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# Heterogeneous effects of the digital economy on high-quality green development of urban economy and its spatial spillovers: evidence from the Upper Yangtze River Economic Belt

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Against the backdrop of deep integration between global digital transformation and sustainable development, the digital economy—with data as its core driver—has reshaped urban development paradigms and emerged as a pivotal force in advancing economic growth and green transformation. The urban agglomerations in the Upper Yangtze River Economic Belt, which balance ecological security and economic growth in western China, provide a strategically significant case for exploring how the digital economy influences high-quality green urban development. Using panel data (2011–2023) from 32 prefecture-level cities in this region, we constructed comprehensive indices to quantify the digital economy and high-quality green development. We applied benchmark regression, quantile regression, and spatial Durbin models to analyze direct effects, mediating pathways, and spatial spillover effects, with robustness validated through variable replacement and sample adjustment, and heterogeneity examined by city scale and resource attributes. The results indicate that the digital economy exerts a stable and positive impact on high-quality green development, a conclusion that remains robust across multiple tests. Innovation capability mediates approximately 20.96% of the total effect. Heterogeneity analysis reveals stronger driving effects in large cities compared to small and medium-sized cities, and in non-resource-based cities relative to resource-based ones. Additionally, the digital economy demonstrates significant spatial spillover effects, fostering coordinated development in neighboring cities, with its most prominent impact on coordinated development among the five sub-dimensions of high-quality green growth. This study confirms that the digital economy serves as a critical new productive force for green transformation. Targeted strategies—including hierarchical enhancement of digital infrastructure, strengthened innovation-mediated mechanisms, mitigation of heterogeneous development dilemmas, and amplification of spatial synergies—offer micro-level evidence and policy insights for underdeveloped regions to advance "digital empowerment + green transformation."

KEYWORDS

**digital economy, high-quality green development of urban economy, innovation capability, mediation mechanisms, spatial spillovers**

# 1 Introduction

Against the backdrop of the deep integration of global digital transformation and the concept of sustainable development, the digital economy, with data elements as its core driving force (Ma and Zhu, 2022), has reshaped the logic of urban development through in-depth penetration into the real economy, emerging as a key force in promoting economic growth and green transformation (Zalutskyy, 2019). As an overlapping region of China's western ecological security barrier and economic growth pole, the upstream urban agglomerations of the Yangtze River Economic Belt have a strategic orientation of "ecological priority and green development". This makes exploring the mechanism by which the digital economy affects the high-quality green development of urban economy of special significance-it not only responds to the practical need to resolve the contradictions between unbalanced regional development, ecological protection and economic growth, but also serves as a typical sample for exploring the path of green rise in underdeveloped areas.

Existing studies have initially confirmed the enabling effect of the digital economy on green development (Ma and Zhu, 2022; Zhang et al., 2022), but there are still obvious deficiencies in systematic research on the upstream urban agglomerations of the Yangtze River Economic Belt: the lack of regionally adaptive measurement tools limits the accuracy of evaluation, and the ambiguity in urban heterogeneous mechanisms and spatial interaction laws restricts policy targeting. Against this backdrop, this paper focuses on the upstream urban agglomerations of the Yangtze River Economic Belt, aiming to construct an index system for digital economy and high-quality green development of urban economy that adapts to regional characteristics, strengthen green dimensions such as ecological efficiency and carbon emission intensity, and accurately quantify the contribution of the digital economy; analyze the heterogeneous enabling paths of cities with different population sizes (large cities, small and medium-sized cities) and resource types (resource-based, non-resource-based cities), highlighting the role of mechanism variables such as demographic dividend and industrial transformation; and use the spatial Durbin model to reveal the spatial spillover effect of the digital economy, explore the "core-periphery" interaction mechanism within the urban agglomerations, so as to provide micro-evidence and policy reference for regional collaborative promotion of "digital empowerment + green transformation".

The innovative value of this study is reflected in three aspects: first, measurement innovation, which breaks through the limitations of traditional indicators, incorporates dimensions such as green digital infrastructure and ecological efficiency, and accurately adapts to the ecological strategic needs of the upstream Yangtze River Economic Belt; second, mechanism innovation, which focuses on the heterogeneity of cities with different scales and resource types in the region, deeply explores the action logic of the digital economy under special contexts such as demographic dividend and transformation pressure, and fills the gap in research on regional segmented mechanisms; third, spatial innovation, which takes urban agglomerations as the unit, uses the spatial Durbin model to analyze the cross-city flow of the digital economy and the "core-periphery" spatial effect, provides a new perspective for solving the problem of regional spatial imbalance, and helps the Yangtze River Economic Belt achieve the coordinated improvement of ecological protection and economic development.

# 2 Literature review

## 2.1 The green empowerment potential of the digital economy

As a new economic form following agricultural economy and industrial economy, the concept of the digital economy was first proposed by Tapscott (1996)and supplemented and improved by Kim et al. (2002). The Organization for Economic Cooperation and Development (OECD) constructed a logical framework from the perspectives of knowledge economy, information economy and internet economy, laying a theoretical foundation. Current studies have confirmed that the digital economy is not only an engine for economic growth, but also shows a significant enabling effect in the field of green development: in the dimension of resource allocation, the digital economy optimizes the matching efficiency between production factors and ecological resources through the efficient flow of data elements (Gao and He, 2024; Chen, 2022), promotes the clean transformation of energy consumption structure (Wang and Shao, 2023). At the industrial transformation level, the digital economy empowers traditional industries to achieve coordinated upgrading of digitalization and greenization (Bai et al., 2023; Chen and Wang, 2019), such as real-time monitoring of carbon emissions through industrial internet, or innovating circular models relying on platform economy (Chiaroni et al., 2021; Mancuso et al., 2023). In addition, green innovation driven by digital technology further strengthens the role of ecological improvement (Yao et al., 2023; Xie et al., 2024), forming a closed-loop path of "digital empowerment-efficiency improvement–low-carbon transformation".

## 2.2 Evolution of the connotation of high-quality green development of urban economy

High-quality green development of urban economy represents a synergistic integration of high-quality economic development and green development, with its core lying in balancing economic vitality, resource efficiency, and ecological well-being. Early research on the economy focused on the expansion of total GDP (Alexander and Lewis, 1957), ignoring the costs to resources and the environment. With the rise of the concept of sustainable development, Kamayev and Chen (1983) was the first to emphasize the quality of growth. Subsequently, Barro et al. (2002) incorporated environmental conditions and income distribution into the evaluation framework, laying the foundation for research on green development. Subsequent studies have further expanded the dimensions: Simms and Boyle (2009) proposed using ecological efficiency (resource consumption and carbon emission intensity per unit of GDP) as a core indicator; Alexandra (2016) included indicators of green employment and environmental regulation; Mlachila et al. (2016) emphasized the adaptation of social welfare and ecological carrying capacity to avoid the "high-growth and high-pollution" model.

In the Chinese context, this concept is guided by the new development philosophy of "innovation, coordination, greenness, openness, and sharing" (Third Plenary Session of the 18th Central Committee of the Communist Party of China, 2015). It achieves a "economic-ecological" win-win situation through paths such as industrial green upgrading, low-carbon energy transformation, and ecological governance. The evaluation system not only includes traditional economic indicators but also highlights ecological dimensions such as green total factor productivity and carbon emission intensity, reflecting the development logic that "lucid waters and lush mountains are invaluable assets".

### 2.3 Research progress on digital economy and high-quality green development of urban economy

The enabling role of the digital economy in the high-quality green development of urban economy has become a research hotspot, with existing achievements mainly focusing on impact effects, mechanisms of action, and spatial characteristics: At the level of impact effects, macroscopically, the digital economy provides impetus for development by promoting clean energy consumption and green industrial agglomeration (Wang and Li, 2024; Luo et al., 2022); microscopically, it accelerates transformation by improving enterprises' environmental management efficiency and driving green technological innovation (Wang and Shao, 2023; Zhuo and Chen, 2023). Empirical evidence shows that for every 1% increase in the digital economy, urban ecological efficiency improves by 0.3%–0.5% and carbon emission intensity decreases by 0.2%–0.4% (Yao et al., 2023; Xie et al., 2024). At the level of mechanisms, technological progress, greening of industrial structure, and institutional innovation have been identified as key paths, among which technological innovation is the core intermediary: the digital economy promotes patent transformation through the integration of data and green technologies (Lv and Wu, 2023). However, most existing studies are based on provincial-level data, with insufficient discussion on the heterogeneity of innovation capabilities at the urban scale (such as differences in resources among cities of different sizes). At the level of spatial characteristics, the cross-regional mobility of the digital economy gives rise to significant spatial spillover effects: Ding et al. (2021) found that the digital economy can drive the improvement of ecological efficiency in neighboring regions through technology diffusion; Tang et al. (2021) pointed out that its unbalanced development may widen the green gap, leading to a "core low-carbonization—periphery high-carbonization" differentiation. Nevertheless, there is limited attention to the spatial interaction mechanisms within urban agglomerations (such as the upstream Yangtze River Economic Belt) and the differentiated spillover effects among different types of cities.

