

Article

Mechanism and Optimization Path of Digital Technology for the Energy Transition in the Yellow River Basin Under Carbon Peaking

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Abstract

As a key energy base in China, the Yellow River Basin sees its energy transition and carbon peaking status closely linked to the timeline for achieving the dual carbon goals. Yet the energy transition across the Yellow River Basin remains arduous, and staged breakthroughs in carbon peaking are hard to achieve. Against this backdrop, digital technology offers new approaches to addressing this challenge. This study empirically investigates 99 cities at or above the prefectural level across the Yellow River Basin during 2013–2024. It analyzes the mechanisms of digital technology in the energy transition and applies the Kaya identity to predict carbon peaking times for these cities under different scenarios. The findings show that digital technology facilitates the energy transition across the Yellow River Basin by strengthening innovation in renewable energy technologies and investment in human capital. Moreover, carbon peaking pressure plays a positive moderating role in digital technology's influence on the energy transition across the Yellow River Basin. Notably, digital technology boosts the energy transition across the Yellow River Basin more significantly in downstream areas and non-resource-based and non-traditional industrial base cities. Meanwhile, while digital technology can significantly promote local energy transition, it also produces negative spatial spillover effects. Finally, compared to the baseline scenario, cities across the Yellow River Basin reach carbon peaking earlier under the accelerated energy transition scenario.

Keywords: Yellow River Basin; digital technology; energy transition; carbon peaking prediction; sustainability

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1. Introduction

Attaining carbon peaking and carbon neutrality is a foundational strategy for tackling global climate challenges, alleviating resource and environmental pressures, and reshaping national energy security, as well as boosting sustainable development. Economic growth and ecological protection should be pursued in tandem [1]. Yet the Yellow River Basin stands as a core nexus for China's energy, chemical, raw material and basic manufacturing industries, accounting for approximately one-third of the nation's carbon emissions [2], which makes it critical to China's journey toward the dual carbon goals [3]. The Yellow River Basin is abundant in coal resources, with coal reserves accounting for more than 50% of China's total [4]. The coal-dominated resource endowment has resulted in a

coal-dominant energy structure and a heavy industry-led industrial structure. Its economic development is characterized by high energy consumption and high carbon emissions [5], which is the main reason for the persistently high carbon emissions in this region. Hence, advancing a green and low-carbon energy transition across the Yellow River Basin represents the top priority for delivering on the dual carbon goals on schedule and boosting sustainable development.

Since the Fourth Industrial Revolution, digital technology, including artificial intelligence and the Internet of Things, has become deeply integrated into all spheres of economic and social advancement, exerting an extensive influence on human production and life. Data elements generated in the application of digital technology after unified collection, analysis, processing and transmission can enhance the synergy between factors and promote efficiency improvement [6]. This logic also applies to the energy sector: through such synergy, digital technology can mitigate the volatility and instability of renewable energy, serving as a powerful tool for building a new energy system [7]. Several Opinions on Accelerating Digital and Intelligent Development in the Energy Sector, issued by China's National Energy Administration in 2023, clearly stresses advancing digital technology in the energy field and fostering a low-carbon, efficient, and secure energy system via intelligent transformation [8]. Digital technology undoubtedly provides a valuable opportunity for advancing the energy transition across the Yellow River Basin. However, in practice, the energy transition in the basin faces multiple constraints, including fragile ecosystems, water scarcity, dependence on high-carbon development paths, and insufficient cross-regional coordination. Can digital technology help the Yellow River Basin break through these constraints? What are the specific operational mechanisms? Given that carbon peaking acts as the precursor to carbon neutrality [9], it carries greater urgency in the present stage. In light of this, this research explores how digital technology impacts the energy transition across the Yellow River Basin from a carbon peaking perspective, seeking to underpin a faster advancement toward the dual carbon goals.

This study advances prior scholarly work in three key respects as follows: First, focusing on the Yellow River Basin—a typical ecologically vulnerable area—this paper systematically investigates the relationship between digital technology and the energy transition. It also analyzes the underlying mechanisms from the two perspectives of strengthening renewable energy technology innovation and human capital investment, aiming to provide solutions to the energy transition challenges in this region. Second, existing studies generally treat carbon peaking as a static research backdrop. Breaking this conventional approach, this paper incorporates carbon peaking pressure, digital technology and the energy transition into a unified research framework and empirically reveals the moderating effect of carbon peaking pressure on the enabling impact of digital technology. Third, by comparing carbon peaking timing projections under business-as-usual and accelerated energy transition conditions, this paper offers precise time references for the basin's overall carbon peaking blueprint, helps policymakers identify key intervention areas, and delivers tailored pathways for prefecture-level cities to design differentiated carbon peaking strategies.

2. Literature Review

The first category of highly relevant research examines the influence of digital technology on the energy transition. Existing studies mainly hold two viewpoints regarding this issue: One view holds that digital technology can reengineer the energy system [10], contributing greatly to raising the share of clean energy and enhancing energy efficiency [11]. It is set to be a decisive factor in the future energy transformation and aid the delivery of carbon peaking and carbon neutrality objectives [12,13]. For instance, Wu and He's theoretical analysis argued that digital technology is deeply embedded in the processes of

energy production, exchange, distribution, and consumption, empowering the transformation and upgrading of the energy system by optimizing energy efficiency and structure, improving energy market mechanisms, adjusting social redistribution, and guiding the direction of energy consumption [14]. Lee et al. empirically found that artificial intelligence, as a digital technology, exerts a favorable effect on the energy transition, and the digital economy plays a positive moderating role in the process [15]. Huang and Lin conducted an empirical study after optimizing the digital economy index, finding that the digital economy can promote the green transition of energy systems [16]. Che et al. conducted a study using panel data on Chinese cities and found that digital empowerment can drive the low-carbon energy transition in Chinese cities [17]. In the field of energy transition, information and communication technology (ICT) is conducive to the integration of intermittent renewable energy sources, improving energy efficiency, building smart grids and distributed energy networks, and enhancing grid reliability [18,19]. Digital technology such as big data can facilitate the grid connection of new energy sources, improve energy efficiency, and comprehensively drive the energy transition [20]. Another view argues that digital technology faces a potential energy rebound effect. While its beneficial role in the energy transition is recognized, attention must be paid to its underlying risks [21]. For one thing, by improving energy production efficiency, digital technology reduces energy prices and unit product costs, which, in turn, leads to increased energy consumption [22]; for another, digital technology and the digital industry itself are energy-intensive sectors. Digital infrastructure generates substantial energy demand and power consumption, posing significant challenges to the stability of clean energy supply and, thus, hindering the energy transition [23,24]. In summary, existing studies still show diverging views on how digital technology affects the energy transition, and no universal consensus has been reached. Moreover, relevant empirical research remains limited, with a clear lack of focus on the Yellow River Basin. This specific region is characterized by a fragile ecosystem and strong dependence on high-carbon development paths.

The second category of literature related to this paper mainly focuses on the background of the dual carbon goals. For example, against the backdrop of carbon peaking and carbon neutrality, Gu empirically examined the emission reduction effect of cultural tourism development and confirmed that it can significantly reduce carbon dioxide emissions [25]. Gu and Lin explored carbon emission reduction performance and its influencing factors in major manufacturing provinces under the dual carbon goals and concluded that these provinces have achieved coordinated progress between manufacturing development and carbon reduction targets, with the share of coal consumption, industrial per capita assets, the presence of high-tech industries and internal R&D expenditure serving as the key factors affecting carbon emission reduction performance [26]. Zhang analyzed the spatial characteristics and influencing factors of energy efficiency under the dual carbon goals, pointing out that energy efficiency shows positive spatial correlation and agglomeration characteristics and that energy consumption structure is the primary influencing factor [27]. Notably, regions and industries differ in their industrial structure, energy dependence, and other dimensions, so they naturally face varying carbon reduction pressures under the dual carbon goals. However, most existing studies treat the dual carbon goals as a static macro background. They overlook the differentiated pressures inherent in this dynamically evolving process and fail to incorporate carbon peaking pressure into their analytical frameworks.

The third category of relevant research focuses on the impact of the energy transition on carbon emissions. The energy transition refers to the evolution of the energy system [12], reflected in shifts in the supply-side energy mix and changes in demand-side energy consumption behavior [28]. The third energy transition currently underway represents a

shift from conventional fossil fuel systems centered on coal and oil toward renewable energy systems [12]. The energy transition involves not only technological changes but also structural transformations across economic, political, and social systems [29]. Renewable energy, which features zero carbon emissions [30], provides strong support for ecological protection and low-carbon transition [31,32]. Therefore, reducing fossil fuel consumption and increasing renewable energy consumption enables carbon emission reduction; that is, the energy transition reduces carbon emissions [33,34]. Some scholars, by simulating energy consumption and greenhouse gas emissions in Zhejiang Province, China, argue that shifting energy toward green power is a critical step to achieve emission reduction targets, and the popularization of new energy vehicles will bring forward the turning point of the EKC [35]. Athari et al. found that replacing fossil fuel power generation with hydropower, a renewable energy source, can reduce emissions at the source [36]. To sum up, existing studies generally recognize the carbon reduction effect of the energy transition. However, there is still a lack of quantitative evidence regarding how the energy transition affects the timing of carbon peaking.

In summary, although scholars have noted the penetration of digital technology into energy systems and hold a dialectical stance on their role, the relevant research remains to be further expanded. First, there remains a controversy in existing research over the nexus between digital technology and the energy transition. No universal consensus has been reached on whether digital technology facilitates or constrains the energy transition. Empirical studies exploring their relationship and underlying mechanisms are limited, and research specifically focused on the Yellow River Basin is particularly scarce. Second, China is now in a critical window for advancing its carbon peaking goals. Nevertheless, most extant studies treat these goals as a static macro backdrop and overlook the inherent heterogeneous pressures they generate. Few studies integrate carbon peaking pressure, digital technology and the energy transition into a unified analytical framework. Third, while most literature confirms that the energy transition contributes to carbon emission reduction, it fails to provide quantitative evidence from the perspective of carbon peaking timing. In addition, there is a lack of projections for the carbon peaking timeline of cities across the Yellow River Basin.

3. Theoretical Analysis and Research Hypotheses

3.1. *The Direct Effect of Digital Technologies on the Energy Transition in the Yellow River Basin*

Digital technologies offer an innovative digital solution for the comprehensive transition of energy sector systems across the Yellow River Basin [37]. Drawing on the technology empowerment theory, exogenous technical elements can be transformed into endogenous capabilities, which can furnish entities with intrinsic developmental momentum [38]. Digital technology boosts the energy transition across the Yellow River Basin through three primary dimensions. First, with respect to energy supply, digital technology contributes to stable and clean energy provision across the Yellow River Basin. While the upper reaches of the Yellow River Basin are rich in wind and solar resources and have significant potential for renewable energy supply, they face challenges related to power generation fluctuations. Digital technology can ensure a stable power supply by accurately forecasting renewable energy output and optimizing the intelligent operation and maintenance of generation units [39]. Furthermore, through smart dispatch, these technologies enable the complementary use of hydropower, thermal power, wind power, and solar power, thereby reducing wind and solar curtailment and increasing the share of clean energy in the basin's supply [40]. Second, as for energy consumption, digital technology drives greater efficiency in energy use among energy-intensive industries in the Yellow River Basin. In the middle and lower reaches of the Yellow River Basin, traditional

energy-intensive industries such as coal, chemicals, and non-ferrous metals are concentrated and characterized by high energy consumption intensity. Digital technology can address this issue by enabling the real-time monitoring and optimization of energy use behavior in these enterprises, thereby helping them improve energy efficiency and promoting more efficient energy consumption [41]. Finally, regarding regional coordination, digital technology enhances the synergy between energy supply and demand in the Yellow River Basin. To address issues such as the unbalanced spatiotemporal distribution of energy supply and demand and regional blockages, digital technology surmounts temporal and spatial restrictions to construct a basin-wide energy coordination and control system, enable cross-regional energy absorption and green power trading, and propel the low-carbon, high-efficiency transition of the Yellow River Basin's energy sector [42]. On this basis, Hypothesis 1 is formulated.

Hypothesis 1. *Digital technology boosts the energy transition in the Yellow River Basin.*

The mechanism underlying the impact of digital technology on the energy transition in the Yellow River Basin under the carbon peaking goal is illustrated in Figure 1.

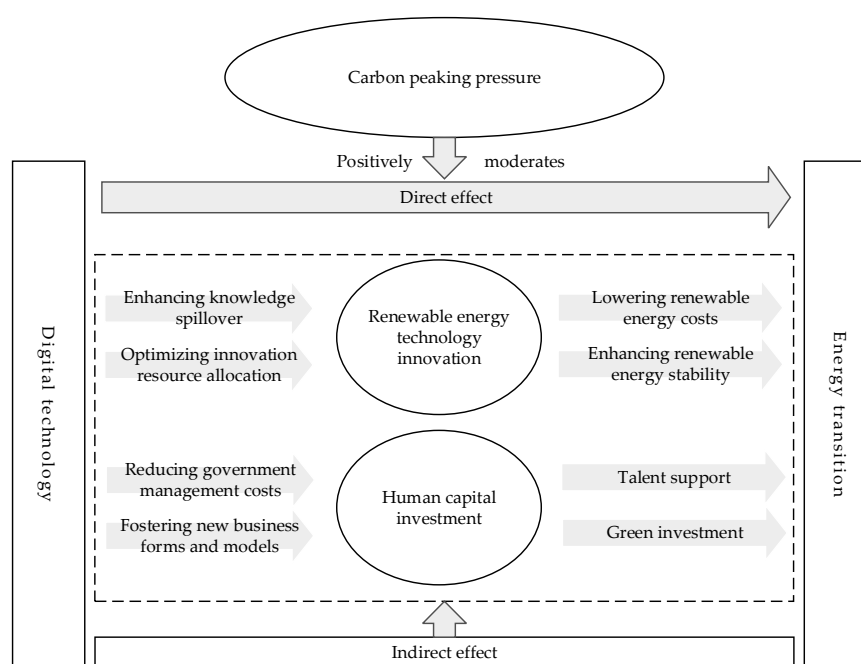


Figure 1. Mechanism of digital technology on energy transition in the Yellow River Basin under the carbon peaking goal.

3.2. The Indirect Effect of Digital Technology on the Energy Transition in the Yellow River Basin

Digital technology can promote renewable energy technology innovation in the Yellow River Basin. From one perspective, according to the theory of knowledge spillovers [43], knowledge exhibits spillover effects. Digital technology can strengthen knowledge spillovers carried by R&D factors; promote cross-regional collaboration among industry, academia, and research institutions by breaking down information barriers in the basin; and reduce the cost of renewable energy technology innovation [44]. From another perspective, digital technology contributes to higher efficiency in allocating innovative resources across the Yellow River Basin, facilitates their effective utilization, and strengthens technological innovation efficiency in renewable energy within the basin [45]. Renewable energy technology innovation is the fundamental way to reduce the cost of green energy and improve its economic efficiency and competitiveness [46]. For the Yellow

River Basin, when technological innovation makes the cost of photovoltaic and wind power lower than that of traditional thermal power and technically solves the problem of intermittency in renewable energy generation, the market endogenous power for energy transition across the entire basin will be greatly stimulated. That is to say, advances in renewable energy technology cut costs and enhance the stability of clean energy sources, thereby facilitating the energy transition across the Yellow River Basin's entire scope [46].

