizen well-being and happiness, reflecting urban digital capability concerning people's lives. Considering data availability, this paper selects mobile subscriptions and Internet penetration rates (per 100 people) as proxies for digital life.

3.1.3. Control Variables

To mitigate omitted variable bias, we incorporate a set of control variables potentially influencing low-carbon innovation. Specifically, we account for:

(1) Economic development. Economic development ensures factor supply and a favorable market environment for innovation activities. Per capita GDP serves as a proxy for regional economic conditions.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

(2) Financial development. Enhanced financial development strengthens innovative entities' investment propensity by alleviating external financing constraints. Financial depth is proxied by the ratio of financial institutions' loan balance to GDP.

(3) Market consumption. Consumer market size, captured by total retail sales of consumer goods, reflects demand scale and incentivizes enterprises toward product innovation.

(4) Public service quality. Prior research indicates that quality public services attract innovation entities while integrating regional innovation resources with entity requirements [43]. Quality public services streamline government innovation services and expedite patent approval procedures. Additionally, government procurement of public services stimulates technological innovation through preferential purchasing of green-certified products. Public service quality is operationalized as the share of public administration and social organization employees within the urban population.

(5) Human capital. Cities abundant in human capital demonstrate superior capacity for absorbing advanced technology, thereby fostering urban low-carbon innovation. Human capital is measured by the college student ratio within the urban population.

(6) Science and technology investment. S&T investment can provide sufficient financial and material protection for innovative activities. Due to the lack of enterprise R&D data, this paper adopts government S&T expenditures as a proxy indicator. We use the share of local fiscal S&T expenditure in GDP to measure government research investment in scientific research.

(7) Foreign direct investment. FDI facilitates regional technological progress via technology spillovers and knowledge transfer. We proxy FDI intensity using the count of foreign-invested enterprises above designated size thresholds.

(8) Green space per capita. This metric captures the ratio of urban vegetation, farmland, forests, shrublands, and grasslands to annual average population.

(9) Urban spread index. Following [20], we construct the urban spread index (USI) using equation (1) to capture temporal changes in urban spatial expansion.

$$usi_i = \frac{\left[urb_{i,t+n} - \left(urb_{i,t} * \left(\frac{pop_{i,t+n}}{pop_{i,t}}\right)\right)\right]}{urb_{i,t}} * 100 \tag{1}$$

Subscripts i, t, and $t+n$ denote city, initial year, and final year, respectively. urb indicates built-up area (km2), while pop corresponds to total population (in 10,000 people).

usi quantifies built-up area expansion relative to population growth. If population shifts, the index captures deviations from the benchmark where built-up area expands proportionally with population. usi equals zero when both remain constant. Positive (negative) values indicate that built-up area growth exceeds (falls below) population growth, signaling decreasing (increasing) urban density.

3.1.4. Mechanism Variables

This paper measures innovation ecosystem coordination from two aspects, inter-city coordination, and intra-city coordination, and uses the entropy method for calculation.

Drawing on the existing literature [18,44], a gravity modeling framework is adopted to quantify interurban coordination within innovation ecosystems. The equation is presented as follows:

$$icc_{ij} = \frac{\ln rd_i \times \ln wage_j}{gd_{ij}^2} \tag{2}$$

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

$$icc_i = \sum_{i=1}^{n} icc_{ij} \tag{3}$$

Here, icc_{ij} represents the innovation ecosystem coordination directed from city i to city j, whereas $icct_i$ captures the aggregate coordination between city i and all other cities. Specifically, rd_i measures the stock of scientific researchers in city i, $wage_j$ denotes the average wage standard in city j, and gd_{ij} indicates the geographical distance separating the two cities.

Generally, when innovation outputs are generated through multi-party cooperation, it reflects closer cooperation between multiple innovation entities. Therefore, this study utilizes collaborative patent counts from industry-university-research partnerships as a proxy to characterize urban innovation ecosystem coordination. A higher number of patent applications for industry-university-research cooperation indicates a higher level of the innovation ecosystem within the city.