### 2.4 Research gaps and contributions

Existing studies have three limitations: first, the measurement system lacks "green" pertinence, and the quantitative indicators for the digital economy and green development are not unified, which affects the accuracy of evaluation; second, mechanism analysis focuses on technological innovation, with insufficient integration of paths such as industrial transformation and accumulation of green skills in human capital; third, spatial research remains at the provincial level, with insufficient exploration of heterogeneity and collaborative mechanisms at the urban scale.

To address the above gaps, this paper makes contributions in the following aspects: first, optimizing the measurement framework by incorporating green digital infrastructure into digital economy indicators and strengthening ecological efficiency and carbon emission intensity in green development indicators to improve quantitative accuracy; second, expanding mechanism analysis by taking innovation capability as the core intermediary, integrating industrial upgrading and energy transformation paths, and constructing a theoretical chain of "digital empowerment–multi-dimensional transmission–green development"; third, focusing on the upstream urban agglomerations of the Yangtze River Economic Belt, using the spatial Durbin model to reveal the heterogeneous impacts and spatial synergy effects of the digital economy on cities of different sizes and resource types, thus providing micro-evidence for regional green coordinated development.

## 3 Materials and methods

### 3.1 Research region

This study investigates the underdevelopment of the digital economy in western China, aiming to uncover its root causes and propose strategies for mitigating regional disparities. Focusing on industrial digitalization and emerging digital industries, we analyze panel data (2011–2023) from 32 prefecture-level cities within the Upper Yangtze River Economic Belt (spanning Sichuan, Guizhou, and Yunnan provinces; see Figure 1). Data were extracted from the China Statistical Yearbook and provincial yearbooks, with anomalies and gaps addressed through linear interpolation.

### 3.2 Variables

#### 3.2.1 Explained variable: level of high-quality green development of urban economy

For the measurement of high-quality green economic development level, scholars usually adopt the single-indicator measurement method and the comprehensive indicator measurement method. Some scholars argue that the quality and efficiency of economic development are closely related to improvement, thus selecting indicators such as total factor productivity (Jia et al., 2020; Balk et al., 2020; Şeker and Saliola, 2018), green total factor productivity (Ji and Zhang, 2019; Qiu et al., 2021), and labor productivity (Aghion et al., 2020) for measurement. However, a single indicator is one-sided and cannot comprehensively measure the level of high-quality economic development. Therefore, most scholars attempt to construct a comprehensive evaluation system from different dimensions. For instance, Qi (2016) constructed a framework through four dimensions: economic scale, economic efficiency, economic structure, and coordination. Kong et al. (2021) measured the level of high-quality economic development from three dimensions:

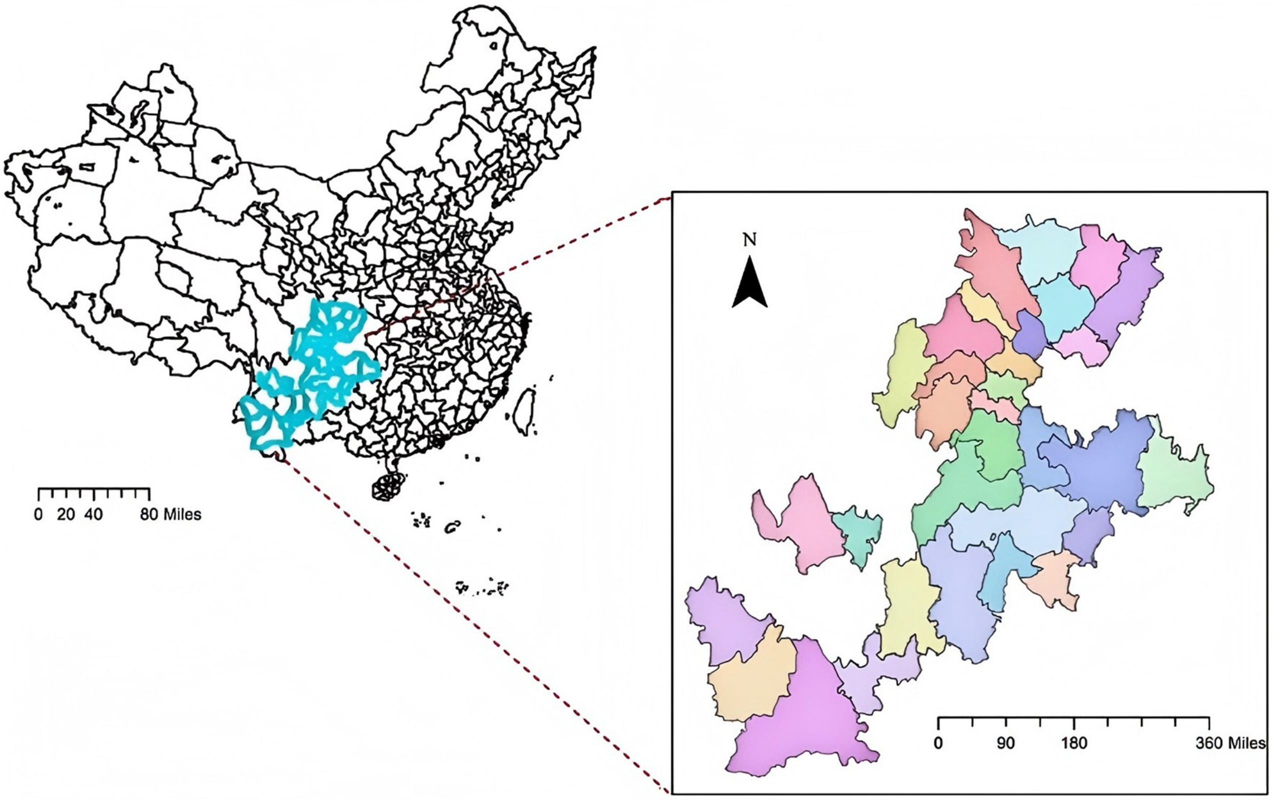


FIGURE 1
Map of the study area.

economic growth efficiency, stability, and sustainability. Drawing on previous research and combining the current national conditions of China, this paper constructs a measurement index system from five dimensions: innovative development, coordinated development, green development, open development, and shared development (see Table 1). The indicators are subjected to dimensionless processing, and weights are determined using the entropy method to calculate the urban high-quality green development index, which is denoted by the symbol HgUE.

### 3.2.2 Core explanatory variable: digital economy

The core of the digital economy lies in the construction of digital infrastructure, and Reynolds et al. (2021), Zhou (2022) and Zhang et al. (2023) have successively conducted research on the relationship between digital infrastructure and economic growth. However, the digital economy does not solely rely on infrastructure construction; it also encompasses the vigorous development of digital industries. For example, Farboodi and Veldkamp (2021) argue that digital industrialization is an output attribute of the digital economy. Additionally, some scholars have explored the role of digital industrialization in high-quality economic development from the perspective of influencing mechanisms such as digital technology (Lekan and Rogers, 2020), technological support (Liu, 2024), and industrial structure upgrading (Ivanovic-Dukic et al., 2019). Furthermore, scholars generally believe that accelerating the digital transformation of traditional industries (Deng et al., 2022; Ran et al., 2023) and promoting intelligent production and lifestyle (Chen et al., 2024) are also conducive to high-quality green economic development. Sustainable development is also an important principle and goal that cannot be ignored in the development of the digital economy, and digital innovation capability is the key to sustainable development (Bag et al., 2021; Ghobakhloo and Fathi, 2019).

Based on previous studies, this paper constructs a measurement system from four dimensions: digital foundation, digital industrialization, industrial digitalization, and digital innovation (see Table 2). The 18 indicators in the system are normalized, and the entropy method is used to determine the weights, so as to calculate the digital economy index, which is denoted by the symbol Dig.

### 3.2.3 Mediating variable: innovation capability

Referring to the "Report on the Innovation Capabilities of Chinese Cities and Industries", the urban innovation index, which is constructed from the dimensions of innovation output, patent value, and innovation-plus-entrepreneurship, is selected to measure the innovation capabilities of cities. This index, by incorporating micro-big data, can comprehensively reflect the innovation levels of cities.