Digital technology can increase human capital investment in the Yellow River Basin. First, digital technology enables the building of digital government in the Yellow River Basin, cutting administrative costs [47]. The fiscal savings can then be reallocated to more productive human capital investment [48]. Second, digital technology gives rise to new industries and models in the Yellow River Basin. Low-skilled, repetitive jobs are being eliminated, whereas high-skilled, creative positions face talent shortages, which may trigger structural unemployment. Both unemployment concerns and greater international competitiveness push the government to increase investment in human capital [49]. Human capital investment is the fundamental support for cultivating talent, which is the carrier of technology. Increased investment in human capital can enhance discipline construction and talent cultivation in frontier and interdisciplinary energy sectors within the Yellow River Basin, offering talent support for the energy transition. Such talent advantages can attract green investment, further promoting energy transition in the region [50]. On this basis, Hypothesis 2 is formulated.

Hypothesis 2. *Digital technology promotes the energy transition across the Yellow River Basin by strengthening renewable energy technology innovation and human capital investment.*

3.3. The Mechanism of Digital Technology Promoting the Energy Transition in the Yellow River Basin in the Context of the Carbon Peaking Objective

The carbon peaking goal exerts a significant influence on the nexus between digital technology and the energy transition in the Yellow River Basin. As one of China's key environmental objectives in the current stage, the carbon peaking goal receives strong emphasis from the central government [51]. The central government undertakes overall macro-level planning, while local governments act as the main implementers of urban carbon peaking initiatives and directly bear the associated regulatory pressures [51,52]. On the one hand, driven by carbon peaking pressures, local governments scale up support for green technological innovation via fiscal and policy incentives [53]. Advances in green technological innovation accelerate the replacement of fossil fuels with clean energy [54], thereby facilitating the energy transition. Additionally, the carbon peaking goal has turned green investment into a new growth driver for urban development. A greater volume of capital has flowed into clean sectors such as clean and renewable energy, which also propels the energy transition [51]. On the other hand, digital technology enables real-time carbon monitoring and management, further amplifying the synergistic effects of carbon peaking pressures and boosting the energy transition more effectively [55]. To sum up, carbon peaking pressures can not only drive the energy transition directly but also strengthen the enabling effect of digital technology on the energy transition through collaborative interaction. On this basis, Hypothesis 3 is formulated.

Hypothesis 3. *Carbon peaking pressure positively moderates the facilitating effect of digital technology on the energy transition in the Yellow River Basin.*

4. Research Design

4.1. Model Setting

This study adopts the two-way fixed effects model for the baseline regression to investigate the role of digital technology in the energy transition across the Yellow River Basin. Compared to the traditional pooled OLS model or random effects model, the two-way fixed effects model can simultaneously control for individual heterogeneity and common time trends, effectively mitigating the estimation bias caused by region-specific inherent characteristics and common macroeconomic shocks that vary over time, thereby improving the robustness and reliability of the core estimation results. The econometric model is specified as follows:

$$ET_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_c X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

In the specification, i and t stand for city and year, respectively. ET_{it} refers to the level of the energy transition, and DT_{it} represents the level of digital technology. X_{it} indicates a vector of control variables, covering economic development (lnPGDP), urbanization level (Urban), population density (Pop), infrastructure (Infra), financial development (Fin), and environmental regulation (ER). α_0 is the constant term. α_1 and α_c are the parameters to be estimated. μ_i and δ_t capture the individual fixed effect and time fixed effect, respectively, in sequence. ε_{it} represents the stochastic disturbance term.

This study does not adopt the traditional mediation model consisting of explanatory variables, mediating variables and dependent variables. As pointed out by Jiang, because mediating variables are affected by explanatory variables, incorporating mediating variables into the model as control variables may lead to estimation bias and inconsistent estimates of the coefficients of explanatory variables, thereby yielding inaccurate indirect effects [56]. When exploring influence mechanisms, researchers may select mediating variables that have a clear theoretical connection with the dependent variable, and they only need to empirically verify the impact of independent variables on mediating variables [57,58]. This paper has theoretically demonstrated the relationships between renewable energy technological innovation, human capital investment and the energy transition. Accordingly, the following econometric models are constructed:

$$M_{it} = \beta_0 + \beta_1 DT_{it} + \beta_c X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

where M_{it} denotes the mediating variables, including renewable energy technology innovation (RETI) and human capital investment (HCI). β_0 stands for the constant, while β_1 and β_c are the coefficients to be estimated. The definitions of the remaining variables are the same as above.

To clarify how carbon peaking pressure moderates the link between digital technology and the energy transition across the Yellow River Basin, the following moderation effect model is developed:

$$ET_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 C_press_{it} + \gamma_3 DT_{it} \times C_press_{it} + \gamma_c X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

where C_press_{it} denotes the moderating variable, carbon peaking pressure. $DT_{it} \times C_press_{it}$ represents the interaction term between digital technology and carbon peaking pressure. γ_0 represents the constant, and γ_1 , γ_2 , γ_3 , and γ_c serve as the coefficients to be estimated. All other variables are defined as previously stated.

4.2. Variable Definitions

4.2.1. Explained Variable

Energy Transition (ET). The goal of China's energy transition is to gradually reduce energy intensity [22]. Accordingly, this study primarily measures the energy transition

using energy intensity, defined as the ratio of total energy consumption to regional real GDP [59]. This is a negative indicator of the energy transition: a lower energy intensity means that less energy is consumed per unit of regional GDP produced, reflecting a higher level of economic output efficiency of energy inputs. Furthermore, considering the broader connotation of the energy transition and based on data availability, this study also employs energy structure as an alternative measure of the energy transition for robustness checks. Energy structure is measured as the share of coal consumption in the total energy consumption, which is also a negative indicator. The calculation of coal consumption follows established practices in the literature and will not be elaborated further here [60]. Due to the lack of city-level energy consumption data, the total energy consumption at the city level is estimated by fitting nighttime light data with provincial energy consumption data [41]. The specific steps in this study are as follows: First, the correlation between provincial energy consumption and provincial nighttime light data in the Yellow River Basin is analyzed. Based on the goodness of fit, a linear correlation is selected, and a linear model without an intercept is constructed:

$$y_{it} = k_t x_{it} \quad (4)$$

y_{it} denotes the total energy use of province i for year t , k_t represents the corresponding coefficient in year t , and x_{it} refers to the overall grid grayscale value of province i for year t . Total urban energy consumption is then derived inversely based on these coefficients and urban nighttime light data.

The spatial distribution evolution of the energy transition levels in the Yellow River Basin from 2013 to 2024 is shown in Figure 2. In 2013, the basin's energy transition level exhibited a pattern decreasing sequentially from the lower reaches to the upper reaches and then to the middle reaches. By 2024, the energy transition level in the upper reaches had declined, and the overall pattern shifted to a sequential decrease from the lower reaches to the middle reaches and then to the upper reaches.

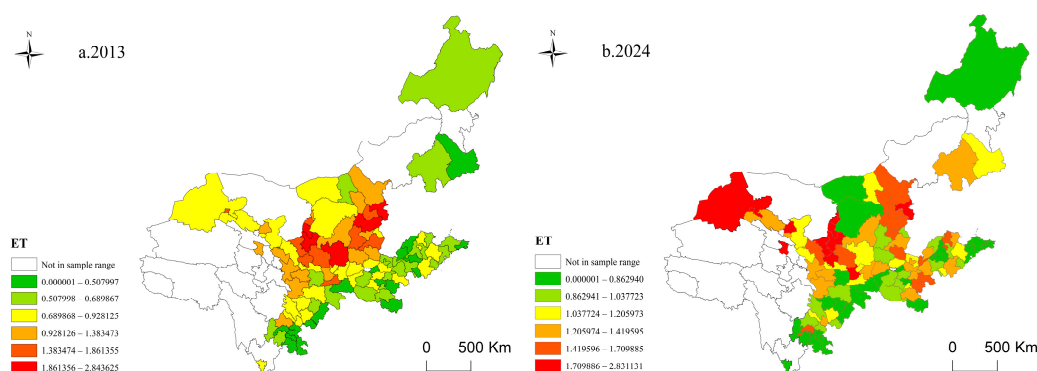


Figure 2. The spatial distribution evolution of energy transition level in the Yellow River Basin.

4.2.2. Explanatory Variable

Digital Technology (DT). From the perspective of the indicator system for measuring digital technology, no authoritative and unified version has yet been established. Drawing on existing research [61], considering the core connotation of digital technology as well as the simplicity, scientific rationality and data availability of the indicator system, this study establishes a comprehensive evaluation index system from three dimensions, as shown in Table 1: digital infrastructure, digital technology application and digital technology innovation. Digital technology is a multi-dimensional composite concept. The indicators selected in this study differ in their theoretical connotation and functional positioning and, thus, do not share equal theoretical importance. In the dimension of digital infrastructure,

two indicators, namely, internet penetration rate and mobile phone penetration rate, are adopted to measure the coverage of broadband and mobile networks. The dimension of digital technology application includes per capita telecommunication business income; the proportion of employees in information transmission, computer services and software industries; and the digital inclusive finance index; which reflect the actual penetration and utilization intensity of digital technology in economic and social activities. For digital technology innovation, we use the number of patent applications for core digital technologies to represent regional technological reserves and innovation capacity in cutting-edge fields such as artificial intelligence. Compared to subjective evaluation methods, including the analytic hierarchy process and grey relational analysis, the entropy weight method is more objective and comprehensive. Therefore, this study applies the entropy weight method to measure the development level of digital technology in cities across the Yellow River Basin. The specific procedures are as follows: first, standardize and dimensionless process the original data; second, calculate the proportion of each sample value to the total sum of all sample values under each indicator; third, compute the information entropy of each indicator; fourth, calculate the redundancy of information entropy; fifth, determine the weight of each evaluation indicator; and sixth, obtain the comprehensive index.

Table 1. Digital technology indicator system.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Indicator Descriptions	Weights	Attributes
Digital technology development composite index	Digital infrastructure	Internet penetration rate	Number of internet broadband subscribers per 100 persons	0.104	Positive
		Mobile phone penetration rate	Number of mobile phone users per 100 persons	0.027	Positive
	Digital technology application	Telecom revenue per capita	Telecom revenue/resident population	0.143	Positive
		Share of employment in information transmission, computer services, and software industry	Employees in information transmission, computer services, and software industry as a percentage of urban unit employees	0.009	Positive
		Digital financial inclusion index	Peking University Digital Financial Inclusion Total Index	0.060	Positive
	Digital technology innovation	Patents for key digital technologies	Number of patent applications for key digital technologies	0.657	Positive

The spatial distribution evolution of the digital technology development levels across the Yellow River Basin from 2013 to 2024 is depicted in Figure 3. In 2013, digital technology levels followed a pattern of gradual decline from the lower reaches to the middle reaches and then to the upper reaches. By 2024, the lower reaches further strengthened their leading position, and the entire basin still retained the distribution pattern of decreasing from the lower reaches to the middle reaches and then to the upper reaches.

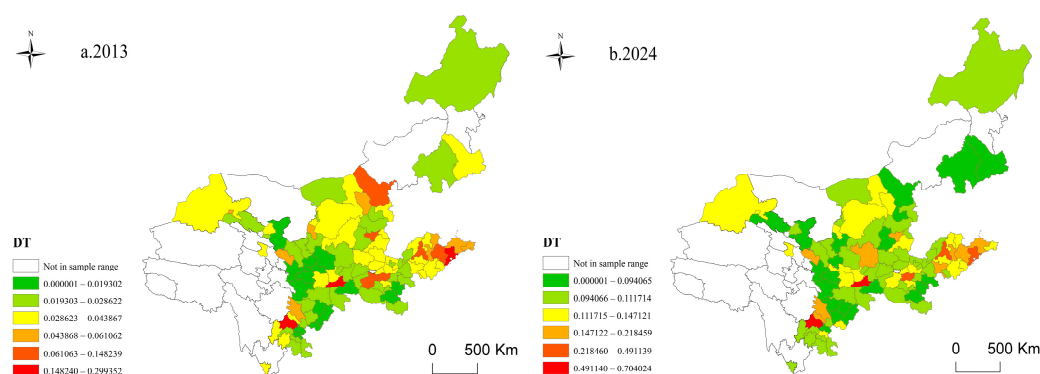


Figure 3. The spatial distribution evolution of digital technology level in the Yellow River Basin.

4.2.3. Mediating Variables

Renewable Energy Technology Innovation (RETI). For urban renewable energy technology innovation levels across the Yellow River Basin, patent applications for renewable energy technologies are selected as the measurement indicator [62]. Following established practice, in the first step, patent classification codes for hydropower, wind power, solar energy, geothermal energy and biomass energy are collected and sorted from the “IPC Green Inventory” issued by the WIPO. In the second stage, data was retrieved from the National Intellectual Property Administration’s Patent Search and Analysis System to search and tally renewable energy patent filings across all cities in the Yellow River Basin. Human capital investment (HCI) is assessed by the proportion of education spending in total government fiscal outlays [50].

4.2.4. Moderating Variable

Carbon Peaking Pressure (C_press). China’s carbon peaking target requires carbon dioxide emissions to reach a peak before 2030 and then decline moderately, which means the growth rate of carbon emissions will turn from positive to negative. Accordingly, a larger positive deviation of the carbon emission growth rate from zero indicates a tighter timeline and greater emission reduction pressure to achieve the 2030 carbon peaking goal. By contrast, when the growth rate approaches zero or turns negative, the pressure will be alleviated. As the national carbon peaking target does not specify quantitative caps on total regional carbon emissions, this study follows existing literature and adopts the average carbon emission growth rate over the past four periods to measure regional carbon peaking pressure [63]. This selection is based on two considerations: local environmental governance intensity hinges on the balance between political incentives and economic decentralization, and the average tenure of officials in China’s prefecture-level cities stands at 3.81 years [63].

4.2.5. Control Variables

For a more precise assessment of the role digital technology plays in the energy transition across the Yellow River Basin, the following control variables are adopted in line with prior studies [64,65]: economic development (lnPGDP), proxied by the log of real per capita GDP; urbanization level (Urban), measured as the share of permanent urban inhabitants in the overall permanent population; population density (Pop), calculated as permanent resident numbers relative to urban land area; infrastructure (Infra), indicated by per capita road coverage; financial development (Fin), captured by the log of financial institutions’ year-end total lending balances; and environmental regulation (ER), measured as the ratio of the frequency of environment-related words to the total word frequency in government work reports [66].

4.3. Data Sources

Considering data accessibility, this research uses pertinent data spanning 2013–2024 for 99 cities at and above the prefectural level across the Yellow River Basin, with Haidong City excluded on account of substantial data gaps. Primary data sources include municipal statistical yearbooks, annual communiqués on national economic and social development, provincial and autonomous regional statistical yearbooks, the National Earth System Science Data Center, the EDGAR database, China’s National Intellectual Property Administration, the Institute of Digital Finance at Peking University, the China City Statistical Yearbook, and the China Energy Statistical Yearbook. Linear interpolation is applied to fill in a small number of missing data points. Descriptive statistics for the variables are presented in Table 2.