The specific searching and processing process of the patent application volume data of industry-university-research cooperation is as follows: The patent database of the State Intellectual Property Office of China serves as the data source for conducting patent searches based on the first patent applicant if there are three or more patent applicants, and "company OR enterprise OR group OR factory OR store", "University OR College OR School OR Graduate School" and "Research Institute OR Academy of Agricultural Sciences OR Chinese Academy of Sciences OR Academy of Engineering OR Academy of Sciences OR Research Institute OR Design Institute OR Research Center OR Research Institute" are used to retrieve data related to industry, science and research innovation respectively. All types of patent applications are included in the data retrieval process, and the retrieved data is summarized by the first patent applicant's municipal location.

Based on previous studies, we use Baidu search indices to proxy public environmental attention [36, 45]. With the development of the Internet, internet search metrics derived from user queries effectively track investors' focus on emerging issues, reflecting their preferences and behavioral intentions [46]. Public environmental concerns are a crucial indicator for societal ecological priorities, coordinating collective action consistency and quantifying civic engagement in sustainability efforts. Specifically, we focus on the keyword "environmental pollution" in the Baidu search index, which encompasses a broader range of environmental issues and more directly reflects the public's overall concern about the increasingly severe environmental problems. The Baidu Index comprises aggregated, desktop, and mobile search components, with the Total Search Index being the weighted sum of the PC Search Index and Mobile Search Index.

Environmental regulation is a government measure aimed at limiting corporate pollution in response to the externalities of environmental problems. However, China's environmental regulatory policy is diverse, making it challenging to obtain high-quality related data. In this study, we quantify regulatory stringency via the frequency of environmental protection within prefecture-level government work reports [47]. These keywords include ecological conservation, pollution mitigation, green development, carbon reduction, environmental assessment, and quality monitoring terminology, covering environmental protection, environment, pollution prevention, pollution control, pollution management, pollution control, greening, green development, low carbon, emission reduction, ecology, sewage treatment environmental impact assessment, environmental protection inspection, harmless domestic waste, environmental quality, and air quality.

3.1.5. Data Sources

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

Table 1 delineates the variable definitions employed in this analysis.

Green patent authorization data originate from valid patent records published by the China Intellectual Property Office (CIPO), classified using IPC Green List codes issued by WIPO alongside the CNRDS platform. Additional datasets are extracted from the China Urban Construction Statistical Yearbook, China Urban Statistical Yearbook, statistical yearbooks of various cities, and the China Research Data Service Platform Database (CNRDS). Digital inclusive finance indicators derive from the Peking University Digital Inclusive Finance Index. Government work reports are collected from official Chinese government websites.

Adhering to principles of data availability and validity, this study utilizes panel data covering prefecture-level cities across 30 Chinese provincial-level administrative regions, excluding those with substantial data gaps or recent administrative boundary adjustments. Linear interpolation addresses sporadic missing values. Consequently, the final dataset comprises 273 prefecture-level cities nationwide: 99 in the eastern region, 98 in the central region, and 76 in the western region.

These 273 cities represent most of China's distribution area, which can comprehensively and accurately reflect China's overall situation. The study period spans from 2011 to 2021.