TABLE 1 Index system for measuring the level of high-quality green development of urban economy.

| Dimensions | 1st-level indicator | 2nd-level indicator | Calculation method | Attributes |
|---|---|---|---|---|
| Innovative development | Innovative inputs | Investment in R&D investment in education | S&T expenditure/ GDP<br>Research funds / Fiscal expenditures<br>education expenditure/GDP<br>Education budget/financial expenditure | +<br>+<br>+<br>+ |
| | Innovation outputs | Patents granted per capita | Number of patent grants/total population | + |
| Coordinated development | Regional coordination | Regional economic | City-level GDP / Province-level GDP | + |
| | Urban and rural coordination | Urbanization rate<br>Urban-rural income gap<br>Urban-rural consumption gap | Urban population/Total population (%)<br>Per capita disposable income of rural residents<br>/Per capita disposable income of urban residents<br>Per capita consumption expenditure of rural residents<br>/Per capita consumption expenditure of urban residents | +<br>+<br>+ |
| | Industrial coordination | Upgrading of industrial structure | Value added of tertiary industry<br>/Value added of secondary industry | + |
| | Economic and social coordination | Level of regional economic development<br>Level of regional financial expenditures | Per capita gross regional product<br>Per capita financial expenditure | +<br>+ |
| Green development | Pollutant emissions | Industrial waste water discharges<br>Industrial waste gas emissions<br>Carbon emission intensity | Industrial wastewater discharge<br>/Industrial output value<br>Industrial sulfur dioxide emissions<br>/Industrial output value<br>Per capita carbon dioxide emissions | -<br>-<br>- |
| | Environmental governance | Pollution disposal<br>Utilization of solid waste<br>Domestic waste disposal | Sewage treatment rate (%)<br>Comprehensive utilization<br>rate of industrial solid waste (%)<br>Non-hazardous treatment rate of domestic waste (%) | +<br>+<br>+ |
| | Greening level | Urban greening<br>Greening construction | Per capita public green space area<br>Green space ratio in built-up areas (%) | +<br>+ |
| | Green production | Green production efficiency<br>Energy consumption intensity<br>Green innovation output | Green total factor productivity<br>Energy consumption per unit of GDP<br>Number of granted green patents | +<br>-<br>+ |
| Open development | Foreign trade | External trade dependence | Total value of imports and exports/GDP | + |
| | Foreign capital level | Utilization of foreign investment | Actual utilization of foreign capital/GDP | + |
| Shared development | Medical Security | Medical and health level | Practicing or assistant<br>physicians per 10,000 persons<br>Hospital and sanatorium beds per 10,000 population | +<br>+ |
| | Urban construction | Density of traffic | Classified road mileage/Land area<br>Per capita road area | +<br>+ |
| | People's welfare | Urban residents' savings<br>Remuneration of workers | Per capita urban residents' savings<br>Average wage of employees | +<br>+ |
| | Cultural construction | Investment in cultural industries<br>Public cultural coverage | Expenditure on cultural industries/ GDP<br>Per capita library book collection quantity | +<br>+ |

### 3.2.4 Control variables

Government support, reflecting the government's support for the digital economy and high-quality green development of urban economy through fiscal subsidies, policy guidance, and other means, is measured by the ratio of urban fiscal expenditure to GDP (Liang and Li, 2023), denoted by the symbol Gov. Marketization level, embodying the decisive role of the market in resource allocation, is calculated as a weighted aggregate of indicators quantifying the government-market relationship, non-state-owned economic development, product market development, factor market development, development of market intermediaries, and legal institutional environment (Chen et al., 2021), denoted by the symbol Mar. Industrialization level, representing the depth and breadth of urban industrial development, is measured by the ratio of industrial added value to regional GDP (Zhang et al., 2024), denoted by the symbol Ind. Industrial agglomeration level, reflecting the concentration of specific industries in geographical space, is calculated by

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TABLE 2 The system of indices for evaluating the digital economy.

| Dimensions | Indicators | Calculation method | Attributes |
|---|---|---|---|
| Digital foundation | Digital infrastructure | Density of long-distance optical cable lines | + |
| | | Number of internet broadband access ports per 100 people | + |
| | | Number of mobile phone users per 100 people | + |
| | | Number of internet users per 100 people | + |
| Digital industrialization | Digital industry output | Per capita total volume of postal Services | + |
| | | Per capita total volume of telecommunication services | + |
| | | Per capita telecommunication service revenue | + |
| | Digital industry input | Proportion of employees in computer services and software | + |
| | | Number of artificial intelligence companies | + |
| Industrial digitization | Digitization of agriculture | Per capita agricultural machinery power | + |
| | | Proportion of administrative villages with internet broadband services opened (%) | + |
| | Industrial digitization | Installation density of industrial robots | + |
| | Digitization of service industry | E-commerce sales/GDP | + |
| | Digital finance | Digital inclusive finance index | + |
| Digital Innovation | Innovation intensity | Intensity of R&D expenditure input (%) | + |
| | | Number of newly-established enterprises per 100 People | + |
| | Innovation environment | Number of regular institutions of higher education | + |
| | | Number of regular institutions of higher education students per 10,000 people | + |

the ratio of the number of employees to the land area of the administrative region (Zheng and He, 2022), denoted by the symbol Ia.

The descriptive statistics of the above variables are shown in Table 3.

## 4 Research methods

This study examines the digital economy's multiple facets of impact on high-quality green development of urban economy (HgUE), including direct effects, innovation-mediated pathways, and spatial spillovers. City-tier heterogeneity and regional developmental imbalances are incorporated to elucidate the causal mechanisms linking digitalization to HgUE. However, as the research sample focuses on the upstream urban agglomerations of the Yangtze River Economic Belt, and this region has particularities due to its ecological sensitivity (such as its positioning as an ecological barrier in the upper reaches of the Yangtze River) and economic development stage (characterized by underdevelopment in western China), the relevant conclusions cannot be directly generalized to eastern coastal urban agglomerations or individual cities, and their external universality needs further verification. The analytical framework (Figure 2) integrates these dimensions through a series of research models.

Construction of the benchmark regression model: A benchmark linear regression model was developed to analyze the digital economy's role in high-quality green development of urban economy (HgUE). The framework incorporates city fixed effects $\lambda_i$ and time fixed effects $\Delta_i$ to isolate the net impacts of digitalization and control variables on HgUE levels.

$$HgUE_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Con_{it} + \lambda_i + \Delta_i + \epsilon_{it} \tag{1}$$

Where: $HgUE_{it}$ stands for the level of high-quality green economic development of city i in period t; $Dig_{it}$ represents the digital economy index; $Con_{it}$ reflects a range of control variables. The model incorporates city fixed effects $\lambda_i$, time fixed effects $\Delta_i$, a random error term $\epsilon_{it}$, and an intercept $\alpha_0$. Coefficients $\alpha_1$ and $\alpha_2$ respectively indicate the influence of the digital economy and control variables on the high-quality green development of urban economy (HgUE).

Adoption of the quantile regression model: To address the potential bias of extreme values in the benchmark regression, a quantile regression framework is employed. This method estimates heterogeneous marginal effects of the digital economy across varying HgUE quantiles, enhancing robustness against outliers.

$$Quant_t = \beta_0 + \beta_1 Dig_{it} + \beta_2 Con_{it} + \lambda_i + \Delta_i + \epsilon_{it} \tag{2}$$

Where: $Quant_t$ represents the quantile corresponding to the quantile point t; $\beta_0$ refers to the intercept term of the model; $\beta_1$ and $\beta_2$ individually reflect the marginal contributions of digital economy factors and control variables to the process of urban economies advancing toward high-quality development at a specific quantile point.