Table 2. The statistical description of variables.

Variables	Obs	Mean	Std. Dev	Max	Min
ET	1188	1.028	0.464	3.473	0.264
DT	1188	0.095	0.094	0.750	0.011
RETI	1188	0.013	0.030	0.262	0.000
HCI	1188	0.173	0.034	0.267	0.044
C_press	1188	0.038	0.091	0.666	−0.047
lnPGDP	1188	10.488	0.491	12.456	9.037
Urban	1188	0.566	0.137	0.969	0.250
Pop	1188	0.400	0.328	1.860	0.006
Infra	1188	1.926	0.940	6.141	0.120
Fin	1188	7.394	1.020	11.099	4.741
ER	1188	0.009	0.003	0.022	0.001

5. Results

5.1. Baseline Results

The results regarding the impact of digital technology on the energy transition in the Yellow River Basin are shown in Table 3. Column (1) only includes the core explanatory variable. The coefficient of digital technology is −0.706 and significantly negative at the 1% level. This indicates that a one-standard-deviation increase in digital technology reduces energy intensity by 0.066 tons of standard coal per ten thousand yuan, demonstrating that digital technology can effectively cut energy consumption per unit output. As energy intensity is a negative proxy indicator for the energy transition, this result preliminarily suggests that digital technology facilitates the energy transition. After a series of control variables are introduced in Column (2), the coefficient of digital technology becomes −0.835, which remains significantly negative at the 1% level. Specifically, a one-standard-deviation increase in digital technology leads to a 0.078 tons of standard coal per ten thousand yuan decline in energy intensity, and the practical energy-saving effect becomes more prominent. Overall, digital technology exerts a significant promoting effect on the energy transition in the Yellow River Basin, which verifies Hypothesis 1.

Table 3. Baseline regression results.

Variables	(1) ET	(2) ET
DT	−0.706 *** (−3.135)	−0.835 *** (−2.960)
lnPGDP		−0.764 *** (−7.236)

Urban		2.040 *
		(1.801)
Pop		−0.765 ***
		(−2.907)
Infra		−0.017
		(−0.533)
Fin		0.205 ***
		(3.109)
ER		−1.958
		(−0.807)
Constant	1.096 ***	6.806 ***
	(51.112)	(6.528)
City fixed effect	YES	YES
Year fixed effect	YES	YES
N	1188	1188
Adj. R ²	0.821	0.860

Note: *** and * denote significance at the 1% and 10% levels, respectively; t statistics are in parentheses.

5.2. Robustness and Endogeneity Tests

This paper conducts robustness checks by replacing the explained variable, adjusting the sample period, and winsorizing the data at the 1% level. The results are presented in Table 4. First, the energy transition is re-measured by the energy structure indicator. As shown in Column (1), the coefficient of digital technology remains significantly negative at the 1% level. Although the absolute value of the coefficient changes compared to the baseline regression, the direction and significance remain stable. Second, to eliminate the interference of the COVID-19 pandemic, the sample period is adjusted from 2013–2024 to 2013–2019. The coefficient in Column (2) is still significantly negative at the 10% level, indicating that the core conclusion is not affected by the adjustment of the sample interval. Finally, to avoid bias caused by extreme values, the core variables are winsorized at the 1% level. The coefficient in Column (3) remains significantly negative at the 1% level. All three robustness checks confirm that the promoting effect of digital technology on the energy transition in the Yellow River Basin is statistically significant, verifying the reliability of the baseline regression results.

Table 4. Robustness test results.

Variables	(1) ET	(2) ET	(3) ET
DT	−0.296 *** (−3.751)	−0.448 * (−1.721)	−0.952 *** (−3.702)
Constant	1.420 *** (3.700)	7.526 *** (5.607)	6.730 *** (6.393)
Control variables	YES	YES	YES
City fixed effect	YES	YES	YES
Year fixed effect	YES	YES	YES
N	1188	693	1188
Adj. R ²	0.780	0.910	0.869

Note: *** and * denote significance at the 1% and 10% levels, respectively; t statistics are in parentheses.

To address potential endogeneity concerns, the two-stage least squares (2SLS) approach is adopted in this study. First, following conventional practices, the one-period lag of the core explanatory variable is selected as an instrumental variable. Second, referring to existing literature [67], we construct another instrumental variable based on the minimum distance from each city to Hangzhou. In terms of correlation: Digital finance represented by Alipay originated in Hangzhou, a major cradle of digital technology development in China. Cities closer to Hangzhou are more susceptible to the radiation and spillover effects of digital technology and digital finance and, thus, tend to have higher levels of digital technology, which satisfies the correlation requirement for instrumental variables. In terms of exogeneity: The geographical distance from a city to Hangzhou is a historically determined exogenous variable and does not directly shape the urban energy transition. Although cities near Hangzhou may boast superior overall development, this paper controls for economic development, urbanization, population density, infrastructure, financial development, environmental regulation and other factors in the regression, which effectively eliminates their direct impacts on the energy transition. Furthermore, Hangzhou is neither a pilot city for special energy policies nor a heavy industrial base. The distance to Hangzhou has no systematic correlation with local environmental regulation intensity, energy subsidy policies or other relevant factors. Therefore, the above instrumental variable meets the exogeneity requirement. Because the above instrumental variable is time-invariant, we interact it with the digital technology level to create a new time-varying instrumental variable.

As shown in Columns (2) and (4) of Table 5, the null hypotheses of underidentification and weak instruments are rejected, which indicates that both instrumental variables are valid. After endogeneity is addressed, the coefficient of digital technology on energy intensity is significantly negative at the 1% statistical level, which further verifies the robustness of the baseline regression results.

Table 5. Endogeneity test results.

Variables	(1) DT	(2) ET	(3) DT	(4) ET
DT		−1.117 *** (−3.565)		−1.211 *** (−4.262)
L. DT	0.785 *** (33.578)			
IV			0.001 *** (8.389)	
Control variables	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
N	1188	1188	1188	1188
Adj. R ²	0.716	0.240	0.809	0.214
Kleibergen–Paap rk LM statistic		5.972 **		6.539 **
Kleibergen–Paap rk Wald F statistic		1127.494{16.38}		70.377{16.38}

Note: *** and ** denote significance at the 1% and 5% levels, respectively; t statistics are in parentheses; { } are 10% critical values for weak identification test.

5.3. Mechanism Tests

The regression results using renewable energy technology innovation as the mechanism variable are presented in Column (1) of Table 6. The regression coefficient of digital technology on renewable energy technology innovation is 0.272, which is significantly positive at the 1% level. This reveals that the development of digital technology indeed

offers solid support for R&D activities in the renewable energy sector, thereby promoting the energy transition in the Yellow River Basin. The underlying mechanism is as follows. On the one hand, digital technology helps refine the allocation of R&D resources. By processing and simulating massive volumes of data, it lowers both the trial-and-error cost and uncertainty involved in technological exploration. On the other hand, digital platforms facilitate knowledge sharing and cross-border collaboration among industry, academia, and research institutions. They break down the spatial and information barriers hindering technological innovation and accelerate knowledge spillovers and innovation diffusion. By fueling innovation in renewable energy technologies, digital technology has generated more efficient and cost-effective renewable energy alternatives, making clean energy more competitive in terms of cost and performance, thereby driving a structural transformation of the energy system.

Table 6. Mechanism test results.

Variables	(1) RETI	(2) HCI
DT	0.272 *** (8.612)	0.057 * (1.710)
Constant	0.072 ** (2.375)	0.586 *** (7.281)
Control variables	YES	YES
City fixed effect	YES	YES
Year fixed effect	YES	YES
N	1188	1188
Adj. R ²	0.958	0.794

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively; t statistics are in parentheses.

The regression results with human capital investment as the mechanism variable are presented in Column (2) of Table 6. The regression coefficient of digital technology on human capital investment is 0.057, which is significantly positive at the 10% level. This suggests that digital technology can advance the energy transition across the Yellow River Basin by raising human capital investment. The underlying mechanism is as follows: On the one hand, digital technology improves the efficiency of government decision-making and management, cuts certain fiscal costs, and creates conditions for increased investment in human capital. On the other hand, new forms of business brought by digital technology raise new requirements for the labor force, which, in turn, pushes the government to increase spending on labor force training. Rising investment in human capital fuels talent development in digital–energy interdisciplinary areas and cutting-edge energy fields, strengthens the initiative for further technological R&D, and solidifies the intellectual support for the energy transition. Hypothesis 2 is, thus, verified.

5.4. Moderating Effect Test

The results for the moderating effect are presented in Table 7. The estimated coefficient of the interaction term between carbon peaking pressure and digital technology is −6.130, which is significantly negative at the 5% level. This outcome reveals that carbon peaking pressure plays a positive moderating role in the nexus between digital technology and the energy transition. Namely, as carbon peaking pressure increases, the promotion effect of digital technology on the energy transition in the Yellow River Basin becomes stronger. The reasons are as follows. The policy-driven “reverse constraint” mechanism

formed by the carbon peaking goal urges local governments and enterprises to utilize digital technology more actively for energy system optimization. This pressure enhances the orientation of technology application and promotes the deep penetration of digital technology into key links such as clean energy dispatch and energy consumption monitoring. Meanwhile, such pressure also accelerates technological iteration and market expansion, fully activating the enabling effect of digital technology under the dual drivers of policy and market and ultimately advancing the energy transition.

Table 7. Moderating effect test results.

Variables	ET
DT	−1.107 *** (−3.574)
C_press	−0.303 * (−1.800)
C_press×DT	−6.130 ** (−2.014)
Constant	6.961 *** (6.960)
Control variables	YES
City fixed effect	YES
Year fixed effect	YES
N	1188
Adj. R ²	0.863

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively; t statistics are in parentheses.

5.5. Heterogeneity Analysis

5.5.1. Regional Heterogeneity

The Yellow River Basin extends as a long and narrow belt from west to east, running through western, central and eastern China. Distinct regional heterogeneity can be observed in ecological conditions and economic growth across its upper, middle and lower reaches. The impact of digital technology on the energy transition may, therefore, exhibit regional heterogeneity within the basin. In view of this, this study adopts the classification approach for the upper, middle, and lower reaches of the Yellow River Basin proposed by Chen et al. to conduct grouped regressions among cities in these three reaches [68]. The empirical findings are presented in Columns (1) to (3) of Table 8. Regression analysis shows that the regression coefficient of digital technology on the energy transition in downstream cities is −1.497, which is significantly negative at the 1% level. This indicates that digital technology has a significant promoting effect on the energy transition in downstream cities of the Yellow River Basin, while such a promoting effect has not yet been observed in upstream or midstream cities. Drawing on the “core-periphery” theory of technology diffusion, downstream regions, as the economic and technological core of the Yellow River Basin, possess more complete digital infrastructure, more diverse industrial scenarios, and stronger attractiveness to talent and capital, leading to higher efficiency in translating technology into the energy system. By contrast, upper- and middle-reaches cities are in the peripheral zone, with weak computing power support and a long adjustment period required for digital solutions to adapt to local heavy and chemical industries. Consequently, the facilitating effect of digital technology on the energy transition has not yet been fully realized.

Table 8. Heterogeneity analysis results.

Variables	(1) Upper	(2) Middle	(3) Lower	(4) Resource-Based	(5) Non-Resource-Based	(6) Old ind. Base	(7) Non-Old ind. Base
DT	−0.236 (−0.804)	−0.576 (−0.526)	−1.497 *** (−4.971)	−0.800 (−0.403)	−0.992 *** (−3.667)	0.465 (0.475)	−0.906 *** (−2.903)
Constant	6.675 *** (3.425)	9.377 *** (5.031)	3.957 *** (2.952)	9.682 *** (5.911)	3.938 *** (3.238)	5.824 *** (4.345)	7.342 *** (5.457)
Control variables	YES	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES	YES
N	432	360	396	600	588	408	780
Adj. R ²	0.896	0.808	0.858	0.816	0.902	0.903	0.844

Note: *** denotes significance at the 1% level; t statistics are in parentheses.

5.5.2. Heterogeneity in Urban Resource Endowments

Resource-based and non-resource-based cities differ systematically in their industrial structure, energy reliance and development pathways, which may generate heterogeneous effects of digital technology on the energy transition. Following the National Sustainable Development Plan for Resource-Based Cities (2013–2020), this research divides urban samples across the Yellow River Basin into resource-based and non-resource-based groups for sub-sample regression estimation. The corresponding empirical outcomes are reported in Table 8, Columns (4) and (5). Regression analysis shows that the regression coefficient of digital technology on the energy transition in non-resource-based cities is −0.992, which is significantly negative at the 1% level, while the coefficient for resource-based cities fails to pass the significance test. This result suggests that the propulsion effect of digitalization on the energy transition is substantially stronger in cities not dependent on natural resources. This discrepancy can be explained by path dependence theory: resource-based cities have long built a complete industrial ecosystem centered on resource extraction and primary processing, with fiscal revenue, employment, and market systems closely tied to resource-intensive industries. The integration of digital technology, thus, faces institutional barriers and path dependence. Non-resource-based cities, by contrast, are free from such path lock-in, with more diversified and flexible industrial structures and richer application scenarios for digital technology. As a result, they can more effectively promote the energy transition through intelligent monitoring, precise scheduling, and energy efficiency improvement.

5.5.3. Heterogeneity in Urban Industrial Attributes

Old industrial bases focus on traditional heavy industries and face transformation pressure, while non-old industrial bases mostly feature emerging industries or service sectors with more flexible economic structures. Following the National Plan for the Adjustment and Transformation of Old Industrial Bases (2013–2022), this research divides prefecture-level cities in the Yellow River Basin into two groups—old industrial bases and non-old industrial bases—so as to implement a sub-sample regression analysis. The corresponding empirical results are displayed in Table 8, Columns (6) and (7). Regression analysis shows that the regression coefficient of digital technology on the energy transition in non-old industrial base cities is −0.906, which is significantly negative at the 1% level, while the coefficient for old industrial base cities is not significant. This indicates that the propelling influence of digital technology toward the energy transition is comparatively stronger in cities not belonging to old industrial bases. According to the tech-

nology lock-in effect, the heavy and chemical industrial systems accumulated over decades in old industrial bases have formed deep technological inertia and organizational rigidity. Specialized equipment and existing process flows constitute implicit barriers to the adoption of digital technology, suppressing both the willingness and capacity for transformation. Non-old industrial base cities, with lighter historical burdens and more flexible industrial structures, can fully leverage the advantages of digital technology in promoting the energy transition.

6. Further Discussion: Spatial Spillover Effects Analysis

Prior to the spatial econometric analysis, this paper employs the Global Moran's I to test for spatial autocorrelation. The results, presented in Table 9, show that the Global Moran's I values are positive and statistically significant at the 1% level for all years from 2013 to 2024. This indicates that the energy transition exhibits a significant positive spatial agglomeration pattern among cities in the Yellow River Basin, meaning that cities with high values tend to be adjacent to other high-value cities, while cities with low values tend to cluster with other low-value cities. These findings suggest that the energy transition across cities is not randomly distributed but rather exhibits clear spatial correlation effects, thereby justifying the use of spatial econometric models in subsequent analysis.