Table 1. Variable Summary

Variable Type	Variable Name	Dimension	Indicator
Dependent Variable	Low-carbon Innovation Level (lci)		Patent Applications for Low Carbon Innovation
Independent Variable	Digital Transformation (dt)	Digital Governance (dg)	Word Frequency of Digital Technology and Digital Applications in Government Work Reports of Prefecture-level Municipalities
		Digital Economy (de)	IT sector employment ratio Total Telecommunications Per Capita Digital Inclusive Finance Index
		Digital Life (dl)	Internet Users Per 100 People Cell Phone Per Subscribers 100 People
Control Variable	Economic Development Level (eco)		Per Capita GDP
	Financial Development Level(fin)		The Share of the Loan Balance of Financial Institutions in GDP
	Market consumption Level (mcl)		Total Retail Sales of Consumer Goods
	Public Service Level (ps)		The Proportion of Public Administration and Social Organization Employees in the Urban Population
	Human Capital (hc)		The proportion of College Students in the Urban Population
	Science and Technology Investment (sti)		the Share of Local Fiscal S&T Expenditure in GDP
	Foreign Direct Investment (fdi)		The Number of Foreign-invested Enterprises above the Designated Scale
	Green Space Per Capita (gs)		The Land Area Covered by Vegetation, Farmland, Forests, Shrublands, and Grasslands in Urban Areas Divided by the Annual Average Population
	Urban Spread Index (usi)		Built-up Area, Annual Average Population
Mediating Variable	Innovation Ecosystem Coordination (iec)	Inter-City Coordination (icct)	The Input of Scientific Researchers, Average Wage Standard, Geographic Distance
		Intra-City Coordination (inc)	The Number of Patents of Industry-University-Research Cooperation
Moderating Variable	Public Environmental Concern (pec)		The Keyword "Environmental Pollution" in the Baidu Search Index
	Environmental Regulation (er)		The Frequency of Keywords Related to Environmental Protection in the Work Reports of Prefecture-Level Municipal Governments

3.1.6. Descriptive Statistics

Table 2 reports the descriptive statistics for primary variables in the model, including the mean, standard deviation, minimum, maximum, and quartile values (25th, 50th, and 75th percentiles). The statistics indicate that cities currently exhibit limited digital transformation progress, with a mean of 0.0657. With a skewness of 7.736, the distribution suggests that fewer

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cities have achieved advanced digital transformation. Consequently, most Chinese cities possess substantial potential for digital transformation. In contrast, low-carbon innovation has a mean value of 5.403 and a skewness of 0.114, exhibiting positive skewness, which highlights a need for improvement in low-carbon innovation across most cities.

Table 2. Descriptive Statistics

Variable	Average Value	Standard Deviation	Minimum Value	Maximum Value	P25	P50	P75
ln(lci)	5.403	1.664	0	10.458	4.263	5.328	6.484
dt	0.0657	0.0642	0.00221	0.891	0.0412	0.0588	0.0778
ln(eco)	7.456	0.915	4.799	10.674	6.845	7.345	8.007
fin	10501	6478.315	1198	96221	6451	8708	12393
ln(mcl)	15.668	1.036	5.472	19.013	15.026	15.614	16.29
ps	134.37	68.767	15.96	1331.02	97.21	120.77	153.05
hc	199.765	247.624	0.592	1445.798	57.51	106.919	224.386
sti	16.672	23.783	0.0563	312.812	4.084	9.453	19.051
fdi	2.991	1.639	0	8.099	1.946	2.708	3.932
gs	0.202	0.335	0	4.283	0.0579	0.109	0.199
usi	0.306	0.598	-5.69	8.395	0.0289	0.171	0.428
iec	0.0266	0.0591	0.001	0.725	0.00359	0.00738	0.725
pec	23.13	25.389	0	140.364	6.958	13.418	28.608
er	0.00345	0.00145	0.000294	0.01239	0.00244	0.00327	0.00428

3.2. Model Settings

3.2.1. Entropy Method

Accurately quantifying the contribution of individual indicators to the composite benefit index across hierarchical levels constitutes a critical challenge in assessing digital transformation and urban innovation ecosystem coordination. This study uses the entropy method to determine the weights of indicators [48], a widely used information weighting model.

