How does Digital Village Construction Influences Carbon Emission? The Case of China

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Research Article

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How does Digital Village Construction Influences Carbon Emission?  
The Case of China  
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Abstract  
Taking 30 provinces in China from 2011 to 2020 as a research sample, this paper empirically tests the impact of digital village construction on carbon emissions. This study found that there is an "inverted U" curve relationship between digital rural construction and rural carbon emissions. Agricultural planting structure and agricultural technical efficiency are important ways for digital village construction to produce carbon emission reduction effects. This study also found that the higher the level of economic development, the stronger the carbon emission reduction effect of digital village construction. In addition, there are also significant differences in the carbon emission reduction effect of digital village construction in regions with different environmental regulation intensities. Finally, in terms of the relationship between digital economic activities and carbon emission reduction, the research conclusions of this paper have important implications.  

Keywords  
digital village construction; digital economy; peak carbon dioxide emissions; carbon neutrality; carbon emission  

Introduction  
The world has entered the era of global climate change, which has become the biggest non-traditional security challenge facing human development. At present, the global problem that countries are concerned about is the massive emission of carbon dioxide (CO2) and other greenhouse gases. With the deepening understanding of the relationship between greenhouse gas emissions and climate change, the call for the international community to take countermeasures to reduce emissions is getting louder. All sectors of society have made unremitting efforts to address global climate change: the first World Climate Conference was held, the United Nations Conference on Environment and Development adopted the United Nations Framework Convention on Climate Change in 1992, and the Kyoto Protocol and the Paris Agreement were successively promulgated. China is the world's most populous country and the world's largest carbon emitter. Coping with carbon emission reduction is the biggest challenge for China and the world to achieve sustainable development. Therefore, it is undoubtedly of great significance to explore an effective path for China to achieve the goal of carbon neutrality.  

At present, the main challenge facing China is that the time from carbon peak to carbon neutrality is "too short". The progress of advancing carbon neutrality varies from country to country. As of 2021, 132 countries and regions around the world have proposed the time to achieve carbon neutrality. In terms of timing, most countries propose to achieve carbon neutrality by 2050. In terms of period, it takes an average of more than 50 years for countries to reach carbon neutrality from carbon peak. At present, China is still in the process of industrialization and urbanization. China's primary energy consumption is still growing, and carbon emissions are still growing. China has announced that the interval from carbon peak to carbon neutrality is 30 years, however, the EU promised a time of 60 to 70 years. The interval time of the latter is more than 2 times that of the former. This indicates that China needs to promote energy conservation and emission reduction targets in various industries and regions in an orderly manner with faster speed and higher efficiency.  

From the existing research, most of the influencing factors of energy-saving and emission reduction take cities as the research objects and pay less attention to agriculture and village. However, village energy issues are increasingly becoming an important source of increased regional carbon emissions. According to the China Energy Statistical Yearbook, village energy consumption has more than doubled in the past two decades. There are prominent problems in village areas, such as backward infrastructure, relatively lagging energy socialization services, unreasonable energy consumption structure, and low degree of waste utilization. These problems seriously hinder the realization of energy conservation, emission reduction, and sustainable development goals. It is worth noting that with the development of internet technology, digital
village construction based on digital elements has gradually demonstrated its carbon emission reduction potential. However, according to the literature available to the author, few studies have paid attention to the impact of digital village construction on carbon emissions.

Compared with the existing research, the possible marginal contributions of this paper are as follows: First, this paper introduces the digital economy as technological progress into the Solow growth model and proposes the theoretical hypothesis that there is an "inverted U" curve relationship between digital villages construction and carbon emissions. Secondly, this paper quantitatively measures China's rural carbon emissions from three perspectives: production, life, and ecology. Based on the regional economic development level and the intensity of environmental regulation, the heterogeneity test was carried out. The research in this paper enriches the empirical evidence on the impact of digital economic activities on carbon emissions.

The rest of this paper is organized as follows. The second section presents a review of the literature on digital economy and carbon emissions. The third section provides the theoretical analysis. The fourth section describes the empirical methods and data resources. The fifth section presents the empirical results and discussions. The last section offers the conclusion and implications.

Literature review

Research on environmental effects of economic activities

Existing studies have paid less attention to carbon emission reductions from rural economic activities. The related literature can be divided into two categories. The first is the relationship between economic growth and environmental quality. This involves the famous Kuznets theory (Grossman and Krueger 1991). The core of this series of literary studies is to incorporate environmental quality as an output target for economic growth. Another line of literature is to study the effects of environmental externalities arising from different economic activities. Factors such as urbanization (Prastiyo and Hardyastuti 2020), FDI (Khan et al. 2022), and economic agglomeration (Ahmad et al. 2021) are the focus of scholars' consideration. At the same time, with the development of information technology and the popularization of the Internet, the impact of digital economic activities on the environment and sustainable development has attracted more and more attention from scholars.