Table 9. Global Moran's I test results.

Year	I	E (I)	Sd (I)	Z	p-Value
2013	0.156	−0.010	0.013	12.787	0.000
2014	0.165	−0.010	0.013	13.486	0.000
2015	0.137	−0.010	0.013	11.295	0.000
2016	0.129	−0.010	0.013	10.805	0.000
2017	0.150	−0.010	0.013	12.453	0.000
2018	0.136	−0.010	0.013	11.349	0.000
2019	0.143	−0.010	0.013	11.703	0.000
2020	0.114	−0.010	0.013	9.530	0.000
2021	0.107	−0.010	0.013	8.957	0.000
2022	0.108	−0.010	0.013	9.073	0.000
2023	0.150	−0.010	0.013	12.208	0.000
2024	0.127	−0.010	0.013	10.503	0.000

This paper conducted the LM test, Hausman test, LR test, and Wald test. The results, as shown in Table 10, indicate that the two-way fixed effects Spatial Durbin Model (SDM) should be selected to examine the spatial spillover effects. The model is specified as follows:

$$ET_{it} = \alpha_0 + \rho_1 \sum_{j=1}^n W_{ij} ET_{it} + \alpha_1 DT_{it} + \rho_2 \sum_{j=1}^n W_{ij} DT_{it} + \alpha_c X_{it} + \rho_3 \sum_{j=1}^n W_{ij} X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

where i and j denote cities and n is the number of sample cities. W is the inverse-distance spatial weight matrix, constructed as the inverse of the geographical distance between each pair of cities, calculated using the latitude and longitude of each city's central point. The meanings of the remaining symbols are the same as those in Equation (1).

Table 10. Specification tests for spatial panel econometric models.

Test	Static SDM	p-Value
LM (lag) test	189.622	0.000
Robust LM (lag) test	16.658	0.000
LM (error) test	224.018	0.000

Robust LM (error) test	51.055	0.000
Wald test spatial lag	33.140	0.000
LR test spatial lag	1829.110	0.000
Wald test spatial error	38.000	0.000
LR test spatial error	26.870	0.003
Hausman test	32.610	0.005

The results of the spatial effect decomposition are presented in Table 11. The coefficient of the direct effect of digital technology on energy intensity is -0.754 ($p < 0.05$), indicating that the development of digital technology in a city can significantly reduce its local energy intensity and effectively promote a local energy transition. By contrast, the coefficient of the indirect effect is 13.166 ($p < 0.05$), suggesting that digital technology progress in neighboring cities significantly increases local energy intensity, showing a negative spatial spillover effect. This phenomenon mainly stems from the “energy consumption transfer” effect caused by the unbalanced development of digital technology within the basin. While cities leading in digital technology improve their local energy efficiency, they may transfer high-energy-consuming production capacities or links to neighboring cities with lower levels of digitalization through mechanisms such as industrial gradient transfer and factor siphoning, thereby indirectly increasing the energy intensity of the latter. Because the magnitude of the indirect effect is much larger than that of the direct effect, the total effect of digital technology on the overall energy intensity of the region is finally 12.411 ($p < 0.10$). This indicates that the current “fragmented” digital transformation model across cities fails to achieve the goal of an overall energy transition in the basin. Local improvements may instead exacerbate regional divergence in energy intensity, which highlights the necessity of establishing a cross-regional collaborative governance mechanism.

Table 11. Decomposition results of spatial effects.

Variables	(1) Direct Effect	(2) Indirect Effect	(3) Total Effect
DT	-0.754^{**} (-2.275)	13.166^{**} (2.001)	12.411^{*} (1.858)
Control variables	YES	YES	YES
City fixed effect	YES	YES	YES
Year fixed effect	YES	YES	YES
N	1188	1188	1188

Note: $**$ and $*$ denote significance at the 5% and 10% levels, respectively; t statistics are in parentheses.

7. Prediction of Carbon Emission Peaking Time in Cities in the Yellow River Basin

Cities in the Yellow River Basin differ in their economic development and industrial structure, so their timelines for achieving carbon peaking naturally vary. To reveal the trend of carbon peaking in these cities and quantify the significance of the energy transition for reaching carbon peaking, this paper attempts to set a baseline scenario and an accelerated energy transition scenario and predicts the carbon peaking time under both scenarios.

7.1. Prediction Method

Drawing on existing studies [69], this study adopts the Kaya identity to forecast the trend of carbon emission peaking among cities across the Yellow River Basin:

$$C_{it} = P_{it} \cdot \frac{GDP_{it}}{P_{it}} \cdot \frac{C_{it}}{GDP_{it}} = P_{it} \cdot E_{it} \cdot CI_{it} \quad (6)$$

where C_{it} represents carbon emissions for city i during period t , P_{it} denotes population size, GDP_{it} refers to regional gross domestic product, E_{it} represents per capita GDP, and CI_{it} stands for carbon emission intensity.

Based on the above equation, if the specific values and growth rates of P_{it} , E_{it} , and CI_{it} in a given period are known, the carbon dioxide emissions for the next period can be calculated, which forms the basic logic of the prediction in this paper. Taking 2024 as the base year, this paper predicts the carbon emission peaking trends of cities across the Yellow River Basin for three periods: 2025, 2026–2030, and 2031–2035. The predicted carbon emissions of individual cities are aggregated to determine the overall carbon peaking time of the Yellow River Basin.

7.2. Scenario Setting

Taking Sanmenxia City as an example, this study establishes a baseline scenario and an accelerated energy transition scenario.

Population Size (P): The National Population Development Plan (2016–2030) states that China's total population will peak around 2030, and the inertial population growth will gradually slow down. Sanmenxia City had a population of 2.04 million in 2020 and 2.01 million in 2024, with an average annual growth rate of -0.37% . Referring to the variation range of growth rates in existing studies [69], this paper defines three stages of average annual population growth rates for Sanmenxia under the baseline scenario: -0.37% for 2025, -0.42% for 2026–2030, and -0.52% for 2031–2035. Given that an accelerated energy transition has little impact on urban population size, the population growth rate under the accelerated energy transition scenario is consistent with that in the baseline scenario.

Per Capita GDP (E): Sanmenxia's 14th Five-Year Plan sets the average annual GDP growth rate at 7% for 2021–2025, while no target for per capita GDP is specified. Based on the quantitative relationship among the growth rates of total GDP, population and per capita GDP, the average annual growth rate of per capita GDP in Sanmenxia is set at 7.37% for 2025 under the baseline scenario. According to the 2026 Government Work Report of Sanmenxia Municipal People's Government, the average annual GDP growth rate is targeted at 5.5% for 2026–2030, and the corresponding average annual per capita GDP growth rate is determined as 5.92% . Combined with the growth rate changes in the above two periods, the average annual per capita GDP growth rate for 2031–2035 is set at 4.47% . Following previous research [70], the growth rates in the accelerated energy transition scenario are 0.34 percentage points lower than those in the baseline scenario, namely, 7.03% , 5.58% and 4.13% .

Carbon Emission Intensity (CI): In accordance with the Notice on Issuing the 14th Five-Year Reduction Target for Carbon Dioxide Emissions per Unit of GDP issued by Henan Province, Sanmenxia is required to achieve a cumulative reduction of 21% in carbon emission intensity during the 14th Five-Year Plan period. Drawing on relevant studies [69], this paper sets the cumulative reduction rates of carbon emission intensity for Sanmenxia at 21% , 23% and 22% for 2025, 2026–2030 and 2031–2035, respectively, under the baseline scenario, corresponding to average annual growth rates of -4.61% , -5.09% and -4.85% , respectively. Based on existing relevant literature [70], the annual growth rates under the accelerated energy transition scenario are 0.6 percentage points lower than the baseline levels, i.e., -5.21% , -5.69% and -5.45% .

In summary, the scenario settings for other cities in the Yellow River Basin follow the same rules. Under the baseline scenario, population growth rates are determined by historical data, while the growth rates of per capita GDP and carbon emission intensity are

formulated in accordance with official government plans. Under the accelerated energy transition scenario, the population growth rate remains unchanged; the growth rates of per capita GDP and carbon emission intensity are reduced by 0.34 and 0.6 percentage points, respectively. Detailed growth rate settings for all cities under the two scenarios are presented in Tables A1 and A2.

7.3. Prediction Results

The predicted carbon peaking years of prefecture-level cities under the two scenarios are presented in Table A3. The results show that the accelerated energy transition scenario can significantly advance the carbon peaking time of cities. Under the baseline scenario, most sample cities will reach their carbon peaks between 2027 and 2030, while a few cities, including Yulin and Luzhou, will achieve carbon peaking in 2031, with a relatively slow overall progress. Under the accelerated energy transition scenario, the carbon peaking years of the vast majority of cities are brought forward to 2025–2028, and the regional carbon peaking process is greatly accelerated.

The total carbon emissions of the Yellow River Basin are shown in Table 12, and obvious differences are observed in carbon peaking characteristics between the two scenarios. Under the baseline scenario, the total carbon emissions of the basin peak at 442,178 ten thousand tons in 2029 and then decline steadily year by year to 417,903 ten thousand tons in 2035. In the accelerated energy transition scenario, the overall carbon peaking of the basin occurs in 2025, with a peak value of 430,556 ten thousand tons. Both the peaking time and peak carbon emission level are notably reduced. Carbon emissions continue to decline afterward, falling to 376,238 ten thousand tons in 2035, which demonstrates remarkable emission reduction effects.

Table 12. Overall carbon emission trends of the Yellow River Basin.

Year	Baseline Scenario	Accelerated Energy Transition Scenario
2025	434,649	430,556
2026	438,122	429,885
2027	440,554	428,172
2028	441,912	425,414
2029	442,178	421,624
2030	441,345	416,827
2031	437,740	409,486
2032	433,565	401,717
2033	428,841	393,554
2034	423,605	385,043
2035	417,903	376,238

The findings indicate that accelerating the energy transition is an effective approach for promoting regional carbon peaking. Measures such as optimizing the energy structure and improving energy utilization efficiency can not only shorten the carbon peaking cycle of individual cities but also cut the peak carbon emissions and accelerate the emission reduction process after peaking. This helps the Yellow River Basin achieve the carbon peaking goal at an earlier stage and steadily advance subsequent carbon reduction work.

7.4. Sensitivity Analysis

Taking the baseline scenario as a reference, this study adjusts a single parameter at an equal rate while keeping the other parameters unchanged so as to evaluate and compare their effects on carbon peaking years. Specifically, each of the three variables is in-

creased by 0.05% to examine variations in carbon peaking time. The overall carbon emissions of the Yellow River Basin are listed in Table 13. Under the baseline scenario, the total carbon emissions of the basin peak at 442,178 ten thousand tons in 2029. After parameter adjustment, the carbon peaking year remains 2029, yet the peak carbon emissions rise across all scenarios. The peak value is the highest when the carbon emission intensity rises, followed by the scenario with an expanded population scale, and it is the lowest under the growth of per capita GDP. The calculation results for prefecture-level cities are presented in Table A4. Disturbances of the three indicators delay the average carbon peaking year of these cities by 0.806 years, 0.714 years and 0.867 years, respectively. The sensitivity level follows the order of carbon emission intensity, population scale and per capita GDP. Overall, carbon emission intensity is the key factor constraining the carbon peaking progress of the Yellow River Basin. In follow-up efforts, we shall prioritize controlling carbon emission intensity, optimize population distribution and develop green economy to ensure that the basin and all its cities achieve the carbon peaking target as scheduled.

Table 13. Overall sensitivity analysis of the Yellow River Basin.

Year	P	E	CI
2025	434,866	434,852	434,875
2026	438,561	438,534	438,579
2027	441,216	441,178	441,245
2028	442,799	442,748	442,837
2029	443,287	443,225	443,336
2030	442,673	442,601	442,733
2031	439,278	439,197	439,346
2032	435,306	435,217	435,383
2033	430,779	430,683	430,864
2034	425,734	425,630	425,826
2035	420,213	420,103	420,313

8. Conclusions and Policy Implications

8.1. Research Conclusions

Using panel data from 99 prefecture-level and above cities in the Yellow River Basin spanning 2013–2024, this study conducts theoretical analysis and empirical tests on the impact of digital technology on the energy transition in the basin, drawing the following conclusions: (1) Digital technology can significantly promote the energy transition in the Yellow River Basin, and this conclusion remains valid after a series of robustness tests. (2) Mechanism tests show that digital technology drives the energy transition by strengthening renewable energy technology innovation and human capital investment. (3) Moderation analysis indicates that carbon peaking pressure plays a positive moderating role in the relationship between digital technology and the energy transition. (4) Heterogeneity analysis reveals that the promoting effect of digital technology is more pronounced in the lower reaches of the basin and in non-resource-based, non-old industrial base cities. (5) While digital technology significantly advances local energy transitions, it also generates negative spatial spillovers that exacerbate regional divergence, which highlights the need for cross-regional collaborative governance. (6) Compared to the baseline scenario, cities in the basin achieve carbon peaking earlier under the accelerated energy transition scenario.

This study contributes to the existing literature in several ways. First, the baseline results are consistent with Zhao et al. [71] and mainstream studies on digital technology-

driven regional energy transitions. Building on this, this study further identifies the positive moderating effect of carbon peaking pressure and two mediating pathways: renewable energy technology innovation and human capital investment. Second, the heterogeneity finding that the effect is stronger in non-resource-based and non-old industrial base cities aligns with Dong et al. [22] on the role of the digital economy in the energy transition. Third, the spatial spillover results validate the argument by Han et al. [72] that digital technology exhibits spatial spillover effects. Fourth, the carbon peaking projections, which show earlier peaking under the accelerated scenario, are consistent with the findings of Liu et al. [70]. Overall, this study extends the analysis of digital technology's impact on the energy transition to the prefecture-level city scale in the Yellow River Basin, systematically explores the underlying mechanisms and spatial effects, and integrates digital technology, the energy transition, and carbon peaking into a unified analytical framework.

8.2. Policy Implications

Based on the aforementioned findings, this study proposes corresponding policy insights as follows:

1. Deepen the application of digital technology. Continue to promote digital upgrading in the energy sector and popularize the application of digital technology such as artificial intelligence, taking digital technology as the core driver of energy transition. All cities in the Yellow River Basin should steadily carry out digital transformation projects according to local development conditions to consolidate the foundational support for a regional energy transition.
2. Strengthen technological innovation and talent guarantees. Establish a cross-regional renewable energy technology innovation alliance for the Yellow River Basin to jointly tackle key technical bottlenecks in the renewable energy industry. Universities within the basin are encouraged to develop interdisciplinary disciplines covering energy and digital technology to cultivate versatile professionals. Regular digital skill training should be provided for practitioners in the energy industry to ensure effective technology implementation and sustainable industrial development.
3. Strengthen the institutional constraints of carbon peaking targets. Decompose the basin's carbon emission reduction and carbon peaking targets scientifically and clarify territorial administrative responsibilities, with improved interim evaluation mechanisms. The carbon emission trading market should be further optimized to incorporate carbon reductions achieved through digital energy conservation. Combining target pressure with market incentives can effectively motivate enterprises to actively implement digital low-carbon transformation.
4. Implement regionally differentiated and targeted governance. Downstream, non-resource-based, and non-old industrial base cities should give full play to their digital and innovative advantages, promote the in-depth integration of digital technology with high-end manufacturing and clean energy industries, and set benchmark examples for the basin-wide energy transition. Upstream and midstream cities should prioritize fiscal investment in digital infrastructure such as 5G networks and industrial internet to make up for hardware deficiencies, narrow the digital gap with downstream regions, and avoid undertaking transferred high-energy-consuming industries. Resource-based cities should build comprehensive energy big data management systems for traditional coal and power sectors so as to optimize energy exploitation, transmission and allocation processes and reduce industrial energy consumption through digital governance. Old industrial base cities should widely promote digital energy management systems in high-energy-consuming industries, including

the steel and chemical sectors, and introduce targeted preferential policies to reduce the cost of digital transformation for traditional industries.