3.2.2. Baseline Regression Model

Construct a baseline model to test hypothesis 1:

$$lci_{it} = \beta_0 + \beta_1 \cdot dt_{it} + \sum_{k=1}^{K} \alpha_k \cdot X_{it}^{k} + u_i + v_t + \varepsilon_{it} \quad (4)$$

Here, i identifies the observed city; t marks the observation year; lci quantifies the extent of low-carbon innovation at the municipal level; dt reflects the magnitude of digital transformation, whereas X denotes the control variables in the model. In addition, u_i captures city-specific fixed effects, v_t controls for time-specific effects, and ε_{it} represents the error term.

3.2.3. Mechanism Testing Models

This paper employs Chang et al.'s mechanism analysis method [17] to investigate the transmission mechanisms of innovation ecosystem coordination in digital transformation for low-carbon innovation in cities. The analysis is divided into two phases. Initially, equation (5) assesses the influence of digital economic development on ecosystem coordination. Subsequently, equation (6) evaluates the effect of such coordination on urban low-carbon innovation.

$$iec_{it} = \beta_0 + \beta_1 \cdot dt_{it} + \sum_{k=1}^{K} \alpha_k \cdot X_{it}^{k} + u_i + v_t + \varepsilon_{it} \quad (5)$$

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$$lci_{it} = \tilde{\beta}_0 + \tilde{\beta}_1 \cdot dt_{it} + \tilde{\beta}_2 \cdot iec_{it} + \sum_{k=1}^{K} \alpha_k \cdot X_{it}^k + u_i + v_t + \varepsilon_{it} \tag{6}$$

Thereafter, to investigate whether environmental regulation (er) and public environmental concern (pec) act as moderators in the nexus between digital transformation and urban low-carbon innovation, we establish a moderating effect model (7) with additional variables (i.e., MO,$MO \triangleq er, pec$) based on model (6).

$$\begin{aligned} lci_{it} = {} & \beta'_0 + \beta'_1 \cdot dt_{it} + \beta'_2 \cdot iec_{it} + \textstyle\sum_{l=1}^{L} \theta_l \cdot MO_{it}^l + \sum_{l=1}^{L} \mu_l \cdot dt_{it} \times MO_{it}^l \\ & + \sum_{l=1}^{L} \varphi_l \cdot iec_{it} \times MO_{it}^l + \sum_{k=1}^{K} \alpha_k \cdot X_{it}^k + u_i + v_t + \varepsilon_{it} \end{aligned} \tag{7}$$

Where $,t, dt, X, u_i, v_t, \varepsilon_{it}$ are the same as in equation (2). The notation MO^1 denotes environmental regulation (er) and MO^2 denotes public environmental concern (pec).

4. EMPIRICAL TESTING AND ANALYSIS

4.1. Benchmark Regression

Table 3 reports the primary regression findings derived from our panel data. The specifications incorporate municipal fixed effects to capture unobservable, time-constant heterogeneity across localities, alongside temporal fixed effects to account for period specific unobserved factors, thereby addressing potential omitted variable bias. We compute standard errors clustered at the provincial level to accommodate arbitrary intra-provincial error correlation. Across specifications, adjusted R2 statistics approximate 0.9, suggesting adequate explanatory power of the estimated models.

Table 3. Benchmark Regression Results

Variable	Model 1	Model 2	Model 3
	lci	lci	lci
eco	0.558***		0.559***
	(0.0255)		(0.0257)
fin	0.0459***		0.0457***
	(0.0101)		(0.0102)
mcl	-0.00283		-0.00335
	(0.0215)		(0.0215)
ps	0.0541**		0.0253**
	(0.0120)		(0.00927)
hc	0.111***		0.109***
	(0.0106)		(0.0106)
sti	0.191***		0.192***
	(0.016)		(0.016)
fdi	0.0289***		0.0282**
	(0.00895)		(0.00896)
gs	-0.0361***		-0.0359***
	(0.00718)		(0.00718)
usi	0.0325***		0.0324**
	(0.00909)		(0.00908)
dt		1.115***	1.0517***
		(0.0599)	(0.0338)
Constant	0.563***	0.811***	0.577***
	(0.0293)	(0.0543)	(0.0307)
R-squared	0.8904	0.8812	0.8905
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Robust standard errors in parentheses are clustered at the province level. ***p<0.001, **p<0.01, *p<0.1. FE, fixed effects.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