Application of the stepwise regression model (Ma and Zhu, 2022): A stepwise regression framework was employed to test the mediating role of innovation capacity in the process through which the digital economy promotes the high-quality green

TABLE 3 Descriptive statistics of variables.

| Variable type | Variable name | Variable symbol | Obs | Min | Max | Avg | SD | Me |
|---|---|---|---|---|---|---|---|---|
| Explained variable | High-quality green development of urban economy | Hqd | 416 | 0.100 | 0.782 | 0.207 | 0.087 | 0.186 |
| Core explanatory variable | Digital economy | Dig | 416 | 0.027 | 0.634 | 0.160 | 0.096 | 0.138 |
| Mediating variable | Innovation capability | Inn | 416 | 0.072 | 343.794 | 10.447 | 31.656 | 1.663 |
| Control variables | Government support | Gov | 416 | 0.092 | 0.675 | 0.245 | 0.108 | 0.206 |
| | Marketization level | Mar | 416 | 6.837 | 18.453 | 12.697 | 2.137 | 12.627 |
| | Industrialization level | Ind | 416 | 0.145 | 6.468 | 1.721 | 1.500 | 1.696 |
| | Industrial agglomeration level | Ia | 416 | 0.0003 | 0.080 | 0.005 | 0.009 | 0.002 |

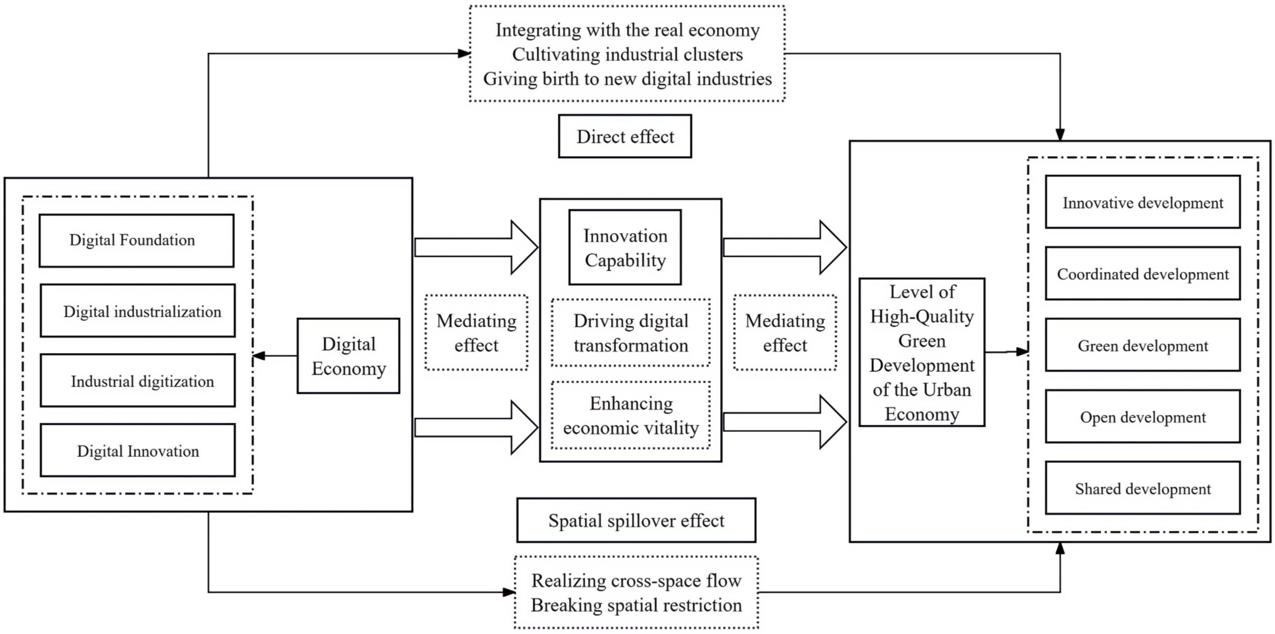


FIGURE 2
Conceptual framework of the internal mechanism of the digital economy's impact on high-quality green development of urban economy.

development of urban economy(HgUE). This approach isolates the indirect pathways through which digitalization enhances HgUE by systematically evaluating incremental contributions of innovation-driven mechanisms.

$$Inn_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Con_{it} + \lambda_i + \Delta_i + \epsilon_{it} \quad (3)$$

$$Hqd_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Inn_{it} + \beta_3 Con_{it} + \lambda_i + \Delta_i + \epsilon_{it} \quad (4)$$

Where: $Inn_{it}$ represents the innovation capability of city i in the t-th year. $\alpha_1$ and $\alpha_2$ denote the degrees to which the digital economy ($Dig_{it}$) and control variables ($Con_{it}$) impact innovation capability; $\beta_1$, $\beta_2$ and $\beta_3$ quantify the contributions of $Dig_{it}$, $Inn_{it}$ and $Con_{it}$ to high-quality green development of urban economy (HgUE).

Construction of the spatial econometric model: Building on the benchmark regression, we extend the framework to a Spatial Durbin Model (SDM) by incorporating spatial interaction terms. An economic-geographical weight matrix (W) is applied to capture cross-regional spillovers of the digital economy.

$$Hqd_{it} = \alpha_0 + \rho WHqd_{it} + \psi_1 WDig_{it} + \alpha_1 Dig_{it} + \psi_2 WCon_{it} + \alpha_2 Con_{it} + \Delta_i + \epsilon_{it} \quad (5)$$

$\rho$: spatial auto-regressive coefficient, W: economic-geographical weight matrix (nested distance and GDP-per-capita metrics). $\psi_1$ and $\psi_2$: elasticities of spatial spillovers from the digital economy ($Dig_{it}$) and control variables ($Con_{it}$).

TABLE 4 The results of benchmark regression analysis.

| Variables | Model (1) | Models (2) | Models (3) | Models (4) | Models (5) | Models (6) |
|---|---|---|---|---|---|---|
| Constant | 0.076***<br>(21.521) | 0.106***<br>(34.289) | 0.095***<br>(17.162) | 0.052***<br>(5.376) | 0.055***<br>(5.848) | 0.057***<br>(6.134) |
| Dig | 0.818***<br>(43.296) | 0.557***<br>(27.882) | 0.575***<br>(26.971) | 0.546***<br>(25.677) | 0.540***<br>(25.966) | 0.526***<br>(25.417) |
| Inn | | 0.001***<br>(18.354) | 0.001***<br>(18.346) | 0.001***<br>(19.459) | 0.001***<br>(20.276) | 0.001***<br>(14.705) |
| Gov | | | 0.032***<br>(2.301) | 0.043***<br>(3.134) | 0.035***<br>(2.589) | 0.034***<br>(2.592) |
| Mar | | | | 0.004***<br>(5.483) | 0.004***<br>(6.298) | 0.004***<br>(6.410) |
| Ind | | | | | -0.004***<br>(-4.613) | -0.005***<br>(-5.646) |
| Ia | | | | | | 0.858***<br>(4.020) |
| $R^2$ | 0.819 | 0.900 | 0.902 | 0.908 | 0.913 | 0.916 |
| $R^2$ (within) | 0.819 | 0.900 | 0.901 | 0.907 | 0.912 | 0.915 |
| Observations | 416 | 416 | 416 | 416 | 416 | 416 |
| Time fixed effect | YES | Yes | Yes | Yes | Yes | Yes |
| Spatial fixed effect | YES | Yes | Yes | Yes | Yes | Yes |
| F-statistic | F(1,414)=1874.587,<br>$p$ = 0.000 | F(2,413)=1866.173,<br>$p$ = 0.0000 | F(3,412)=1258.815,<br>$p$ = 0.000 | F(4,411)=1018.220,<br>$p$ = 0.000 | F(5,410)=859.027,<br>$p$ = 0.000 | F(6,409)=745.019,<br>$p$ = 0.000 |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

# 5 Results and discussion

## 5.1 Benchmark regression analysis

To assess the influence of control variables on high-quality green development of urban economy (HgUE), a benchmark regression analysis was conducted (Table 4). Model 1 shows the regression results without including control variables, where the coefficient of the digital economy reaches 0.818 (t = 43.296), significantly positive at the 1% level. With the gradual inclusion of control variables (Models 2–6), the coefficient decreases to 0.526 (Model 6) but remains significant at the 1% level, indicating that the promoting effect of the digital economy on the high-quality green development of urban economy is robust. The $R^2$ of the models increases gradually from 0.819 (Model 1) to 0.916 (Model 6), reflecting the enhanced synergistic explanatory power of the digital economy and control variables, which confirms its core role in driving high-quality green economic development. Innovation capability (Inn): The coefficient stably remains at 0.001 (significant at the 1% level), indicating that innovation promotes the transformation of growth models (from factor-driven to innovation-driven), improves production efficiency and product added value, and thus facilitates high-quality green economic development. Government support (Gov): The coefficient ranges from 0.032 to 0.043 (significant at the 1% level), suggesting that scientific government planning can accurately allocate resources and guide the economy toward a high-quality green path. Marketization level (Mar): The coefficient is 0.004 (significant at the 1% level), reflecting that marketization optimizes resource allocation, stimulates enterprise vitality and innovation, and promotes diversified and stable industrial development. Industrial agglomeration (Ia): The coefficient is 0.858 (significant at the 1% level). Due to economies of scale (resource sharing and cost reduction), knowledge spillover, and collaborative innovation, it enhances industrial competitiveness and supports high-quality green economic development. Industrialization level (Ind): The coefficient is -0.005 (significant at the 1% level), revealing that high industrialization tends to cause excessive resource consumption and environmental pollution, disrupt the ecological-economic balance, and exert a negative impact on high-quality green economic development. In summary, the digital economy and control variables work synergistically to shape the pattern of high-quality green development of urban economy.