5. Construct a cross-regional collaborative governance system. Break through administrative boundary restrictions and establish a unified basin-wide supervision mechanism for industrial layout and energy consumption to constrain the disorderly cross-regional transfer of high-energy-consuming industries. Build an integrated energy data and technology sharing platform to promote the exchange of energy-saving technologies and governance experience, thereby mitigating the adverse spatial spillover effects of digital technology and alleviating regional energy transition divergence.
6. Implement accelerated energy transition strategies. All cities in the Yellow River Basin should formulate more proactive emission reduction targets and implementation pathways based on the empowering potential of digital technology. In particular, cities with a delayed carbon peaking schedule, such as Yulin and Luzhou, should fully rely on digital means to accelerate the energy system transition, thereby substantially advancing their carbon peaking timeline.

8.3. Research Limitations and Future Research Directions

This paper systematically discusses the mechanism of digital technology in the energy transition and the carbon peaking trend across the Yellow River Basin through empirical analysis, but it still has the following deficiencies. First, this study centers on the specific region of the Yellow River Basin, where the energy mix, industrial characteristics and policy environment carry obvious regional features. Whether the findings can be applied to other basins or the national level requires further verification. Second, the analysis of influencing mechanisms concentrates on renewable energy technological innovation and human capital investment, without fully accounting for other potential channels such as institutional factors. Third, this paper adopts the Kaya identity to forecast carbon peaking trends across cities in the Yellow River Basin. While it boasts a clear structure and relatively low data demand, the method, as an identity decomposition in essence, is limited by its neglect of spatial dimensions and stock changes. Fourth, there are limitations in the measurement of core variables. (1) Urban energy consumption estimated via nighttime light data is susceptible to cloud cover, urban light spillover and other interferences, which leads to inherent measurement errors. (2) Using the number of patent applications for renewable energy to proxy technological innovation fails to reflect patent commercialization efficiency and the practical application effects of relevant technologies. (3) The proportion of government expenditure on education is adopted as the proxy for human capital investment, which only reflects the overall input of regional educational resources at the macro level and, thus, has limitations in comprehensiveness and representativeness. (4) Regional carbon peaking pressure is measured by the average growth rate of historical carbon emissions, which results in a one-dimensional evaluation. Fifth, the empirical model suffers from omitted-variable bias and constraints in causal identification. The interplay between digital technology and the energy transition is affected by a variety of complex factors, so the problem of omitted variables cannot be fully ruled out. In addition, this study adopts the two-way fixed effects model for empirical analysis, which cannot completely address endogeneity issues such as two-way causality and sample self-selection. Hence, rigorous causal inference cannot be achieved.

Future research can be further expanded and optimized along these avenues. First, comparative analyses across different basins or on a national scale can be conducted to clarify the heterogeneous conditions for digital technology to promote the energy transition and the boundaries of spatial promotion, thereby refining theoretical models with greater universality or differentiation. Second, the multi-dimensional mechanisms by

which digital technology affects the energy transition should be deeply analyzed. In particular, perspectives from institutional economics can be introduced to examine the role of institutional factors such as local government behavior and public participation. Finally, more comprehensive and dynamic methods for carbon emission projection should be explored. The Kaya identity approach can be extended, or other, more reasonable carbon emission forecasting methods can be investigated, so as to offer more scientific support for decision-making on carbon peaking pathway design. Fourth, it is necessary to further improve the measurement system and calculation methods for core variables. To mitigate errors of nighttime light data, data fusion and deviation correction can be conducted by combining official energy statistics and the micro-level energy consumption data of enterprises. For the one-sidedness of the indicators regarding renewable energy technological innovation, human capital investment and carbon peaking pressure, comprehensive indicator systems or more appropriate measurement approaches can be adopted to realize full-scale quantification. Fifth, optimize the empirical model to strengthen endogeneity treatment and causal identification. Future research may apply econometric methods, including difference-in-differences and propensity score matching, to alleviate endogeneity problems such as two-way causality and sample self-selection. Meanwhile, expanding the set of explanatory variables and incorporating other vital influencing factors will help reduce deviations caused by omitted variables.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Average annual growth rates under the baseline scenario.

City	P			E			CI		
	2025	2026–2030	2031–2035	2025	2026–2030	2031–2035	2025	2026–2030	2031–2035
Sanmenxia	−0.37%	−0.42%	−0.52%	7.37%	5.92%	4.47%	−4.61%	−5.09%	−4.85%
Dongying	0.19%	0.09%	−0.11%	5.31%	4.91%	4.51%	−4.48%	−4.97%	−4.73%
Zhongwei	0.27%	0.17%	−0.03%	6.73%	5.83%	4.93%	−3.43%	−4.89%	−4.71%
Linyi	−0.40%	−0.45%	−0.55%	6.40%	5.45%	4.50%	−4.48%	−4.67%	−4.53%
Ulanqab	−1.74%	−1.79%	−1.89%	8.74%	6.79%	4.84%	−4.48%	−4.64%	−4.51%
Wuhai	0.03%	−0.07%	−0.27%	4.97%	4.57%	4.17%	−3.89%	−4.26%	−4.13%
Leshan	−0.09%	−0.14%	−0.24%	6.59%	5.64%	4.69%	−4.25%	−4.73%	−4.48%

Xinyang	−0.98%	−1.03%	−1.13%	8.48%	6.03%	3.58%	−4.13%	−4.61%	−4.36%
Lanzhou	0.39%	0.29%	0.09%	6.11%	5.21%	4.31%	−3.43%	−4.49%	−4.26%
Neijiang	−0.66%	−0.71%	−0.81%	6.66%	6.21%	5.76%	−3.89%	−4.86%	−4.73%
Baotou	0.55%	0.45%	0.25%	6.45%	4.55%	2.65%	−3.89%	−4.86%	−4.13%
Nanchong	−0.54%	−0.59%	−0.69%	9.04%	6.09%	3.14%	−4.13%	−4.61%	−4.36%
Nanyang	−0.70%	−0.75%	−0.85%	8.20%	5.75%	3.30%	−4.13%	−4.61%	−4.36%
Luliang	−0.55%	−0.60%	−0.70%	8.55%	5.60%	2.65%	−3.89%	−4.36%	−4.13%
Wuzhong	0.64%	0.54%	0.34%	5.86%	4.46%	3.06%	−3.43%	−3.89%	−3.66%
Zhoukou	−1.10%	−1.15%	−1.25%	7.10%	6.65%	6.20%	−3.66%	−4.89%	−4.69%
Hulunbuir	−1.09%	−1.14%	−1.24%	6.09%	5.64%	5.19%	−3.89%	−4.16%	−4.03%
Hohhot	1.32%	1.22%	1.02%	4.68%	3.78%	2.88%	−3.89%	−4.36%	−4.13%
Xianyang	0.75%	0.65%	0.45%	6.25%	5.35%	4.45%	−3.20%	−4.96%	−4.73%
Shangqiu	−0.61%	−0.66%	−0.76%	8.61%	6.66%	4.71%	−4.36%	−4.85%	−4.61%
Shangluo	−0.49%	−0.54%	−0.64%	6.99%	5.54%	4.09%	−2.75%	−4.76%	−3.80%
Jiayuguan	0.47%	0.37%	0.17%	6.03%	4.63%	3.23%	−3.89%	−4.36%	−4.13%
Guyuan	−0.07%	−0.12%	−0.22%	7.37%	5.12%	2.87%	−3.43%	−3.89%	−3.66%
Datong	−0.41%	−0.46%	−0.56%	8.91%	5.46%	2.01%	−3.89%	−4.36%	−4.13%
Tianshui	−0.76%	−0.81%	−0.91%	7.26%	6.81%	6.36%	−3.89%	−5.36%	−5.13%
Taiyuan	0.89%	0.79%	0.57%	7.61%	4.21%	0.79%	−4.01%	−4.48%	−4.23%
Weihai	0.03%	−0.07%	−0.27%	5.47%	5.07%	4.67%	−4.48%	−4.67%	−4.53%
Ankang	−0.40%	−0.45%	−0.55%	6.90%	5.45%	4.00%	−3.66%	−4.13%	−3.89%
Anyang	−0.41%	−0.46%	−0.56%	6.41%	5.46%	4.51%	−3.89%	−4.36%	−4.13%
Dingxi	−0.51%	−0.56%	−0.66%	7.21%	5.56%	3.91%	−3.89%	−4.36%	−4.13%
Yibin	0.10%	0.00%	−0.20%	8.20%	5.50%	2.80%	−3.89%	−4.36%	−4.13%
Baoji	−0.53%	−0.58%	−0.68%	7.53%	6.08%	4.63%	−3.20%	−4.06%	−3.83%
Bazhong	−0.97%	−1.02%	−1.12%	6.97%	6.52%	6.07%	−3.89%	−4.96%	−4.73%
Bayannur	−0.76%	−0.81%	−0.91%	5.76%	5.31%	4.86%	−3.89%	−4.26%	−4.03%
Pingliang	−1.03%	−1.08%	−1.18%	7.53%	6.08%	4.63%	−3.89%	−4.36%	−4.13%
Pingdingshan	−0.56%	−0.61%	−0.71%	7.56%	5.61%	3.66%	−4.61%	−4.69%	−4.65%
Guangyuan	−0.85%	−0.90%	−1.00%	7.85%	6.40%	4.95%	−3.89%	−4.36%	−4.13%
Guang'an	−0.20%	−0.25%	−0.35%	7.20%	5.75%	4.30%	−3.89%	−4.36%	−4.13%
Qingyang	−0.57%	−0.62%	−0.72%	7.57%	6.62%	5.67%	−3.89%	−4.96%	−4.73%
Yan'an	−0.33%	−0.38%	−0.48%	6.83%	5.38%	3.93%	−3.89%	−4.36%	−4.13%
Kaifeng	−0.68%	−0.73%	−0.83%	9.18%	5.73%	2.28%	−3.89%	−4.36%	−4.13%
Zhangye	−0.67%	−0.72%	−0.82%	7.17%	5.72%	4.27%	−3.89%	−4.36%	−4.13%
Dezhou	−0.60%	−0.65%	−0.75%	6.60%	6.15%	5.70%	−4.48%	−4.97%	−4.73%
Deyang	−0.05%	−0.10%	−0.20%	6.55%	6.10%	5.65%	−3.89%	−5.46%	−5.23%
Xinzhou	−0.79%	−0.84%	−0.94%	8.79%	5.84%	2.89%	−3.89%	−4.36%	−4.13%
Chengdu	0.62%	0.52%	0.32%	5.38%	4.98%	4.58%	−3.89%	−4.96%	−4.73%
Panzhihua	0.14%	0.04%	−0.16%	7.36%	5.46%	3.56%	−3.89%	−4.36%	−4.13%
Xinxiang	−0.60%	−0.65%	−0.75%	7.10%	5.65%	4.20%	−4.36%	−4.65%	−4.51%
Rizhao	−0.35%	−0.40%	−0.50%	6.85%	5.40%	3.95%	−4.48%	−4.67%	−4.53%
Jinzhong	−0.30%	−0.35%	−0.45%	9.30%	5.35%	1.40%	−3.89%	−4.36%	−4.13%
Jincheng	−0.39%	−0.44%	−0.54%	9.39%	5.44%	1.49%	−3.89%	−4.36%	−4.13%
Shuozhou	−0.34%	−0.39%	−0.49%	8.34%	5.39%	2.44%	−3.89%	−4.36%	−4.13%
Zaozhuang	−0.32%	−0.37%	−0.47%	6.32%	5.37%	4.42%	−4.48%	−4.67%	−4.53%
Yulin	−0.07%	−0.12%	−0.22%	6.57%	5.12%	3.67%	−4.13%	−4.61%	−4.36%
Wuwei	−0.68%	−0.73%	−0.83%	7.18%	5.73%	4.28%	−3.89%	−4.36%	−4.13%
Hanzhong	−0.39%	−0.44%	−0.54%	7.39%	6.44%	5.49%	−3.20%	−4.86%	−4.73%
Tai'an	−0.87%	−0.92%	−1.02%	6.37%	5.92%	5.47%	−4.48%	−4.67%	−4.53%
Luzhou	0.08%	−0.02%	−0.22%	7.92%	5.52%	3.12%	−3.89%	−4.36%	−4.13%
Luoyang	0.07%	−0.03%	−0.23%	8.43%	5.03%	1.63%	−3.89%	−4.36%	−4.13%
Jinan	0.72%	0.62%	0.42%	6.28%	4.38%	2.48%	−4.48%	−4.77%	−4.63%