In column (1) of Table 3, we only assess the influence of all control variables on low-carbon innovation across Chinese cities. The coefficient symbols of control variables remain consistent across all equation forms, although they vary slightly in magnitude and statistical significance. Overall, the results show that a city's level of low-carbon innovation is positively correlated with economic development level, financial development level, public service, human capital, science and technology investment, foreign direct investment, and green space per capita. These findings are generally consistent with the results of other studies. The coefficient of the urban spread index is negative and statistically significant at the 0.001 level, indicating that the expansion of city size inhibits low-carbon innovation. Similarly, the coefficient of market consumption level is negative but lacks statistical significance, possibly due to regional variations in market consumption levels. Column (2) of Table 3 presents a baseline specification examining how digital transformation affects urban low-carbon innovation, excluding additional controls. The coefficient on digital transformation is positive and highly significant at the 0.001 level, suggesting a positive nexus between digitalization and low-carbon innovation in Chinese cities. Column (3) of Table 3 augments the regression by introducing control variables together with digital transformation indicators. Digital transformation retains statistical significance, with its coefficient sign consistent with that reported in column (2), thereby corroborating its positive effect on low-carbon innovation.

Table 4. Robustness Tests

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	lci	lci	lci	lci	lci
eco	0.558*** (0.0255)	0.559*** (0.0255)	0.560*** (0.0256)	0.561*** (0.0266)	0.567*** (0.0259)
fin	0.0457*** (0.0102)	0.0464*** (0.0101)	0.0457*** (0.0102)	0.0433*** (0.0107)	0.0477*** (0.0102)
mcl	-0.00297 (0.0216)	-0.00269 (0.0215)	-0.00252 (0.0216)	-0.0175 (0.0226)	-0.0185 (0.0217)
ps	0.0251** (0.00928)	0.0256** (0.00927)	0.0252** (0.00928)	0.0343** (0.0116)	0.0196* (0.00909)
hc	0.111*** (0.0106)	0.111*** (0.0106)	0.110*** (0.0106)	0.105*** (0.0113)	0.107*** (0.0107)
sti	0.0325*** (0.00909)	0.0329*** (0.00908)	0.0334** (0.00913)	0.0359** (0.00972)	0.0285** (0.00888)
fdi	0.191*** (0.016)	0.193*** (0.0161)	0.191*** (0.016)	0.195*** (0.0169)	0.190*** (0.0162)
gs	0.0289*** (0.00895)	0.0270** (0.00898)	0.0285** (0.00896)	0.0260** (0.00971)	0.0302*** (0.00899)
usi	-0.0361*** (0.00718)	-0.0353*** (0.00719)	-0.0359*** (0.00718)	-0.0366*** (0.00775)	-0.0363*** (0.00700)
dg	1.002*** (0.00843)				
de		1.0564*** (0.026)			
dl			1.0648*** (0.0717)		
dt				1.0432*** (0.0369)	1.0520*** (0.0335)
Constant	0.563*** (0.0293)	0.587*** (0.0313)	0.574*** (0.0318)	0.619*** (0.0332)	0.635*** (0.0304)
R-squared	0.8904	0.8906	0.8905	0.8927	0.8944
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses are clustered at the province level. ***p<0.001, **p<0.01, *p<0.1. FE, fixed effects.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

4.2. Robustness Tests

Table 4 presents the robustness analysis. To verify the stability of our baseline findings, columns (1) and (2) re-estimate the model by disaggregating the dependent variable into three distinct sub-dimensions: digital governance, digital economy, and digital life. Furthermore, columns (3) and (4) employ alternative sample periods (2011-2020 and 2012-2021) to ensure the reliability of results. Across all specifications, the digital transformation coefficients remain consistently positive and statistically significant at the 0.001 level. The robustness test further confirms the significant contribution of the degree of urban digital transformation to low-carbon innovation.