There is no consensus on the impact of digital economic activity on carbon emissions. On the one hand, some scholars believe that the digital economy can achieve the goal of reducing carbon emissions by improving the energy structure (Li et al. 2021). Moreover, the carbon emission reduction effect of digital economic activities shows heterogeneity with the change in the economic circle, and there is a spatial spillover effect (Meng and Zhao 2022). The intervention of digital elements can not only promote the transformation of industrial development to green and low-carbon but also effectively solve technical problems such as emission monitoring (Rajkumar et al. 2017). The application of Internet communication technology is good for environmental improvement (Haseeb et al. 2019). As an important platform for disseminating information on pollution prevention and control, the Internet often uses informal channels to improve air quality (Bhujabal et al. 2021). However, on the other hand, some scholars have proposed that the use of digital technology will increase power consumption (Salahuddin and Alam 2015). Especially in regions where the energy structure is biased towards fossil fuels, the total carbon emissions have increased significantly (Hamdi et al. 2014).

Research on digital village construction

China's "Digital Village Development Strategy Outline" pointed out that "Digital village construction is the application of digital technology in agricultural and rural economic and social development. As well as the endogenous agricultural and rural modernization development and transformation process due to the improvement of farmers' modern information skills." As a key path to reshaping rural economic and social development, digital village construction is an important driving force for promoting the transformation of low-carbon and green development in agriculture and rural areas. The current research on digital village construction mainly focuses on the measurement.
There is no consensus on the measurement method. Zeng et al. (2021) constructed an evaluation index system for digital village construction from five perspectives: digital infrastructure, data resources, digital industrialization, industrial digitization, and governance. Qi et al. (2021) used the Internet penetration, the development level of rural e-commerce, and the development of rural inclusive finance as indicators to measure the construction of digital villages. Cui and Feng (2020) used digital environment, digital investment, digital benefit, and digital service as evaluation indicators to construct a digital rural economic index system. Studies have shown that digital village construction is conducive to optimizing the efficiency of resource allocation and improving traditional agricultural production methods (Xia et al. 2019). Digital village construction is increasingly becoming an important engine for the transformation of agricultural and rural development.

Through literature review, it is found that the existing literature affirms the importance of digital elements for the green and low-carbon transformation of economic development. However, few scholars have studied the carbon emission reduction effect of digital village construction from the perspective of the digital and low-carbon transformation of agriculture and rural areas. Logically, the various positive externalities generated by the application of digital technology in agriculture have an important impact on rural economic growth, energy use efficiency, and pollutant emissions. Examining the energy-saving and emission reduction effects of digital village construction is conducive to a more comprehensive understanding of the green economic effects of digital production factors. Therefore, on the basis of theoretical analysis, this paper uses Chinese provincial data to empirically test the impact of digital village construction on carbon emissions and its mechanism, in order to provide experience and reference for achieving the goal of carbon neutrality.

Theoretical analysis

Typical facts about the impact of digital village construction on carbon emissions

First, digital village construction provides a basic guarantee for the low-carbon development of agriculture. Based on technological innovation, it deeply integrates digital technologies such as big data, AI, and cloud computing with the entire agricultural industry chain and ecological protection. This will help to form a high-quality and stable rural industrial green ecosystem. The typical fact is that the traditional agricultural production mode of "depending on the weather" is transformed into a "controllable" intelligent production mode. Through precision planting and breeding, the carbon emissions of the agricultural system are reduced.

Second, digital village construction can help guide the low-carbon development of agriculture from the demand side. On the one hand, the application of digital technology in the production and consumption of agricultural products has changed the current situation of weak competitiveness and high resource consumption of green agriculture. On the other hand, a breakthrough in market demand was achieved through the establishment of the agricultural product quality and safety traceability management information platform and the organic product certification traceability information system. The cultivation of green agricultural product network brands can drive the development of characteristic green agriculture and guide the low-carbon development of agriculture from the demand side.

Third, digital village construction has promoted financial support for agricultural green transformation. The main reason is that digital inclusive financial services have increased the application and promotion of green finance in rural areas, thereby promoting the progress and promotion of agricultural low-carbon technologies. At the same time, financial institutions use digital technology to control the risks of farmers using low-carbon production technologies, reducing the cost of farmers adopting green production technologies.