Jining	−0.51%	−0.56%	−0.66%	6.51%	5.56%	4.61%	−4.48%	−4.67%	−4.53%
Zibo	−0.35%	−0.40%	−0.50%	7.35%	5.40%	3.45%	−4.48%	−4.67%	−4.53%
Weinan	−0.59%	−0.64%	−0.74%	7.09%	6.14%	5.19%	−3.20%	−4.46%	−4.33%
Binzhou	−0.39%	−0.44%	−0.54%	6.39%	5.94%	5.49%	−4.48%	−4.97%	−4.73%
Luohe	−0.32%	−0.37%	−0.47%	6.82%	5.37%	3.92%	−4.61%	−4.69%	−4.65%
Weifang	−0.20%	−0.25%	−0.35%	7.20%	5.25%	3.30%	−4.48%	−4.67%	−4.53%
Puyang	−0.53%	−0.58%	−0.68%	7.03%	5.58%	4.13%	−4.36%	−4.65%	−4.51%
Yantai	−0.22%	−0.27%	−0.37%	5.22%	5.27%	5.32%	−4.48%	−4.67%	−4.73%
Jiaozuo	−0.14%	−0.19%	−0.29%	6.64%	5.19%	3.74%	−3.89%	−4.36%	−4.13%
Baiyin	−0.48%	−0.53%	−0.63%	6.98%	5.53%	4.08%	−3.89%	−4.36%	−4.13%
Meishan	0.03%	−0.07%	−0.27%	7.47%	5.57%	3.67%	−3.89%	−4.36%	−4.13%
Shizuishan	−0.40%	−0.45%	−0.55%	6.90%	5.45%	4.00%	−3.43%	−3.89%	−3.66%
Mianyang	0.25%	0.15%	−0.05%	7.25%	5.85%	4.45%	−3.89%	−4.36%	−4.23%
Liaocheng	−0.65%	−0.70%	−0.80%	6.65%	5.70%	4.75%	−4.48%	−4.67%	−4.53%
Zigong	−0.81%	−0.86%	−0.96%	7.81%	7.36%	6.91%	−3.89%	−5.86%	−5.63%
Heze	−0.83%	−0.88%	−0.98%	6.83%	5.88%	4.93%	−4.48%	−4.67%	−4.53%
Xining	0.11%	0.01%	−0.19%	5.39%	4.99%	4.59%	−3.89%	−4.36%	−4.23%
Xi'an	0.40%	0.30%	0.10%	6.10%	5.20%	4.30%	−3.20%	−4.36%	−4.23%
Xuchang	−0.11%	−0.16%	−0.26%	6.61%	5.16%	3.71%	−3.66%	−4.13%	−3.89%
Ziyang	−0.99%	−1.04%	−1.14%	8.49%	7.04%	5.59%	−3.89%	−4.36%	−4.23%
Chifeng	−0.63%	−0.68%	−0.78%	6.63%	6.18%	5.73%	−3.89%	−4.86%	−4.73%
Dazhou	−0.41%	−0.46%	−0.56%	8.91%	5.96%	3.01%	−3.89%	−4.36%	−4.13%
Yuncheng	−0.54%	−0.59%	−0.69%	10.54%	5.59%	0.64%	−3.89%	−4.36%	−4.13%
Tongliao	−0.77%	−0.82%	−0.92%	6.77%	6.32%	5.87%	−3.89%	−4.96%	−4.73%
Suining	−0.58%	−0.63%	−0.73%	6.58%	6.13%	5.68%	−3.89%	−4.96%	−4.73%
Zhengzhou	0.92%	0.82%	0.62%	6.08%	4.18%	2.28%	−4.13%	−4.61%	−4.36%
Ordos	0.96%	0.86%	0.66%	4.04%	3.64%	3.24%	−3.89%	−4.26%	−4.13%
Jiuquan	−0.36%	−0.41%	−0.51%	7.36%	5.41%	3.46%	−3.89%	−4.36%	−4.13%
Jinchang	−0.44%	−0.49%	−0.59%	7.44%	5.49%	3.54%	−3.89%	−4.36%	−4.13%
Tongchuan	−0.35%	−0.40%	−0.50%	7.35%	6.40%	5.45%	−2.52%	−4.97%	−4.75%
Yinchuan	0.42%	0.32%	0.12%	5.58%	4.68%	3.78%	−3.43%	−3.99%	−3.86%
Changzhi	−0.63%	−0.68%	−0.78%	8.63%	5.68%	2.73%	−3.89%	−4.36%	−4.13%
Yangquan	−0.73%	−0.78%	−0.88%	8.73%	5.78%	2.83%	−3.89%	−4.36%	−4.13%
Longnan	−0.78%	−0.83%	−0.93%	7.78%	5.83%	3.88%	−3.89%	−4.36%	−4.13%
Ya'an	−0.10%	−0.15%	−0.25%	7.10%	6.65%	6.20%	−3.89%	−5.76%	−5.63%
Qingdao	0.82%	0.72%	0.52%	6.18%	4.28%	2.38%	−4.48%	−4.77%	−4.63%
Zhumadian	−1.09%	−1.14%	−1.24%	8.09%	6.14%	4.19%	−3.66%	−4.13%	−3.89%
Hebi	−0.16%	−0.21%	−0.31%	6.66%	5.21%	3.76%	−3.89%	−4.36%	−4.13%

Table A2. Average annual growth rates under the accelerated energy transition scenario.

City	P			E			CI		
	2025	2026–2030	2031–2035	2025	2026–2030	2031–2035	2025	2026–2030	2031–2035
Sanmenxia	−0.37%	−0.42%	−0.52%	7.03%	5.58%	4.13%	−5.21%	−5.69%	−5.45%
Dongying	0.19%	0.09%	−0.11%	4.97%	4.57%	4.17%	−5.08%	−5.57%	−5.33%
Zhongwei	0.27%	0.17%	−0.03%	6.39%	5.49%	4.59%	−4.03%	−5.49%	−5.31%
Linyi	−0.40%	−0.45%	−0.55%	6.06%	5.11%	4.16%	−5.08%	−5.27%	−5.13%
Ulanqab	−1.74%	−1.79%	−1.89%	8.40%	6.45%	4.50%	−5.08%	−5.24%	−5.11%
Wuhai	0.03%	−0.07%	−0.27%	4.63%	4.23%	3.83%	−4.49%	−4.86%	−4.73%
Leshan	−0.09%	−0.14%	−0.24%	6.25%	5.30%	4.35%	−4.85%	−5.33%	−5.08%
Xinyang	−0.98%	−1.03%	−1.13%	8.14%	5.69%	3.24%	−4.73%	−5.21%	−4.96%
Lanzhou	0.39%	0.29%	0.09%	5.77%	4.87%	3.97%	−4.03%	−5.09%	−4.86%
Neijiang	−0.66%	−0.71%	−0.81%	6.32%	5.87%	5.42%	−4.49%	−5.46%	−5.33%

Baotou	0.55%	0.45%	0.25%	6.11%	4.21%	2.31%	−4.49%	−5.46%	−4.73%
Nanchong	−0.54%	−0.59%	−0.69%	8.70%	5.75%	2.80%	−4.73%	−5.21%	−4.96%
Nanyang	−0.70%	−0.75%	−0.85%	7.86%	5.41%	2.96%	−4.73%	−5.21%	−4.96%
Luliang	−0.55%	−0.60%	−0.70%	8.21%	5.26%	2.31%	−4.49%	−4.96%	−4.73%
Wuzhong	0.64%	0.54%	0.34%	5.52%	4.12%	2.72%	−4.03%	−4.49%	−4.26%
Zhoukou	−1.10%	−1.15%	−1.25%	6.76%	6.31%	5.86%	−4.26%	−5.49%	−5.29%
Hulunbuir	−1.09%	−1.14%	−1.24%	5.75%	5.30%	4.85%	−4.49%	−4.76%	−4.63%
Hohhot	1.32%	1.22%	1.02%	4.34%	3.44%	2.54%	−4.49%	−4.96%	−4.73%
Xianyang	0.75%	0.65%	0.45%	5.91%	5.01%	4.11%	−3.80%	−5.56%	−5.33%
Shangqiu	−0.61%	−0.66%	−0.76%	8.27%	6.32%	4.37%	−4.96%	−5.45%	−5.21%
Shangluo	−0.49%	−0.54%	−0.64%	6.65%	5.20%	3.75%	−3.35%	−5.36%	−4.40%
Jiayuguan	0.47%	0.37%	0.17%	5.69%	4.29%	2.89%	−4.49%	−4.96%	−4.73%
Guyuan	−0.07%	−0.12%	−0.22%	7.03%	4.78%	2.53%	−4.03%	−4.49%	−4.26%
Datong	−0.41%	−0.46%	−0.56%	8.57%	5.12%	1.67%	−4.49%	−4.96%	−4.73%
Tianshui	−0.76%	−0.81%	−0.91%	6.92%	6.47%	6.02%	−4.49%	−5.96%	−5.73%
Taiyuan	0.89%	0.79%	0.57%	7.27%	3.87%	0.45%	−4.61%	−5.08%	−4.83%
Weihai	0.03%	−0.07%	−0.27%	5.13%	4.73%	4.33%	−5.08%	−5.27%	−5.13%
Ankang	−0.40%	−0.45%	−0.55%	6.56%	5.11%	3.66%	−4.26%	−4.73%	−4.49%
Anyang	−0.41%	−0.46%	−0.56%	6.07%	5.12%	4.17%	−4.49%	−4.96%	−4.73%
Dingxi	−0.51%	−0.56%	−0.66%	6.87%	5.22%	3.57%	−4.49%	−4.96%	−4.73%
Yibin	0.10%	0.00%	−0.20%	7.86%	5.16%	2.46%	−4.49%	−4.96%	−4.73%
Baoji	−0.53%	−0.58%	−0.68%	7.19%	5.74%	4.29%	−3.80%	−4.66%	−4.43%
Bazhong	−0.97%	−1.02%	−1.12%	6.63%	6.18%	5.73%	−4.49%	−5.56%	−5.33%
Bayannur	−0.76%	−0.81%	−0.91%	5.42%	4.97%	4.52%	−4.49%	−4.86%	−4.63%
Pingliang	−1.03%	−1.08%	−1.18%	7.19%	5.74%	4.29%	−4.49%	−4.96%	−4.73%
Pingdingshan	−0.56%	−0.61%	−0.71%	7.22%	5.27%	3.32%	−5.21%	−5.29%	−5.25%
Guangyuan	−0.85%	−0.90%	−1.00%	7.51%	6.06%	4.61%	−4.49%	−4.96%	−4.73%
Guang'an	−0.20%	−0.25%	−0.35%	6.86%	5.41%	3.96%	−4.49%	−4.96%	−4.73%
Qingyang	−0.57%	−0.62%	−0.72%	7.23%	6.28%	5.33%	−4.49%	−5.56%	−5.33%
Yan'an	−0.33%	−0.38%	−0.48%	6.49%	5.04%	3.59%	−4.49%	−4.96%	−4.73%
Kaifeng	−0.68%	−0.73%	−0.83%	8.84%	5.39%	1.94%	−4.49%	−4.96%	−4.73%
Zhangye	−0.67%	−0.72%	−0.82%	6.83%	5.38%	3.93%	−4.49%	−4.96%	−4.73%
Dezhou	−0.60%	−0.65%	−0.75%	6.26%	5.81%	5.36%	−5.08%	−5.57%	−5.33%
Deyang	−0.05%	−0.10%	−0.20%	6.21%	5.76%	5.31%	−4.49%	−6.06%	−5.83%
Xinzhou	−0.79%	−0.84%	−0.94%	8.45%	5.50%	2.55%	−4.49%	−4.96%	−4.73%
Chengdu	0.62%	0.52%	0.32%	5.04%	4.64%	4.24%	−4.49%	−5.56%	−5.33%
Panzhihua	0.14%	0.04%	−0.16%	7.02%	5.12%	3.22%	−4.49%	−4.96%	−4.73%
Xinxiang	−0.60%	−0.65%	−0.75%	6.76%	5.31%	3.86%	−4.96%	−5.25%	−5.11%
Rizhao	−0.35%	−0.40%	−0.50%	6.51%	5.06%	3.61%	−5.08%	−5.27%	−5.13%
Jinzhong	−0.30%	−0.35%	−0.45%	8.96%	5.01%	1.06%	−4.49%	−4.96%	−4.73%
Jincheng	−0.39%	−0.44%	−0.54%	9.05%	5.10%	1.15%	−4.49%	−4.96%	−4.73%
Shuozhou	−0.34%	−0.39%	−0.49%	8.00%	5.05%	2.10%	−4.49%	−4.96%	−4.73%
Zaozhuang	−0.32%	−0.37%	−0.47%	5.98%	5.03%	4.08%	−5.08%	−5.27%	−5.13%
Yulin	−0.07%	−0.12%	−0.22%	6.23%	4.78%	3.33%	−4.73%	−5.21%	−4.96%
Wuwei	−0.68%	−0.73%	−0.83%	6.84%	5.39%	3.94%	−4.49%	−4.96%	−4.73%
Hanzhong	−0.39%	−0.44%	−0.54%	7.05%	6.10%	5.15%	−3.80%	−5.46%	−5.33%
Tai'an	−0.87%	−0.92%	−1.02%	6.03%	5.58%	5.13%	−5.08%	−5.27%	−5.13%
Luzhou	0.08%	−0.02%	−0.22%	7.58%	5.18%	2.78%	−4.49%	−4.96%	−4.73%
Luoyang	0.07%	−0.03%	−0.23%	8.09%	4.69%	1.29%	−4.49%	−4.96%	−4.73%
Jinan	0.72%	0.62%	0.42%	5.94%	4.04%	2.14%	−5.08%	−5.37%	−5.23%
Jining	−0.51%	−0.56%	−0.66%	6.17%	5.22%	4.27%	−5.08%	−5.27%	−5.13%
Zibo	−0.35%	−0.40%	−0.50%	7.01%	5.06%	3.11%	−5.08%	−5.27%	−5.13%
Weinan	−0.59%	−0.64%	−0.74%	6.75%	5.80%	4.85%	−3.80%	−5.06%	−4.93%

Binzhou	−0.39%	−0.44%	−0.54%	6.05%	5.60%	5.15%	−5.08%	−5.57%	−5.33%
Luohe	−0.32%	−0.37%	−0.47%	6.48%	5.03%	3.58%	−5.21%	−5.29%	−5.25%
Weifang	−0.20%	−0.25%	−0.35%	6.86%	4.91%	2.96%	−5.08%	−5.27%	−5.13%
Puyang	−0.53%	−0.58%	−0.68%	6.69%	5.24%	3.79%	−4.96%	−5.25%	−5.11%
Yantai	−0.22%	−0.27%	−0.37%	4.88%	4.93%	4.98%	−5.08%	−5.27%	−5.33%
Jiaozuo	−0.14%	−0.19%	−0.29%	6.30%	4.85%	3.40%	−4.49%	−4.96%	−4.73%
Baiyin	−0.48%	−0.53%	−0.63%	6.64%	5.19%	3.74%	−4.49%	−4.96%	−4.73%
Meishan	0.03%	−0.07%	−0.27%	7.13%	5.23%	3.33%	−4.49%	−4.96%	−4.73%
Shizuishan	−0.40%	−0.45%	−0.55%	6.56%	5.11%	3.66%	−4.03%	−4.49%	−4.26%
Mianyang	0.25%	0.15%	−0.05%	6.91%	5.51%	4.11%	−4.49%	−4.96%	−4.83%
Liaocheng	−0.65%	−0.70%	−0.80%	6.31%	5.36%	4.41%	−5.08%	−5.27%	−5.13%
Zigong	−0.81%	−0.86%	−0.96%	7.47%	7.02%	6.57%	−4.49%	−6.46%	−6.23%
Heze	−0.83%	−0.88%	−0.98%	6.49%	5.54%	4.59%	−5.08%	−5.27%	−5.13%
Xining	0.11%	0.01%	−0.19%	5.05%	4.65%	4.25%	−4.49%	−4.96%	−4.83%
Xi'an	0.40%	0.30%	0.10%	5.76%	4.86%	3.96%	−3.80%	−4.96%	−4.83%
Xuchang	−0.11%	−0.16%	−0.26%	6.27%	4.82%	3.37%	−4.26%	−4.73%	−4.49%
Ziyang	−0.99%	−1.04%	−1.14%	8.15%	6.70%	5.25%	−4.49%	−4.96%	−4.83%
Chifeng	−0.63%	−0.68%	−0.78%	6.29%	5.84%	5.39%	−4.49%	−5.46%	−5.33%
Dazhou	−0.41%	−0.46%	−0.56%	8.57%	5.62%	2.67%	−4.49%	−4.96%	−4.73%
Yuncheng	−0.54%	−0.59%	−0.69%	10.20%	5.25%	0.30%	−4.49%	−4.96%	−4.73%
Tongliao	−0.77%	−0.82%	−0.92%	6.43%	5.98%	5.53%	−4.49%	−5.56%	−5.33%
Suining	−0.58%	−0.63%	−0.73%	6.24%	5.79%	5.34%	−4.49%	−5.56%	−5.33%
Zhengzhou	0.92%	0.82%	0.62%	5.74%	3.84%	1.94%	−4.73%	−5.21%	−4.96%
Ordos	0.96%	0.86%	0.66%	3.70%	3.30%	2.90%	−4.49%	−4.86%	−4.73%
Jiuquan	−0.36%	−0.41%	−0.51%	7.02%	5.07%	3.12%	−4.49%	−4.96%	−4.73%
Jinchang	−0.44%	−0.49%	−0.59%	7.10%	5.15%	3.20%	−4.49%	−4.96%	−4.73%
Tongchuan	−0.35%	−0.40%	−0.50%	7.01%	6.06%	5.11%	−3.12%	−5.57%	−5.35%
Yinchuan	0.42%	0.32%	0.12%	5.24%	4.34%	3.44%	−4.03%	−4.59%	−4.46%
Changzhi	−0.63%	−0.68%	−0.78%	8.29%	5.34%	2.39%	−4.49%	−4.96%	−4.73%
Yangquan	−0.73%	−0.78%	−0.88%	8.39%	5.44%	2.49%	−4.49%	−4.96%	−4.73%
Longnan	−0.78%	−0.83%	−0.93%	7.44%	5.49%	3.54%	−4.49%	−4.96%	−4.73%
Ya'an	−0.10%	−0.15%	−0.25%	6.76%	6.31%	5.86%	−4.49%	−6.36%	−6.23%
Qingdao	0.82%	0.72%	0.52%	5.84%	3.94%	2.04%	−5.08%	−5.37%	−5.23%
Zhumadian	−1.09%	−1.14%	−1.24%	7.75%	5.80%	3.85%	−4.26%	−4.73%	−4.49%
Hebi	−0.16%	−0.21%	−0.31%	6.32%	4.87%	3.42%	−4.49%	−4.96%	−4.73%