Table 5. Endogeneity Tests

Dependent Variable	Model 1	Model 2
	dt	lci
pts1984	0.0609*** (0.0118)	
tn1984	0.00749* (0.00431)	
eco	0.0159 (0.0139)	0.573*** (0.0257)
fin	0.00373 (0.00556)	0.0398*** (0.0102)
mcl	-0.00474 (0.0117)	-0.0174 (0.0218)
ps	0.00140 (0.00506)	0.0315** (0.00937)
hc	0.00638 (0.00614)	0.0859*** (0.0120)
sti	0.00363 (0.00493)	0.0295** (0.00909)
fdi	0.00909 (0.00872)	0.202*** (0.0162)
gs	0.0138** (0.00498)	0.0112 (0.00983)
usi	-0.00269 (0.00391)	-0.0299*** (0.00731)
dt		1.419*** (0.331)
Constant	0.257*** (0.0164)	0.577*** (0.0307)
Endogeneity Test		-1.406***
Over-Identification Constraint Test		4.107*
Weak Instrumental Variables Test		13.912***
R-squared	0.968	0.891
City FE	Yes	Yes
Year FE	Yes	Yes

Note: Robust standard errors in parentheses are clustered at the province level. ***p<0.001, **p<0.01, *p<0.1. FE, fixed effects.

4.3. Endogeneity Tests

The benchmark estimates offer preliminary evidence that digital transformation fosters low-carbon innovation. To mitigate endogeneity concerns stemming from reverse causality, omitted variable bias, and measurement error, we adopt an instrumental variable (IV) approach to corroborate the baseline findings. Referring to previous studies, we select the total volume of

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

post and telecommunications services at the end of 1984 (pts1984) and the number of fixed telephones per 100 people at the end of 1984 (tn1984) as instrumental variables. The endogeneity test is performed by two-stage least squares (2SLS), and the results of IV estimation are shown in Table 5.

In column (1) of Table 5, we report the estimation results of the first-stage regressions using instrumental variables. The coefficients of the two instrumental variables are positive and statistically significant at the 0.001 and 0.1 levels, respectively. These estimates reveal a robust positive association between instrumental variables and digital transformation. In column (2) of Table 5, we report the estimation results of the two-stage regression. The correlation coefficient for digital transformation is 1.419, statistically significant at the 0.001 level. The model with instrumental variables passes the endogeneity test, over-identification constraint test, and weak instrumental variables test. These findings demonstrate that digital transformation continues to exert a significant positive effect on low-carbon innovation after addressing potential endogeneity issues, thereby validating the robustness of the baseline estimates.

Table 6. Results of the Mediating Effects Analysis

Variable	Model 1	Model 2	Model 3
	lci	iec	lci
dt	1.420*** (0.331)	2.180*** (0.309)	-0.0609 (0.0424)
iec			0.539*** (0.123)
eco	0.573*** (0.0257)	-0.0842*** (0.0240)	0.618*** (0.0288)
fin	0.0398*** (0.0102)	-0.0242* (0.00956)	0.0545*** (0.0103)
mcl	-0.0174 (0.0218)	-0.148 (0.0203)	0.0687* (0.0270)
ps	0.0314*** (0.00936)	-0.00755 (0.00876)	0.0346*** (0.00949)
hc	0.0859*** (0.0120)	0.268*** (0.0113)	-0.0616 (0.0404)
sti	0.0295** (0.00909)	0.0378*** (0.00849)	0.00869 (0.0105)
fdi	0.202*** (0.0162)	0.0912*** (0.0151)	0.149*** (0.0188)
gs	0.0112*** (0.00983)	-0.0213* (0.00919)	0.0263** (0.00894)
usi	-0.0299*** (0.00731)	0.0133* (0.00684)	-0.0385*** (0.00719)
Constant	0.952*** (0.0955)	0.764*** (0.0893)	0.4527*** (0.0417)
R-squared	0.8911	0.9047	0.8912
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Robust standard errors in parentheses are clustered at the province level. ***p<0.001, **p<0.01, *p<0.1. FE, fixed effects.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