## 5.2 Quantile regression analysis

After screening variables through stepwise regression, there may still be cases where the degree of influence of independent variables on the dependent variable varies across different quantile levels. Quantile regression can further reveal the differences in the impact of the digital economy on urban high-quality green development at different quantile levels. This paper selects five quantiles (15%, 35%, 55%, 75%, 95%) for detailed verification.

As shown in Table 5, at all quantiles (0.15–0.95), the coefficient of the digital economy (Dig) is positive and significant at the 1% level, verifying that it has a positive effect on the high-quality green development of cities at different development levels, with a universal promotional effect. The Dig coefficient exhibits a “first

TABLE 5 Quantile regression results.

| Variables | 15% | 35% | 55% | 75% | 95% |
|---|---|---|---|---|---|
| Constant | 0.029*** (3.002) | 0.032*** (3.611) | 0.050*** (5.557) | 0.068*** (6.835) | 0.086*** (5.364) |
| Dig | 0.433*** (18.006) | 0.478*** (25.066) | 0.511*** (24.962) | 0.557*** (23.178) | 0.492*** (12.312) |
| Control variables | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| Spatial fixed effect | Yes | Yes | Yes | Yes | Yes |
| Observations | 416 | 416 | 416 | 416 | 416 |
| $R^2$ | 0.571 | 0.613 | 0.653 | 0.706 | 0.808 |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

TABLE 6 Results of the pooled regression model.

| Variables | Innovative development | Coordinated development | Green development | Open development | Shared development |
|---|---|---|---|---|---|
| Dig | 0.497*** (12.871) | 0.860*** (13.167) | 0.136*** (4.555) | 0.531*** (8.522) | 0.364*** (8.686) |
| Control Variables | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| Spatial fixed effect | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.700 | 0.714 | 0.803 | 0.595 | 0.680 |
| Observations | 416 | 416 | 416 | 416 | 416 |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

rising then falling" pattern across quantiles: from the 0.15th to the 0.75th quantile, the coefficient increases from 0.433 to 0.557; from the 0.75th to the 0.95th quantile, it drops to 0.492. This reflects the dynamic changes in the marginal effect intensity of the digital economy on high-quality green development—the promotional effect is stronger in the middle stage of development (medium to high quantiles), while in the later stage (extremely high quantiles), the effect weakens possibly due to "diminishing marginal returns to technology" and "traditional path dependence", revealing the dynamic complexity of their relationship.

As the quantile increases (from 0.15 to 0.95), the model's $R^2$ rises from 0.571 to 0.808, indicating that the higher the level of urban high-quality green development (higher quantiles), the stronger the explanatory power of the variables included in the model for the development level. In other words, the influencing factors in the high-end development stage are more easily captured and explained by the model. At all quantiles, the control variables, time fixed effects, and city fixed effects are all significant and consistent, suggesting that the promotional effect of the digital economy and the model relationships are not disturbed by quantile differences, and the research results are robust.

In summary, the digital economy's promotional effect on urban high-quality green development is universal, but the marginal effect fluctuates dynamically with the development stage (stronger in the middle stage and weaker in the later stage), and the model has better explanatory power for the high-end development stage.

## 5.3 Mechanism effect analysis

To examine the magnitude of the digital economy's impact on the five sub-dimensions of urban high-quality green development, a pooled regression model was constructed, with results presented in Table 6. In all models, the coefficients of the digital economy passed the test at the 1% significance level. The findings indicate that the digital economy exhibits varying intensities of promotional effects on the five sub-dimensions, specifically in the order: coordinated development (0.860***) > open development (0.531***)> innovative development (0.497***) > shared development (0.364***)> green development (0.136***).

The digital economy exerts the most significant and stable promotional effect on coordinated development, suggesting that digital technologies can effectively break down development barriers between urban and rural areas, industries, and regions. Its prominent positive impact on open development reflects its ability to overcome geographical constraints. While the digital economy significantly drives innovative development, this dimension remains constrained by traditional factors such as research investment and talent reserves, limiting the direct pull of the digital economy alone–hence its weaker effect compared to the coordinated and open dimensions. The digital economy facilitates shared development by enhancing the inclusiveness of development outcomes, but its impact is relatively moderate due to issues like the digital divide and lagging regulation. Although the digital economy's positive effect on green development is

TABLE 7 Mediated effects model test.

| Variables | HgUE | Inn | HgUE |
|---|---|---|---|
| Dig | 0.666***<br>(29.302) | 138.733***<br>(10.445) | 0.526***<br>(25.417) |
| Inn | | | 0.001***<br>(14.705) |
| Control variables | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes |
| Spatial fixed effect | Yes | Yes | Yes |
| Observations | 416 | 416 | 416 |
| $R^2$ | 0.872 | 0.673 | 0.916 |
| Adjustment $R^2$ | 0.870 | 0.669 | 0.915 |
| Sobel test | | | $P = 0.001$ |
| Proportion of mediating effect | | | 20.964% |
| Bootstrap test | | | 0.077 ~0.226 |
| F-statistic | $F(5,410)=557.901$, $p = 0.000$ | $F_{(}5, 410) = 168.706$, $p = 0.000$ | $F_{(}6, 409) = 745.019$, $p = 0.000$ |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

significant, its coefficient is the lowest, primarily because green transformation is constrained by path dependence in traditional industries and energy structure limitations, resulting in relatively limited short-term effects.

## 5.4 Mediation mechanisms

In the regression analysis of Table 7, the total effect of the digital economy (Dig) on urban high-quality green development (HgUE) is significant. When no mediating variable is included, the regression coefficient of Dig on HgUE is 0.666 ($p<0.01$), indicating that the digital economy can directly drive urban high-quality green development and is one of the core promoting factors. The previous research results show that the digital economy has a significant driving effect on the innovation dimension of urban high-quality green development. To further explore the mechanism of innovation capability, a mediating effect model test was conducted. The test results show that the impact of the digital economy on innovation capability (Inn) is significant, with the regression coefficient of Dig on Inn reaching 138.733 ($p<0.01$), suggesting that the development of the digital economy can effectively improve urban innovation level. After introducing Inn as a mediating variable, the coefficient of Dig on HgUE decreases to 0.526 ($p<0.01$), while the coefficient of Inn on HgUE is 0.001 ($p<0.01$). Combined with the Sobel test ($p = 0.001<0.05$) and the Bootstrap test confidence interval (0.077, 0.226) excluding 0, it can be verified that the mediating effect of innovation capability is significant, accounting for approximately 20.964%.

In summary, the digital economy has a dual-role path of "direct driving + innovation mediation" on urban high-quality green development: it not only directly empowers through its own development but also indirectly contributes by enhancing innovation capability, and the two synergistically support the process of urban high-quality green development.

## 5.5 Robustness tests

This paper conducts robustness tests on the research results through multiple methods, including replacing the explained variable, replacing the core explanatory variable, two-way winsorizing, and adjusting the sample interval. The results are shown in Table 8. Under different test methods, the core explanatory variable (Dig) is mostly positively significant at the 1% level, indicating that the basic regression results are robust and reliable.

First, replacing the explained variable. The CRITIC weighting method is used to reassign values to the urban high-quality economic dimension indicators, and the new weight index is obtained as the new explained variable. At this time, the coefficient of the core explanatory variable (Dig) is 0.398, which is positively significant at the 1% level. This shows that even if the measurement method of urban high-quality green development level is changed, the digital economy still has a significant positive impact on it, and the original research conclusion remains valid when the explained variable is replaced, without being affected by the change in measurement method.

Second, replacing the core explanatory variable. The core explanatory variable (digital economy) is replaced with its first and second lagged terms for re-regression. From the results, the coefficient of the first lagged term of the digital economy is 0.335, and that of the second lagged term is 0.205, both of which are positively significant at the 1% level. This indicates that after replacing the core explanatory variable, the positive impact of the digital economy on urban high-quality green development remains significant, suggesting that the original research conclusion is not affected by the selection of the core explanatory variable and is robust.