Table A3. Carbon peaking timeline for cities in the Yellow River Basin.

City	Baseline Scenario	Accelerated Energy Transition Scenario	City	Baseline Scenario	Accelerated Energy Transition Scenario	City	Baseline Scenario	Accelerated Energy Transition Scenario
Sanmenxia	2028	2025	Bayannur	2028	2025	Puyang	2029	2025
Dongying	2027	2025	Pingliang	2029	2025	Yantai	2028	2025
Zhongwei	2029	2027	Pingdingshan	2029	2025	Jiaozuo	2028	2026
Linyi	2029	2025	Guangyuan	2028	2027	Baiyin	2028	2026
Ulanqab	2028	2025	Guang'an	2029	2027	Meishan	2029	2027
Wuhai	2029	2025	Qingyang	2029	2027	Shizuishan	2030	2027
Leshan	2028	2027	Yan'an	2028	2026	Mianyang	2029	2028
Xinyang	2028	2025	Kaifeng	2028	2026	Liaocheng	2029	2025
Lanzhou	2029	2027	Zhangye	2028	2026	Zigong	2029	2025
Neijiang	2029	2025	Dezhou	2028	2025	Heze	2029	2025
Baotou	2027	2025	Deyang	2029	2025	Xining	2029	2025
Nanchong	2029	2026	Xin Zhou	2029	2026	Xi'an	2029	2027

Nanyang	2028	2025	Chengdu	2028	2026	Xuchang	2029	2027
Luliang	2030	2025	Panzhihua	2029	2027	Ziyang	2029	2028
Wuzhong	2028	2027	Xinxiang	2028	2025	Chifeng	2029	2025
Zhoukou	2028	2025	Rizhao	2029	2025	Dazhou	2029	2027
Hulunbuir	2029	2025	Jinzhong	2030	2025	Yuncheng	2029	2026
Hohhot	2028	2027	Jincheng	2029	2025	Tongliao	2028	2025
Xianyang	2029	2027	Shuozhou	2030	2025	Suining	2028	2025
Shangqiu	2028	2027	Zaozhuang	2028	2025	Zhengzhou	2028	2025
Shangluo	2027	2025	Yulin	2031	2025	Ordos	2029	2025
Jiayuguan	2030	2025	Wuwei	2028	2026	Jiuquan	2028	2026
Guyuan	2028	2027	Hanzhong	2029	2027	Jinchang	2030	2025
Datong	2030	2025	Tai'an	2028	2025	Tongchuan	2029	2027
Tianshui	2030	2025	Luzhou	2031	2027	Yinchuan	2028	2027
Taiyuan	2029	2025	Luoyang	2029	2026	Changzhi	2029	2026
Weihai	2029	2025	Jinan	2028	2025	Yangquan	2029	2026
Ankang	2028	2027	Jining	2029	2025	Longnan	2029	2026
Anyang	2029	2025	Zibo	2028	2025	Ya'an	2029	2026
Dingxi	2028	2026	Weinan	2029	2027	Qingdao	2028	2025
Yibin	2029	2027	Binzhou	2028	2025	Zhumadian	2030	2026
Baoji	2029	2028	Luohe	2029	2025	Hebi	2028	2026
Bazhong	2028	2025	Weifang	2029	2025	Puyang	2029	2025

Table A4. Sensitivity analysis of cities in the Yellow River Basin.

City	P	E	CI
Sanmenxia	2028	2028	2028
Dongying	2027	2027	2027
Zhongwei	2033	2033	2033
Linyi	2030	2030	2030
Ulanqab	2028	2028	2028
Wuhai	2030	2030	2030
Leshan	2029	2029	2029
Xinyang	2028	2028	2028
Lanzhou	2029	2029	2029
Neijiang	2029	2029	2029
Baotou	2027	2027	2027
Nanchong	2030	2030	2030
Nanyang	2028	2028	2028
Luliang	2030	2030	2030
Wuzhong	2029	2029	2029
Zhoukou	2029	2029	2029
Hulunbuir	2030	2030	2030
Hohhot	2028	2028	2028
Xianyang	2029	2029	2034
Shangqiu	2028	2028	2028
Shangluo	2028	2028	2028
Jiayuguan	2030	2030	2030
Guyuan	2028	2028	2028
Datong	2030	2030	2030
Tianshui	2035	2035	2035
Taiyuan	2029	2029	2029
Weihai	2030	2030	2030
Ankang	2028	2028	2028

Anyang	2030	2030	2030
Dingxi	2029	2029	2029
Yibin	2029	2029	2029
Baoji	2031	2031	2031
Bazhong	2029	2029	2029
Bayannur	2028	2028	2028
Pingliang	2029	2029	2029
Pingdingshan	2030	2030	2030
Guangyuan	2029	2029	2029
Guang'an	2029	2029	2029
Qingyang	2032	2032	2032
Yan'an	2029	2029	2029
Kaifeng	2029	2029	2029
Zhangye	2029	2029	2029
Dezhou	2028	2028	2028
Deyang	2031	2030	2031
Xinzhou	2029	2029	2029
Chengdu	2028	2028	2028
Panzhuhua	2029	2029	2029
Xinxiang	2028	2028	2028
Rizhao	2030	2030	2030
Jinzhong	2030	2030	2030
Jincheng	2030	2030	2030
Shuozhou	2030	2030	2030
Zaozhuang	2028	2028	2028
Yulin	2031	2031	2031
Wuwei	2029	2029	2029
Hanzhong	2029	2029	2029
Tai'an	2028	2028	2028
Luzhou	2031	2031	2031
Luoyang	2029	2029	2029
Jinan	2030	2030	2030
Jining	2030	2030	2030
Zibo	2029	2029	2029
Weinan	2030	2030	2030
Binzhou	2028	2028	2028
Luohe	2030	2030	2030
Weifang	2029	2029	2030
Puyang	2030	2029	2030
Yantai	2035	2029	2035
Jiaozuo	2028	2028	2028
Baiyin	2029	2029	2029
Meishan	2029	2029	2029
Shizuishan	2030	2030	2030
Mianyang	2035	2035	2035
Liaocheng	2030	2030	2030
Zigong	2030	2030	2030
Heze	2030	2030	2030
Xining	2035	2035	2035
Xi'an	2035	2035	2035
Xuchang	2029	2029	2029
Ziyang	2035	2034	2035
Chifeng	2029	2029	2029

Dazhou	2029	2029	2029
Yuncheng	2029	2029	2029
Tongliao	2028	2028	2028
Suining	2028	2028	2028
Zhengzhou	2028	2028	2028
Ordos	2029	2029	2029
Jiuquan	2028	2028	2028
Jinchang	2030	2030	2030
Tongchuan	2029	2029	2029
Yinchuan	2029	2029	2029
Changzhi	2029	2029	2029
Yangquan	2029	2029	2029
Longnan	2029	2029	2029
Ya'an	2029	2029	2029
Qingdao	2028	2028	2028
Zhumadian	2030	2030	2030
Hebi	2028	2028	2028

References

1. Su, Z.; Park, K.; Liu, Z.; Su, M. Key Factors for Non-Polar Use of the Northern Sea Route: A Korean Point of View. *J. Transp. Geogr.* **2025**, *124*, 104183. <https://doi.org/10.1016/j.jtrangeo.2025.104183>.
2. Fang, L.; Li, L.; Li, J. A Study on the Impact of Two-way Direct Investment Coordinated Development on Carbon Productivity in the Yellow River Basin. *J. Shaanxi Norm. Univ. Philos. Soc. Sci. Ed.* **2025**, *54*, 87–101. <https://doi.org/10.15983/j.cnki.sxss.2025.0107>.
3. Zhao, J.; Zhang, J.; Li, W.; Liu, Q. Impact of Urban Sprawl on Carbon Emissions in the Yellow River Basin: Empirical Research Based on Nighttime Light Data. *Prog. Geogr.* **2025**, *44*, 1596–1616. <https://doi.org/10.18306/dlkxjz.2025.08.004>.
4. Liu, Y.; Xu, J.; Liu, Y. Research on the Coupling and Coordination Relationship between Ecological Environment and Cultural Tourism Industry in the Yellow River Basin. *Econ. Probl.* **2024**, *46*, 105–112. <https://doi.org/10.16011/j.cnki.jjw.2024.02.011>.
5. Xu, X.; Li, W. Synergistic Effects and Mechanisms of Industrial Green Development on Pollution and Carbon Reduction: A Case Study of the Yellow River Basin. *J. China Univ. Geosci. Soc. Sci. Ed.* **2025**, *25*, 95–109. <https://doi.org/10.16493/j.cnki.42-1627/c.20250702.001>.
6. Cai, Y.; Niu, X. Scale Measurement and Structural Analysis of the Value-added of China's Digital Economy. *Soc. Sci. China* **2021**, *42*, 4–30+204.
7. Pang, R.; Wang, H. Digital Economy and Urban Green Development: Empowerment or Negative Energy? *Stud. Sci. Sci.* **2024**, *42*, 1397–1408. <https://doi.org/10.16192/j.cnki.1003-2053.20230802.001>.
8. National Energy Administration. Several Opinions on Accelerating the Digital and Intelligent Development of the Energy Sector. 2023. Available online: https://www.gov.cn/zhengce/zhengceku/2023-04/02/content_5749758.htm (accessed on 29 May 2026).
9. Hu, A. China's Goal of Achieving Carbon Peak by 2030 and Its Main Approaches. *J. Beijing Univ. Technol. Soc. Sci. Ed.* **2021**, *21*, 1–15. <https://doi.org/10.12120/bjutskb202103001>.
10. Ge, L.; Mo, L.; Huang, N. Development of Digital Economy, Upgrading of Industrial Structure and Urban Carbon Emission. *Mod. Financ. Econ.-J. Tianjin Univ. Econ.* **2022**, *42*, 20–37. <https://doi.org/10.19559/j.cnki.12-1387.2022.10.002>.
11. Jiang, Y.; Liu, M.; Yang, C. Driving Mechanisms of Digitalization on the Coordinated Development of Economic Growth and the Ecological Environment. *China Popul. Resour. Environ.* **2023**, *33*, 171–181.
12. Shahbaz, M.; Wang, J.; Dong, K.; Zhao, J. The Impact of Digital Economy on Energy Transition Across the Globe: The Mediating Role of Government Governance. *Renew. Sustain. Energy Rev.* **2022**, *166*, 112620. <https://doi.org/10.1016/j.rser.2022.112620>.
13. Chen, X.; Hu, D.; Cao, W.; Liang, W.; Xu, X.; Tang, X.; Wang, Y. Path of Digital Technology Promoting Realization of Carbon Neutrality Goal in China's Energy Industry. *Bull. Chin. Acad. Sci.* **2021**, *36*, 1019–1029. <https://doi.org/10.16418/j.issn.1000-3045.20210807004>.
14. Wu, X.; He, A. Digital Technology Boosts Construction of China's Modern Energy System: Enabling Mechanisms, Practical Problems and Implementation Paths. *Inq. Econ.* **2024**, *45*, 1–14.