5. MECHANISM ANALYSIS

5.1. Mediating Effects Analysis

Table 6 presents the empirical results of the mediating effects. In column (1) of Table 6, we report the total effect of digital transformation on low-carbon innovation. The estimated coefficients are positive and statistically significant at the 0.001 level. In other words, digital transformation can effectively promote low-carbon innovation in cities. In column (2) of Table 6, we investigate how digital transformation influences innovation ecosystem coordination. The estimated coefficients are statistically positive and significant at the 0.001 level, indicating that digital transformation substantially enhances innovation ecosystem coordination. In column (3) of Table 6, we test whether innovation ecosystem coordination serves as an intermediary in the nexus between digital transformation and low-carbon innovation. While the coefficient on digital transformation becomes statistically non-significant, that on innovation ecosystem coordination remains positive and significant at the 0.001 level. This suggests that innovation ecosystem coordination mediates the relationship between digital transformation and low-carbon innovation. In other words, digital transformation promotes low-carbon innovation by improving innovation ecosystem coordination. The possible explanation is that digital transformation improves innovation and ecosystem coordination. The enhancement of the coordination of the innovation ecosystem promotes the flow, clustering, and integration of innovation factors, thus promoting low-carbon innovation.

Table 7. Results of the Moderating Effects Analysis

Variable	Results of Baseline Regression		Results of the Heterogeneity Analysis of er		Results of the Heterogeneity Analysis of pec	
	iec	lci	iec	lci	iec	lci
dt	2.180*** (0.309)		2.131*** (0.306)		1.838*** (0.304)	
iec		0.432*** (0.0978)		0.426*** (0.0976)		0.415*** (0.0992)
er			-0.0235*** (0.00635)	0.0233*** (0.00692)		
dt*er			-0.0709*** (0.00884)			
iec*er				-0.0109 (0.00816)		
pec					0.119*** (0.0167)	0.0946*** (0.0188)
dt*pec					0.0565*** (0.00608)	
iec*pec						-0.0168** (0.00534)
R-squared	0.9047	0.8911	0.9071	0.8917	0.9103	0.8922
Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses are clustered at the province level. ***p<0.001, **p<0.01, *p<0.1. FE, fixed effects

5.2. Moderating Effects Analysis

To explore whether there is heterogeneity in the relationship between digital transformation and low-carbon innovation under different environmental regulatory intensities and public environmental concern levels, this paper introduces interaction terms based on model (14), and the results are shown in Table 7.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202605_12(5).0003

Results indicate that the dt*er coefficient is significantly negative ($p < 0.001$), demonstrating that environmental regulation weakens the promoting effect of digital transformation on innovation ecosystem coordination. This stems from increased production costs and reduced R&D investment incentives under regulatory pressure. Although digital transformation facilitates innovation factor mobility, diminished innovation activity ultimately impedes ecosystem coordination. Consequently, the facilitating effect of digital transformation on innovation ecosystem coordination is lower in cities with more stringent environmental regulations. In contrast, the dt*pec coefficient is significantly positive ($p < 0.001$), suggesting that digital transformation exerts a stronger catalytic influence on ecosystem coordination in contexts of elevated public environmental awareness. Heightened public environmental awareness transmits prompt feedback signals to innovators, prompting firms to reallocate innovation resources toward low-carbon initiatives, thereby strengthening ecosystem coordination.