Third, conducting two-way winsorizing. The explanatory variables are winsorized at the 5% level to eliminate the impact of outliers. After processing, the coefficient of Dig is 0.515, which is positively significant at the 1% level. This means that even after handling outliers in the data, the positive promoting effect of the digital economy on urban high-quality green development remains stable, further proving the reliability of the research results.

Finally, adjusting the sample interval. Considering the impact of the COVID-19 pandemic on the development of the digital economy, the data from 2020 to 2022 are excluded for re-regression. The results show that the coefficient of Dig is 0.529, which is positively significant at the 1% level. This indicates that after adjusting the sample interval and excluding the impact of the pandemic, the research conclusion still holds, reflecting that the original research results are robust when the sample interval changes.

TABLE 8 Robustness test results.

| Variables | Replacing explained variable | Replacing core explanatory variable | | Two-way winsorization | Adjusting the sample interval |
|---|---|---|---|---|---|
| Constant | 0.141***<br>(11.767) | 0.040***<br>(3.200) | 0.039***<br>(2.679) | 0.053***<br>(5.612) | 0.058***<br>(5.428) |
| Dig | 0.398***<br>(14.825) | 0.335***<br>(14.252) | 0.205***<br>(8.499) | 0.515***<br>(24.428) | 0.529***<br>(22.338) |
| Inn | 0.000***<br>(4.156) | 0.001***<br>(16.931) | 0.002***<br>(17.171) | 0.001***<br>(16.596) | 0.001***<br>(9.468) |
| Gov | 0.042**<br>(2.476) | 0.015<br>(0.895) | -0.006<br>(-0.301) | 0.036***<br>(2.691) | 0.042***<br>(3.253) |
| Mar | 0.013***<br>(15.958) | 0.008***<br>(9.886) | 0.010***<br>(11.020) | 0.004***<br>(6.670) | 0.003***<br>(4.487) |
| Ind | 0.005***<br>(4.053) | -0.006***<br>(-4.972) | -0.007***<br>(-5.223) | -0.005***<br>(-5.497) | -0.006***<br>(-5.563) |
| Ia | 0.232*<br>(0.838) | 0.950***<br>(3.433) | 1.319***<br>(4.360) | 1.009***<br>(4.632) | 1.678***<br>(4.548) |
| $R^2$ | 0.789 | 0.859 | 0.825 | 0.912 | 0.912 |
| Adjustment $R^2$ | 0.786 | 0.857 | 0.823 | 0.911 | 0.910 |
| Observations | 416 | 415 | 414 | 416 | 320 |
| F-statistic | $F_{(6,409)} = 254.946$,<br>p = 0.000 | $F_{(6,408)} = 414.629$,<br>$p = 0.000$ | $F_{(6,407)} = 320.662$,<br>$p = 0.000$ | $F_{(6,409)} = 707.057$,<br>$p = 0.000$ | $F_{(6,313)} = 538.670$,<br>$p = 0.000$ |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

## 5.6 Endogeneity problem

There exists a reverse causal relationship between the digital economy and the high-quality green development of urban economy, which will affect the accuracy of the research results. To address potential endogeneity, we employ two instrumental variables: Historical fixed-line telephone penetration (1984) (Ft) : Regions with higher historical telecommunications infrastructure likely inherited technological advantages that persist in modern digital economies, satisfying the relevance condition. Geodesic distance to Hangzhou (Gd): Proximity to Hangzhou—a hub for digital firms like Alibaba—may enhance local digital development through knowledge spillovers, while geographic distance itself is unlikely to directly influence contemporary urban economic quality, ensuring exogeneity. These IVs leverage historical path dependency and spatial spillover dynamics, effectively isolating exogenous variation in digital economy development.

As can be seen from Table 9, in the first-stage regression model, the coefficient of the instrumental variable Ft is 0.019, significant at the 5% significance level, and the coefficient of Sd is -0.000, significant at the 1% significance level. Additionally, the F-test value is $F_{(6,409)} = 128.505$, which is much larger than 10, with an $R^2$ of 0.740 and an adjusted $R^2$ of 0.648. These data indicate that the instrumental variables have passed the weak instrumental variable test, suggesting that the selected instrumental variables are significantly correlated with the development level of the digital economy, can effectively explain changes in the digital economy's development level, and there is no issue of weak instrumental variables. In the second-stage regression model, the regression coefficient of the digital economy (Dig) on the level of urban high-quality green development is 0.299, significant at the 1% significance level, with an $R^2$ of 0.891 and an adjusted $R^2$ of 0.890. This implies that the digital economy, along with variables such as innovation capability, government support, marketization level, industrialization level, and industrial agglomeration level, can explain 89.1% of the changes in urban

TABLE 9 Results of 2sls model analysis.

| Phase I | | Phase II | |
|---|---|---|---|
| Constant | 0.223***<br>(8.284) | Constant | 0.078***<br>(6.448) |
| Inn | 0.002***<br>(8.284) | Dig | 0.299***<br>(4.288) |
| Gov | -0.171***<br>(11.812) | Inn | 0.001***<br>(10.741) |
| Mar | 0.008***<br>(-6.016) | Gov | -0.011<br>(-0.566) |
| Ind | -0.011***<br>(6.126) | Mar | 0.006***<br>(6.644) |
| Ia | 1.552***<br>(-5.109) | Ind | -0.006***<br>(-5.783) |
| Sd | -0.000***<br>(-7.210) | Ia | 1.246***<br>(4.691) |
| Ft | 0.019**<br>(2.415) | | |
| Observations | 416 | Observations | 416 |
| R2 | 0.653 | $R^2$ | 0.891 |
| Adjustment $R^2$ | 0.648 | Adjustment $R^2$ | 0.890 |
| F-statistic | $F_{(6,409)} = 128.505$,<br>$p = 0.000$ | Wald $\chi^2$ | $\chi^2(6) = 3019.634$,<br>$p = 0.000$ |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

TABLE 10 Results of heterogeneity analysis.

| Variables | Types of cities by different scales | | Types of cities by different resource attributes | |
|---|---|---|---|---|
| | Large cities | Small and medium-sized cities | Resource-based cities | Non-resource-based cities |
| Constant | 0.042***<br>(3.713) | 0.088***<br>(6.264) | 0.041***<br>(3.754) | 0.042***<br>(3.034) |
| Dig | 0.591***<br>(23.020) | 0.392***<br>(9.501) | 0.413***<br>(11.927) | 0.511***<br>(18.717) |
| Inn | 0.001***<br>(9.170) | 0.000*<br>(1.938) | 0.000***<br>(3.104) | 0.001***<br>(5.674) |
| Gov | -0.021<br>(-0.942) | -0.003<br>(-0.196) | 0.067***<br>(4.374) | -0.029<br>(-1.204) |
| Mar | 0.005***<br>(4.917) | 0.004***<br>(4.478) | 0.005***<br>(7.611) | 0.007***<br>(6.260) |
| Ind | -0.002<br>(-1.530) | -0.004*<br>(-1.891) | -0.002<br>(-1.466) | -0.006***<br>(-4.356) |
| Ia | 1.218***<br>(4.134) | 0.036<br>(0.124) | 0.141<br>(0.676) | 2.304***<br>(5.270) |
| $R^2$ | 0.951 | 0.657 | 0.684 | 0.944 |
| Adjustment $R^2$ | 0.949 | 0.645 | 0.675 | 0.942 |
| Observations | 234 | 182 | 221 | 195 |
| F-statistic | $F(6,227) = 728.413$,<br>$p = 0.000$ | $F(6,175) = 55.867$,<br>$p = 0.000$ | $F(6,214) = 77.323$,<br>$p = 0.000$ | $F(6,188) = 530.577$,<br>$p = 0.000$ |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

high-quality green development. Consistent with the regression results of the benchmark model above, this further confirms the robustness and reliability of the previous research conclusions. Specifically, the endogeneity problem has been effectively addressed through the instrumental variable method, making the estimation of the digital economy's impact on urban high-quality green development more accurate.

## 5.7 Heterogeneity analysis

In accordance with the "Notice of the State Council on Adjusting the Standards for Classifying Urban Sizes", the upstream urban agglomerations of the Yangtze River Economic Belt are divided into large cities and small-to-medium cities based on the permanent population in urban areas. The impact of the digital economy on the high-quality green development of these two types of cities differs.

Large cities, equipped with complete digital infrastructure and coupled with demographic dividends, attract a large number of high-quality talents. This facilitates the in-depth integration of digital technologies with high-end industries such as finance and technology innovation. By improving production efficiency and driving green technological innovation, the coefficient of Dig reaches 0.591*** ($t = 23.020$), which is significant and strong in intensity. Endowed with abundant innovation resources, the coefficient of Inn is 0.001*** ($t = 9.170$), indicating that innovation and the digital economy are deeply synergistic, amplifying green effects.