15. Lee, C.C.; Fang, Y.; Quan, S.; Li, X. Leveraging the Power of Artificial Intelligence Toward the Energy Transition: The Key Role of the Digital Economy. *Energy Econ.* **2024**, *135*, 107654. <https://doi.org/10.1016/j.eneco.2024.107654>.
16. Huang, C.; Lin, B. How Digital Economy Index Selection and Model Uncertainty Will Affect Energy Green Transition. *Energy Econ.* **2024**, *136*, 107774. <https://doi.org/10.1016/j.eneco.2024.107774>.
17. Che, S.; Tao, M.; Wang, H.; Roubaud, D. The Power of Digital Empowerment in the Process of Energy Low-Carbon Transition: Dimension Decomposition and Path Exploration. *Energy Econ.* **2026**, *155*, 109215. <https://doi.org/10.1016/j.eneco.2026.109215>.
18. Chen, G.; Eweade, B.S.; Ozsahin, D.U. The Industrialization Paradox under Energy-Transition Policies: Do ICT, Economic Growth and Natural Resource Rents Promote Renewable Energy Adoption? *Environ. Prog. Sustain. Energy* **2026**, *45*, e70226. <https://doi.org/10.1002/ep.70226>.
19. Jin, X.; Eweade, B.S.; Ozsahin, D.U.; Uzun, B. Do Energy Policy Uncertainty, Trade Openness, and Renewable Energy Drive Artificial Intelligence Investment? Evidence from the United States. *Humanit. Soc. Sci. Commun.* **2026**, *13*, 679. <https://doi.org/10.1057/s41599-026-06955-0>.
20. Khan, A.; Sun, C. Digital Economy, Green Growth, and Global Energy Transition. *China World Econ.* **2026**, *34*, 173–197. <https://doi.org/10.1111/cwe.70009>.
21. Xu, J.; Chen, Y.; Yang, N.; Shao, S. The Impact of Artificial Intelligence on the Energy Transition: Evidence From Chinese Cities. *World Dev.* **2025**, *195*, 107126. <https://doi.org/10.1016/j.worlddev.2025.107126>.
22. Dong, Y.; Yuan, K.; Zhao, X.; Gong, X. Digital Economy Enabling Urban Energy Transition: Based on the Perspective of Heterogeneous Constraints of Government and the Public. *China Popul. Resour. Environ.* **2025**, *35*, 100–111.
23. Xie, D.; Wei, W.; Li, Y. Data and Computing Power Economy: A General Equilibrium Theory of the Digital Economy. *Manag. World* **2026**, *42*, 37–56+77+57–63. <https://doi.org/10.19744/j.cnki.11-1235/f.2026.0033>.
24. Endeer, B.; Eweade, B.S.; Djafar Henni, M.; Uzun, B. Industrialization, ICT, and China's Environmental Transition Toward Carbon Neutrality: Evidence from Wavelet Cross-Quantile Regression. *Environ. Sci. Eur.* **2026**, *38*, 48. <https://doi.org/10.1186/s12302-026-01353-4>.
25. Gu, Z. Emission Reduction Effect of Cultural Tourism in the Context of Carbon Peaking and Carbon Neutrality: An Empirical Study Based on Panel Data of Counties in China. *Tour. Sci.* **2024**, *38*, 58–83. <https://doi.org/10.16323/j.cnki.lykx.2024.02.002>.
26. Gu, Q.; Lin, L. The Effectiveness, Influencing Factors, and Peak Pathing of Carbon Reduction in the Manufacturing Industry Under the “Dual Carbon” Target: Based on Panel Data Analysis of Manufacturing Province. *Econ. Probl.* **2024**, *46*, 57–63. <https://doi.org/10.16011/j.cnki.jjw.2024.02.008>.
27. Zhang, Y. Analysis of China's Energy Efficiency and Influencing Factors Under Carbon Peaking and Carbon Neutrality Goals. *J. Clean. Prod.* **2022**, *370*, 133604. <https://doi.org/10.1016/j.jclepro.2022.133604>.
28. Fan, Y.; Yi, B. Evolution, Driving Mechanism, and Pathway of China's Energy Transition. *Manag. World* **2021**, *37*, 95–105. <https://doi.org/10.19744/j.cnki.11-1235/f.2021.0109>.
29. Dai, W.; Eweade, B.S.; Brika, S.K.; Uzun, B.; Dong, C. Do Globalization, Foreign Direct Investment, Trade Openness, and Urbanization Propel Renewable Energy Transition? Empirical Evidence from Kernel Regularized Quantile Regression Modeling. *Environ. Prog. Sustain. Energy* **2025**, *44*, e70038. <https://doi.org/10.1002/ep.70038>.
30. Chen, W.; Tian, Y.; Bai, C.; Ma, Y. Renewable Energy Maintenance Strategies for Power Supply Chain Considering Extreme Weather. *Chin. J. Manag. Sci.* **2025**, *33*, 359–368. <https://doi.org/10.16381/j.cnki.issn1003-207x.2022.2669>.
31. Eweade, B.S. Do Natural Resources, Renewable Energy, Urbanisation, and Economic Growth Drive Brazil's Ecological Footprint? A Quantile ARDL Approach. *Geol. J.* **2025**, 1–15. <https://doi.org/10.1002/gj.70145> (accessed on 8 June 2026).
32. Eweade, B.S.; Seraj, M.; Ozdeser, H. Synchronising Sustainability: Do Technological Advancement, Financial Development and Renewable Energy Matter in Finland? *Geol. J.* **2026**, 1–17. <https://doi.org/10.1002/gj.70287> (accessed on 8 June 2026).
33. Lu, Y.; Guo, Y. Overview and Prospect of Carbon Neutrality. *J. Beijing Univ. Technol. Soc. Sci. Ed.* **2024**, *24*, 116–134. <https://doi.org/10.12120/bjutskb.202401116>.
34. Amin, A.; Peng, S.; Magazzino, C.; Sharif, A.; Kamran, H.W. Driving Sustainable Development: The Impact of Energy Transition, Eco-innovation, Mineral Resources, and Green Growth on Carbon Emissions. *Renew. Energy* **2025**, *238*, 121879. <https://doi.org/10.1016/j.renene.2024.121879>.
35. Liu, D.; Zhang, Y. Empirical Simulation Research on the Impact of Energy Transition on the Carbon Peak Inflection Point in Zhejiang Province. *Resour. Sci.* **2024**, *46*, 1699–1708. <https://doi.org/10.18402/resci.2024.09.03>.
36. Athari, S.A.; Eweade, B.S.; Awosusi, A.A.; Kirikkaleli, D. Beyond Fossil Fuels: How Iceland's Oil Efficiency, Hydro Energy, and Fiscal Decentralization Propel a Cleaner Environment: Evidence from Wavelet Quantile Methods. *Environ. Sustain. Indic.* **2025**, *28*, 101040. <https://doi.org/10.1016/j.indic.2025.101040>.

37. Li, J.; Li, J. How Do Algorithms Exploit Nature: Ecological Critique of Digital Capitalism and Reconstruction of Its Landscape. *J. Shanxi Univ. Philos. Soc. Sci. Ed.* **2026**, *49*, 123–130. [https://doi.org/10.13451/j.cnki.shanxi.univ\(phil.soc.\).2026.03.013](https://doi.org/10.13451/j.cnki.shanxi.univ(phil.soc.).2026.03.013).
38. Xu, X.; Yang, W.; Wu, B. Multiple Pathways for Rural Digital Economy Empowering Agricultural Total Factor Productivity: A Configuration Analysis Based on County-level Data from Zhejiang Province. *Chin. Rural Econ.* **2024**, *40*, 84–103. <https://doi.org/10.20077/j.cnki.11-1262/f.2024.10.005>.
39. Pan, Z.; Gao, H. Artificial Intelligence Penetration and Global Carbon Emission Reduction: An Empirical Analysis Based on Panel Data of 61 Countries. *Inq. Econ.* **2025**, *46*, 73–90.
40. Wang, F.; Dong, Z.F. The Impact of Digital Economy on Carbon Emissions in China: Empirical Analysis Based on Provincial Panel Data. *Reform* **2023**, *36*, 76–90.
41. Yang, G.; Wang, H.; Fan, H.; Yue, Z. Carbon Reduction Effect of Digital Economy: Theoretical Analysis and Empirical Evidence. *China Ind. Econ.* **2023**, *41*, 80–98. <https://doi.org/10.19581/j.cnki.ciejournal.2023.05.005>.
42. Tang, T.; Wu, S.; Chen, D. The Impact of Digital Technology Innovation on Carbon Unlock Efficiency—An Empirical Analysis of the Yangtze River Economic Belt. *China Bus. Mark.* **2026**, *40*, 99–112. <https://doi.org/10.14089/j.cnki.cn11-3664/f.2026.01.008>.
43. Romer, P.M. Increasing Returns and Long-Run Growth. *J. Political Econ.* **1986**, *94*, 1002–1037.
44. Jiang, X.; Hu, D. An Evolutionary Game Study on Government Participation in Industrial Chain Collaborative Innovation under the Background of Digitalization—Based on the Perspective of Chain Chief System. *J. China Univ. Geosci. Soc. Sci. Ed.* **2024**, *24*, 116–130. <https://doi.org/10.16493/j.cnki.42-1627/c.20240718.002>.
45. Yang, Z.; Fang, Y. Innovation Network Governance for New Quality Productive Forces. *Tianjin Soc. Sci.* **2026**, *46*, 99–107. <https://doi.org/10.16240/j.cnki.1002-3976.2026.03.005>.
46. Yang, G.; Zhang, G.; Cao, D. How Can Renewable Energy Technological Innovation Drive City-level Energy Transition? An Investigation from the Comprehensive Energy Balance Table. *Syst. Eng. Theory Pract.* **2025**, *45*, 1113–1130. <https://doi.org/10.12011/SETP2023-1006>.
47. Gao, Y.; Wang, L. How Can Digital Government Construction Enhance Local Government Governance? Evidence Based on the Reform of Big Data Management Institutions. *Inq. Econ.* **2025**, *46*, 18–36.
48. Qin, Y.; Wang, Y. The Multidimensional Starting Points, Connotative Implications and Subjective Actions of the Construction of a Leading Country in Education. *China Educ. Technol.* **2024**, *45*, 1–6+44.
49. Luo, Y.; Wang, Y. Digital Economy Development and Skilled Wage Gap: Theoretical Analysis and Empirical Test. *Inq. Econ. Issues* **2024**, *45*, 152–167.
50. Sun, Q.; Li, G.; Xue, J. Digital Economy Development Mitigating Carbon Emission Inequality: Evidence from Biased Technical Progress. *China Popul. Resour. Environ.* **2025**, *35*, 16–26.
51. Zhang, B.; Dong, A.; Duan, Y. How Does the Carbon Peak Target Lead the Low-Carbon Transformation of Cities? Evidence from Quasi-Natural Experiments. *J. Quant. Technol. Econ.* **2024**, *41*, 177–196. <https://doi.org/10.13653/j.cnki.jqte.20240523.001>.
52. Yang, W.; Yang, Y.; Zhu, C. Digital Economy and Dual Carbon Goals: Theory and Evidence. *J. Syst. Manag.* **2025**, *34*, 541–556. <https://doi.org/10.3969/j.issn.2097-4558.2025.02.018>.
53. Xu, Y.; He, L. Spatial Correlation Network of the Digital Economy and Urban Green Development: Carbon Reduction or Carbon Rebound? *J. Shanghai Jiaotong Univ. Philos. Soc. Sci. Ed.* **2026**, *34*, 116–141. <https://doi.org/10.13806/j.cnki.issn1008-7095.2026.05.009>.
54. Hou, X.; Li, Z.; Wang, X.; Xie, X. Spatial Effect of Green Financial Agglomeration on Carbon Peak Pressure at the Provincial Level. *Econ. Geogr.* **2026**, *46*, 161–170. <https://doi.org/10.15957/j.cnki.jjdl.2026.01.016>.
55. Jian, R. A Research on the Influence of Enterprise Digital Transformation on Carbon Information Disclosure. *Southeast Acad. Res.* **2024**, *37*, 86–96. <https://doi.org/10.13658/j.cnki.sar.2024.02.007>.
56. Jiang, T. Mediating Effects and Moderating Effects in Causal Inference. *China Ind. Econ.* **2022**, *40*, 100–120. <https://doi.org/10.19581/j.cnki.ciejournal.2022.05.005>.
57. Dong, K. Research on the Impact of Digital Economy on Urban-Rural Integration—An Empirical Analysis Based on the Chengdu-Chongqing Economic Circle. *Ref. Econ. Syst.* **2024**, *42*, 61–69.
58. Li, W.; Liu, Y.; Cao, Y. Digital Inclusive Finance, Dynamic Capabilities and Growth Performance of Entrepreneurial Firms. *Manag. Rev.* **2026**, *38*, 135–148. <https://doi.org/10.14120/j.cnki.cn11-5057/f.2026.02.016>.
59. Lee, C.C.; Song, H.; An, J. The Impact of Green Finance on Energy Transition: Does Climate Risk Matter? *Energy Econ.* **2024**, *129*, 107258. <https://doi.org/10.1016/j.eneco.2023.107258>.

60. Zhang, J.; Yang, D.; Zhang, S.; Ji, Y.; Meng, H.; Wan, M.; Yang, H. The Spatiotemporal Change and Correlation of Energy Transition and Urban-Rural Income Gaps in the Yangtze River Economic Belt. *Resour. Sci.* **2024**, *46*, 1780–1792. <https://doi.org/10.18402/resci.2024.09.09>.
61. Liu, J.; Chen, Y. Digital Technology Development, Temporal and Spatial Effects, Regional Carbon Emissions. *Stud. Sci. Sci.* **2023**, *41*, 841–853. <https://doi.org/10.16192/j.cnki.1003-2053.20220325.002>.
62. Wang, J.; Wang, W.; Liu, Y. How Can New Energy Vehicles Drive Renewable Energy Technology Innovation? A Test Based on the Difference-in-differences Model. *Ind. Econ. Res.* **2024**, *23*, 115–129. <https://doi.org/10.13269/j.cnki.ier.2024.02.006>.
63. Cao, Y.; Zou, X. Regional Carbon Peak Pressure and Corporate Environmental Information Disclosure: Incentive or Catering? *J. Cent. South Univ. Soc. Sci. Ed.* **2023**, *29*, 92–103. <https://doi.org/10.11817/j.issn.1672-3104.2023.06.010>.
64. Wang, Z.; Cao, X.; Ren, X.; Gozgor, G. Digital Finance and the Energy Transition: Evidence from Chinese Prefecture-level Cities. *Glob. Financ. J.* **2024**, *61*, 100987. <https://doi.org/10.1016/j.gfj.2024.100987>.
65. Zhang, S.; Dou, W.; Ji, R.; Afthanorhan, A.; Hao, Y. Can Green Finance Promote the Low-carbon Transformation of the Energy System? New Evidence from City-level Data in China. *J. Environ. Manag.* **2024**, *365*, 121577. <https://doi.org/10.1016/j.jenvman.2024.121577>.
66. Chen, S.; Chen, D. Air Pollution, Government Regulations and High-quality Economic Development. *Econ. Res. J.* **2018**, *53*, 20–34.
67. Guo, A.; Xu, Y.; Yang, C. The Nonlinear Relationship Between Digital Technology, Industrial Structure and Urban Innovation Quality: An Empirical Study Based on 282 Cities in China. *Inq. Econ.* **2025**, *46*, 90–106.
68. Chen, M.; Yue, H.; Hao, Y.; Liu, W. The Spatial Disparity, Dynamic Evolution and Driving Factors of Ecological Efficiency in the Yellow River Basin. *J. Quant. Technol. Econ.* **2021**, *38*, 25–44. <https://doi.org/10.13653/j.cnki.jqte.2021.09.002>.
69. Zou, X.; Yang, L.; Sun, X.; Liu, S. Measurement, Spatio-temporal Evolution, and Influencing Factors of Carbon Peak Levels in the Yangtze River Delta Urban Agglomeration. *Soft Sci.* **2025**, *39*, 64–71. <https://doi.org/10.13956/j.ss.1001-8409.2025.11.08>.
70. Liu, H.; Xu, Y.; Tang, Y.; Zhang, M. Prediction of Carbon Peak Under Multiple Scenarios for Provincial Administrative Units in the Yangtze River Economic Belt. *Resour. Environ. Yangtze Basin* **2025**, *34*, 467–478. <https://doi.org/10.11870/cjlyzyyhj202503001>.
71. Zhao, Z.; Zhao, Q.; Li, S.; Yan, J. Artificial Intelligence-Driven Regional Energy Transition: Evidence from China. *Econ. Anal. Policy* **2025**, *85*, 48–60. <https://doi.org/10.1016/j.eap.2024.10.004>.
72. Han, J.; Wei, W.; Ge, W.; Liu, S.; Chou, Y. Digital Technology and Agricultural Production Agglomeration: Mechanisms, Spatial Spillovers, and Heterogeneous Effects in China. *Sustainability* **2025**, *17*, 4387. <https://doi.org/10.3390/su17104387>.

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