The iec*er coefficient registers negatively ($p < 0.001$), implying that ecosystem coordination exerts diminished influence on low-carbon innovation under rigorous environmental regulations. Likewise, the iec*pec coefficient is significantly negative ($p < 0.01$), suggesting that ecosystem coordination's role in advancing low-carbon innovation attains in environments with pronounced public environmental consciousness. Moreover, columns (5) and (6) in Table 8 reveal that the coefficients of er and pec are positive and statistically significant ($p < 0.001$), indicating that regulatory stringency and public environmental awareness positively influence low-carbon innovation. Despite the theoretical expectation that innovation ecosystem coordination would have a more prominent facilitating effect under more stringent environmental regulation or higher public environmental concern, the leading position of low-carbon innovation in cities with stringent environmental regulation or high public environmental concern in practice limits the space for the promotion of the innovation ecosystem coordination on low-carbon innovation.

6. CONCLUSIONS AND RECOMMENDATIONS

Leveraging panel regression analysis of 273 Chinese cities, this study examines digital transformation's influence on urban eco-innovation through the prism of innovation ecosystem coordination. Environmental regulation and public environmental awareness are embedded into the analytical framework to capture heterogeneous effects on urban low-carbon innovation. Empirical findings reveal that digital transformation markedly advances low-carbon innovation. Innovation ecosystem coordination functions as a mediating mechanism: digitalization enhances low-carbon performance by reinforcing ecosystem coordination. Under current developmental conditions, rigorous environmental regulations attenuate digital transformation's positive effects on innovation ecosystem coordination. In contrast, intensifying public environmental concerns strengthens these promotional effects. Nevertheless, the mediating influence of ecosystem coordination on low-carbon innovation weakens in contexts characterized by stringent regulatory frameworks or elevated environmental consciousness.

Based on the above findings, this study offers the following implications.

First, it is essential to fully utilize digital transformation as a driving force for urban low-carbon innovation. On the one hand, this can be achieved by accelerating the process of urban digital transformation. The government should fully leverage financial funds' guiding role, increase financial funds' investment in digital infrastructure and economy, and promote urban digital transformation. On the other hand, the application of digital technology in urban low-carbon development should be promoted. For example, enterprises and residents should be

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incentivized through preferential policies and subsidies to adopt intelligent energy management systems to improve energy efficiency and reduce carbon emissions.

Second, innovation ecosystem coordination constitutes a pivotal mechanism through which digital transformation drives urban low-carbon innovation. Consequently, governance efforts should prioritize systemic alignment to optimize efficacy. Specifically, authorities ought to mobilize and integrate societal innovation resources, expedite talent acquisition, and foster inter-organizational collaboration. Furthermore, developing regional technology exchange platforms is essential for cultivating tightly coordinated innovation networks. Moreover, strengthening accessibility to public innovation resources and infrastructure is imperative to enable the seamless circulation of innovation inputs across cities.

Third, the government should formulate environmental policies tailored to regional specificities, strengthen environmental publicity, popularize environmental education, and enhance public environmental awareness. When formulating environmental policies, the government should account for regional economic endowment and development levels, optimize the rigor of environmental oversight, and pursue harmony between ecological sustainability and economic advancement. For cities with high levels of low-carbon innovation, environmental regulation can be appropriately relaxed to provide more space for digital transformation and promote the development of urban innovation ecosystems. Increasing public attention to environmental issues through environmental awareness and popularization of environmental education can not only promote the driving effect of digital transformation on low-carbon innovation but also form an adequate supervision of enterprises and governments in environmental protection through public participation.

This paper still has some limitations. First, data availability constrains the temporal scope to 2021. Incorporating more recent observations could yield additional insights into China's ongoing developmental dynamics. Second, this study specifically examines the digital transformation–low-carbon innovation nexus within Chinese cities.

However, given that the general applicability of the conclusions is still unknown, it would be worthwhile to revisit the topic by comparing different economies. Whether these findings generalize across different economies remains unclear; cross-national comparative analyses thus represent a promising avenue for future inquiry.

7. DATA AVAILABILITY STATEMENT

Data will be made available on request.

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