In contrast, small-to-medium cities suffer from lagging digital infrastructure, with industries dominated by traditional manufacturing and agriculture, and limited scenarios for digital applications. Although the coefficient of Dig is 0.392*** ($t = 9.501$), showing a significant positive effect, its intensity is weaker than that in large cities. Moreover, due to insufficient innovation investment and brain drain, the coefficient of Inn is 0.000* ($t=1.938$, significant only at the 10% level), meaning that innovation provides limited support for the digital economy's enabling role. It is necessary to strengthen the synergy between "digital infrastructure construction and innovation introduction/cultivation" to narrow the gap with large cities.

The role of the digital economy also differs between resource-based and non-resource-based cities. Resource-based cities, facing industrial transformation pressures, leverage the digital economy through smart mines and circular economy platforms to promote green resource development and industrial diversification, making it a key driver of transformation. The coefficient of Dig is 0.413*** ($t=11.927$), showing a significant positive effect. However, their innovation mostly focuses on green transformation technologies, with a narrow scope and limited investment, resulting in an Inn coefficient of 0.000*** ($t=3.104$), which provides weak support for the digital economy.

Non-resource-based cities, with a higher degree of industrial diversification, exhibit better compatibility between the digital economy and green industries, leading to more direct empowerment. The coefficient of Dig is 0.511*** ($t = 18.717$), indicating a stronger impact. These cities boast a sound innovation ecosystem with collaborative R&D across multiple fields, reflected in an Inn coefficient of 0.001*** (t

TABLE 11 Results of Moran's I index.

| Year | HgUE | | | Dig | | |
|---|---|---|---|---|---|---|
| | Moran Index | *z*-value | *p*-value | Moran Index | *z*-value | *p*-value |
| 2011 | 0.101 | 1.846 | 0.065 | 0.174 | 2.570 | 0.010 |
| 2012 | 0.095 | 1.791 | 0.073 | 0.152 | 2.250 | 0.024 |
| 2013 | 0.095 | 1.773 | 0.076 | 0.175 | 2.573 | 0.010 |
| 2014 | 0.117 | 1.993 | 0.046 | 0.165 | 2.475 | 0.013 |
| 2015 | 0.103 | 1.860 | 0.063 | 0.159 | 2.423 | 0.015 |
| 2016 | 0.097 | 1.849 | 0.065 | 0.171 | 2.528 | 0.011 |
| 2017 | 0.097 | 1.875 | 0.061 | 0.165 | 2.448 | 0.014 |
| 2018 | 0.098 | 1.906 | 0.057 | 0.151 | 2.281 | 0.023 |
| 2019 | 0.101 | 1.984 | 0.047 | 0.159 | 2.375 | 0.018 |
| 2020 | 0.083 | 1.833 | 0.067 | 0.162 | 2.387 | 0.017 |
| 2021 | 0.078 | 1.771 | 0.077 | 0.122 | 1.920 | 0.055 |
| 2022 | 0.082 | 1.837 | 0.066 | 0.129 | 2.051 | 0.040 |
| 2033 | 0.083 | 1.831 | 0.067 | 0.136 | 2.154 | 0.031 |

= 5.674), where innovation serves as a core bridge for digital empowerment.

Furthermore, resource-based cities rely on government policies to drive digital transformation, as evidenced by a significantly positive Gov coefficient of 0.067*** (t = 4.374); in contrast, non-resource-based cities are more prominently driven by market forces. Non-resource-based cities face acute conflicts between traditional industries and green development, with a significantly negative Ind coefficient of -0.006*** (t=-4.356), necessitating accelerated "digital + industrial greening" transformation. For resource-based cities, where industry is dominated by resource development, the digital economy plays a more significant role in offsetting the negative impact of industrialization.The specific data are shown in Table 10.

## 5.8 Spatial spillover effects

### 5.8.1 Test of spatial autocorrelation

To analyze spatial interdependence between the digital economy and high-quality green development of urban economy (HgUE), we computed the global Moran's I index using a hybrid economic-geographical matrix($W_{ij}$). This matrix synthesizes two dimensions: geographical proximity (physical distance between cities), and economic linkage (intensity of inter-city economic interactions), thereby capturing both spatial adjacency and economic interdependence. The composite matrix is formalized as:

$$W_{ij} = We_{ij} * Wd_{ij} \tag{6}$$

$$We_{ij} = |1/(E_i - E_j)|, Wd_{ij} = 1/D_{ij} \tag{7}$$

The hybrid economic-geographical matrix ($W_{ij}$) integrates two dimensions: the economic distance ($We_{ij}$) is measured as the absolute difference in the average high-quality economic development index between city i and city j over 2011–2023, i.e., $We_{ij}$=|$E_i$-$E_j$|, where $E_i$ and $E_j$ denote the HgUE indices for cities i and j, respectively. Geographical distance ($Wd_{ij}$)is defined as the inverse of the physical distance $D_{ij}$ between cities i and j.The composite matrix Equation 6 thus captures both economic disparity and spatial proximity.

As shown in Table 11, the Moran's I indices for both the digital economy and urban high-quality green development are greater than 0, and the p-values corresponding to the z-values pass the significance test at least at the 10% level. These results indicate that there exists positive spatial autocorrelation in the economic geographical space for both the digital economy and the level of urban high-quality green development, meaning that cities with similar development levels exhibit a spatially agglomerated distribution pattern.

The positive spatial autocorrelation suggests the presence of spatial effects in the digital economy and urban high-quality green development. The development of the digital economy or the achievement of high-quality green development in one city can exert an impact on neighboring cities. Cities with a well-developed digital economy may drive the development of the digital economy in surrounding cities through information dissemination, industrial linkages, and other channels; similarly, cities with a high level of high-quality green development may generate a demonstration effect within the region, promoting the improvement of development quality in neighboring cities.

### 5.8.2 Tests for spatial econometric models

To further explore the spatial effects of the digital economy and urban high-quality green development in geographical space, appropriate spatial econometric models were selected through various tests. First, the LM test was conducted. According to the LM test results, both the LM error test and R-LM error test passed

TABLE 12 Results of spatial panel model analysis.

| Variables | Spatial Durbin Model (SDM) | | Spatial Error Model (SEM) | | Spatial Lag Model (SLM) | |
|---|---|---|---|---|---|---|
| | Economic geography matrix | Geographic matrix | Economic geography matrix | Geographic matrix | Economic geography matrix | Geographic matrix |
| Dig | 0.570*** (22.20) | 0.500*** (24.44) | 0.524*** (25.07) | 0.511*** (24.72) | 0.520*** (21.71) | 0.516*** (25.24) |
| Inn | 0.001*** (14.31) | 0.001*** (14.39) | 0.001*** (14.71) | 0.001*** (14.35) | 0.001*** (14.11) | 0.001*** (13.91) |
| Gov | 0.027** (2.09) | 0.046* (3.60) | 0.065** (4.59) | 0.062* (4.39) | 0.017* (1.35) | 0.016** (1.22) |
| Mar | 0.003*** (3.06) | 0.003** (2.45) | 0.001 (0.96) | 0.001 (1.15) | 0.001 (0.93) | 0.001 (1.03) |
| Ind | -0.010*** (-9.54) | -0.006*** (-4.22) | -0.007*** (-7.01) | -0.006*** (-7.35) | -0.006*** (-6.64) | -0.006*** (-6.71) |
| Ia | 0.955*** (4.61) | 1.234*** (5.66) | 0.978*** (4.87) | 1.090*** (5.28) | 1.069*** (5.16) | 1.069*** (5.23) |
| WDig | 0.303*** (3.56) | 0.256*** (3.03) | | | | |
| WInn | 0.001*** (2.60) | 0.001** (2.08) | | | | |
| WGov | 0.029 (0.58) | 0.144 (1.40) | | | | |
| WMar | 0.034*** (3.18) | 0.037*** (3.55) | | | | |
| WInd | 0.014*** (5.14) | -0.010* (-1.70) | | | | |
| WIa | 0.910 (1.49) | 3.141 (1.56) | | | | |
| Spatial rho | 0.391** (3.60) | 0.474** (2.32) | 0.306*** (3.28) | 0.397*** (1.95) | 0.141*** (1.50) | 0.122*** (1.13) |
| Observations | 416 | 416 | 416 | 416 | 416 | 416 |
| $R^2$ | 0.923 | 0.850 | 0.909 | 0.911 | 0.911 | 0.904 |
| Log | 992.782 | 981.337 | 972.421 | 969.622 | 967.573 | 968.237 |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

the significance test at the 1% level, indicating that the spatial panel autoregressive model (SAR) is more appropriate for use in this context. Second, the SDM fixed-effect test was performed. The Hausman test result was significant at the 5% level (chi2(13) = 38.41, $p$ = 0.0002<0.05), suggesting that individual effects are correlated with explanatory variables. Thus, compared with the panel random-effect model, the fixed-effect model can more accurately reflect data characteristics and relationships between variables, making it preferable. Fixed effects are categorized into individual fixed effects, time fixed effects, and dual fixed effects. Further LR tests ultimately determined that time fixed effects should be adopted for analysis. Third, the SDM model simplification test was carried out. The LR test results rejected the null hypothesis that SDM can be converted into SAR or SEM at the 1% significance level; the Wald test showed that the regression coefficients of the SDM model do not satisfy the null hypothesis for conversion into SAR or SEM models. In summary, based on the above tests and Moran's I results, this paper selects the SDM model with temporal-spatial time fixed effects for estimation.

To assess the robustness of spatial effects, we estimated multiple spatial econometric models using both economic-geographical and pure geographical matrices. As shown in Table 12, spatial auto-correlation coefficients remain statistically significant (p<0.01 or p<0.05) across all specifications, confirming persistent positive spatial interdependence in high-quality green development of urban economy (HgUE). There exist inter-dependencies among cities regarding high-quality green development of urban economy. The development of one city can generate spatial spillover effects on its surrounding cities, and the intensity of these spatial spillover effects varies under different model specifications and spatial weight matrix formulations.

The Spatial Durbin Model (SDM) incorporates spatial lag terms (e.g., WDig, WInn) to capture intercity dependencies. Results show significant coefficients for several spatial lag variables, confirming cross-regional interactions in digital economy and high-quality development dynamics. Notably, the magnitude of these coefficients is smaller than those in the benchmark regression, likely due to the SDM's explicit adjustment for spatial

TABLE 13 Analysis of spatial spillover effects.

| Variable | Direct effect | Indirect (spillover) effect | Total effect |
|---|---|---|---|
| Dig | 0.573***<br>(16.56) | 0.174**<br>(2.36) | 0.747***<br>(7.43) |

***, **, and *indicate the level of significance of 1%, 5%, and 10%, respectively.

autocorrelation and unobserved heterogeneity across regions. To disentangle the mechanisms underlying these spatial effects, we decompose them into direct (local) and indirect (spillover) components following LeSage and Pace (2008). This decomposition reveals: Direct effects indicate that local policy and technological inputs predominantly drive intra-city development. Indirect effects indicate that neighboring cities' digital advancements and institutional innovations exert measurable spillovers, moderated by economic-geographical proximity. This analytical refinement underscores the dual nature of spatial processes—endogenous growth and exogenous spillovers—that collectively shape regional development trajectories.

As Table 13 measurement results indicate, the digital economy exerts a statistically significant direct effect on high-quality green development of urban economy (HgUE) ($\beta$ = 0.573, p<0.01). This indicates that the integration of digital technologies and industrial expansion directly stimulate innovation, accelerate industrial transitions, and optimize resource efficiency, collectively elevating HgUE performance. The application of digital technologies and the growth of digital industries can directly fuel innovation, drive industrial upgrading, and optimize resource allocation in the city, thereby enhancing the level of HgUE.

Indirect (spillover) effects: the digital economy exhibits significant spatial spillovers ($\beta$ = 0.174, p<0.05), indicating that advancements in one city's digital economy can stimulate high-quality green development of urban economy (HgUE) in neighboring regions. This cross-regional propagation operates through mechanisms such as knowledge dissemination, technology diffusion, and industrial linkages, which collectively enhance both digital transformation and sustainable economic transitions in adjacent areas.

Total effects: the aggregate impact of the digital economy is strongly positive ($\beta$ = 0.747, $p$<0.01), combining direct intra-city growth ($\beta$ = 0.573) and indirect spillovers ($\beta$ = 0.174). The findings advocate for coordinated regional strategies to leverage spatial inter-dependencies, ensuring equitable diffusion of digital dividends across urban hierarchies.

# 6 Conclusions and recommendations

## 6.1 Research conclusions

Robustness of the digital economy in driving urban high-quality green development: The digital economy exerts a significant and stable positive promoting effect on the high-quality green development of the upstream urban agglomerations in the Yangtze River Economic Belt. After verification through multiple methods, the core conclusion remains unaffected by interference factors such as variable measurement, outliers, and endogeneity, confirming that the digital economy, as a new productive force, serves as a key support for green transformation.

Mediating logic of innovation capability: Innovation capability plays a mediating role between the digital economy and urban high-quality green development, indicating that the digital economy promotes the synergy between economic growth and ecological protection through the path of "technological empowerment-innovation breakthrough–green transformation," which drives improvements in production efficiency and reductions in pollutant emissions.

Practical reflection of heterogeneity: The heterogeneous results regarding urban scale and resource endowment reflect the advantages of large cities in terms of digital infrastructure and talent reserves, as well as the transformation dilemmas faced by resource-based cities due to industrial path dependence, highlighting the necessity of precise policy adjustments. Synergistic value of spatial spillover: The spatial spillover effect of the digital economy reveals the potential of regional linkage development–digital technologies and industrial models from core cities can radiate to surrounding areas through factor mobility, providing new momentum for the green and coordinated development of urban agglomerations.

## 6.2 Policy recommendations

Promoting digital infrastructure in a hierarchical manner: Large cities should focus on building "digital + green" integration platforms to strengthen the empowerment of the digital economy for high-end green industries. Small and medium-sized cities and resource-based cities should prioritize addressing shortcomings in basic infrastructure such as 5G networks and data centers, and catch up through the path of "complementing digital infrastructure weaknesses-digitally transforming traditional industries–achieving breakthroughs in green transformation".

Activating the effectiveness of innovation as a mediator: Establish a "digital economy innovation fund" to provide tax credits and R&D subsidies for enterprises engaged in green technology research, with a focus on supporting interdisciplinary innovation integrating big data with carbon capture and new energy. Build cross-regional "digital + green" innovation alliances to facilitate collaboration between universities, research institutions, and enterprises, accelerating the transformation of innovation achievements.

Addressing heterogeneity dilemmas: For resource-based cities, implement special policies for "digital economy + ecological restoration", encouraging traditional industries such as coal and steel to adopt digital technologies for green technological transformation, while developing emerging industries such as digital cultural tourism and ecological agriculture. For small and medium-sized cities, launch a "digital partnership program," where large cities export mature digital industry models to lower the threshold for local industrial digital transformation.

Amplifying spatial synergy effects: Establish a "Digital Economy Collaborative Development Alliance" for the upstream urban agglomerations of the Yangtze River, unifying the planning of digital industry layouts and breaking down administrative barriers. Set up a cross-regional digital economy collaboration fund to support inter-city projects involving the sharing of digital technologies, talents, and data, and promote the cross-city replication of green development experiences.

### 6.3 Future research directions

Dynamic Evolution and Long-Term Effects: The current study focuses on the static cross-section from 2011 to 2023. Future research could extend the time dimension and combine machine learning to track the long-term impact of the evolving forms of the digital economy on urban high-quality green development, analyzing the "marginal changes" and "inflection point characteristics" of the driving effects amid technological iterations.

Subdivided Mechanisms and Multiple Pathways: Existing research has verified innovation capability as a single mediating variable. Subsequent studies could decompose innovation capability into dimensions such as "technological innovation, management innovation, and model innovation", while introducing moderating variables like "environmental regulation" and "green finance" to reveal the complex pathways through which the digital economy influences high-quality green development.

Micro-Subjects and Heterogeneity Expansion: Extending from the macro urban level to micro enterprises and households, future research could explore the impact of the digital economy on firms' green production decisions (e.g., green investment, carbon footprint management) and residents' green consumption behaviors (e.g., participation in the sharing economy, low-carbon lifestyles), supplementing micro-level evidence for macro conclusions. Additionally, expanding the research scope to compare upstream and downstream regions of the Yangtze River Economic Belt, as well as urban agglomerations in eastern, central, and western China, would help verify the universality of the conclusions.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

QF: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Writing – original draft. JY: Methodology, Project administration, Supervision, Validation, Writing – review & editing. YS: Conceptualization, Data curation, Software, Visualization, Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declare that no Gen AI was used in the creation of this manuscript.

## Publisher's note



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