Finally, digital village construction helps to form a good human living environment. Rural residents participate in environmental network supervision through the APP, thereby improving the monitoring ability of the water environment and water ecology in rural areas. The improvement of rural environmental disposal information management capabilities has improved the level of sewage and waste management. Therefore, digital village construction provides a basic guarantee for building a new development pattern of agricultural and rural green development.
We assume that the introduction of technological progress follows Harrods neutral technology, and the general production form can be obtained as follows:

\[ Y = F(K, DL) \]  

(1)

\( Y \) is the total output, \( K \) is the total capital, \( L \) is the total labor force, and \( D \) is the digital village construction. Digital village construction can improve the allocation of production factors and increase labor productivity. Therefore, we regard the digital village construction level as the technical level of the economy. The production function is assumed to have constant returns to scale and diminishing marginal productivity. Eq.(1) is a second-order classical production function, continuously differentiable, and satisfies the following conditions:

\[ F(\lambda K, \lambda L) = \lambda F(K, L), \lambda > 0 \]  

(2)

\[ F_i > 0, F_{ii} < 0, F_{ij} > 0, F_{ii} < 0 \]  

(3)

\[ F(0, L) = F(K, 0) = 0, \lim_{x_i \to +\infty} F_i(x_i, x_j) = +\infty, \lim_{x_i \to +\infty} F_{ij}(x_i, x_j) = 0, i = 1, 2 \]  

(4)

Based on the assumption of constant returns to scale, the production function can be rewritten in dense form as Eq.(5):

\[ \hat{y} = Y/ DL = F(K/ DL, 1) = f(\hat{k}) \]  

(5)

\( \hat{k} \) is the capital stock of effective labor per capita. \( \hat{y} \) is the output of effective labor per capita. Eq.(5) gives the functional relationship between per capita effective capital and per capita effective output. Assuming that the labor force and digital village construction both grow at a constant rate:

\[ \dot{L} = nL \]  

(6)

\[ \dot{D} = g_D D \]  

(7)

We assume that total output is used for consumption and investment. The depreciation rate is \( \delta \). Then, we can obtain the following equation for capital change:

\[ \dot{K} = sY - \delta K - C \]  

(8)

\( s \) is the fixed savings rate. \( C \) is the cost of disposing of carbon dioxide. We assume that there are two ways to reduce carbon dioxide, one is to change the energy consumption structure, and the other is to increase the level of carbon sequestration. The cost formulas are shown in Eq.(9) and Eq.(10). \( Z \) is the firm’s emissions, linked to the level of output. \( \theta \) is the processing cost per unit of carbon emissions.

\[ C = \theta z(Y) \]  

(9)

\[ \dot{C} = C/ DL = \theta z(Y)/ DL = \theta z(\hat{y}) = \theta z(\hat{k}) \]  

(10)

Substituting Eq.(9) and Eq.(10) into Eq.(8), we can get Eq.(11):

\[ \dot{\hat{k}}/K = SY/K - \delta - C/K = \left[ sf(\hat{k}) - \hat{C} \right] / \hat{k} - \delta \]  

(11)

Therefore, the dynamic equation of effective capital per capita is written as Eq.(12). Eq.(13) is obtained by arranging Eq.(12):

\[ \dot{\hat{k}}/k = \dot{\hat{k}}/K - \delta \dot{L}/L - \dot{L}/L = \left[ sf(\hat{k}) - \hat{C} \right] / \hat{k} - \delta - g_D - n \]  

(12)

\[ \hat{k} = sf(\hat{k}) - \theta z(\hat{k}) - \hat{C}(\delta + g_D + n) \]  

(13)

\[ z(\hat{k}) = sf(\hat{k})/ \theta - \hat{k}(\delta + g_D + n)/ \theta \]  

(14)

When the economy is in equilibrium, the growth rate of effective capital per capita is 0, which means \( \dot{\hat{k}} = 0 \). Therefore, the relationship between per capita effective carbon dioxide emissions and digital village construction is determined by Eq. (14). In addition, the digital village growth rate and labor force growth rate are expressed as \( g_D \) and \( n \). In Eq.(14), the per capita
effective carbon dioxide emissions are on the left. On the right-hand side of the equation, the first
term means that the increase in output accumulates due to continued capital, thereby increasing
carbon dioxide emissions. The second item means that with the continuous improvement of the
digital village level, the carbon dioxide emissions in the production process are gradually reduced.
The initial effective capital per capita is 0, which means that the firm does not produce and emits
zero carbon dioxide. The inverted U-shaped relationship between CO2 emissions and digitization
shows that as the digital village develops, CO2 emissions first rise and then decrease, which is
consistent with the assumptions of the environmental Kuznets curve.

In the initial stage of digital village construction, positive externalities such as technology
spillovers and knowledge sharing are difficult to have a significant inhibitory effect on carbon
emissions. This is reflected in the fact that the CO2 emissions caused by the mass production of
enterprises are greater than the CO2 emissions reduced by digitalization, and the CO2 emissions
are faster than CO2 processing. In addition, the factors and markets in rural areas are relatively
scattered, the production and management costs of energy required by enterprises are relatively
high, and economies of scale are not obvious. At the same time, residents have relatively low
requirements for environmental quality, and environmental regulations are relatively loose,
resulting in a continuous increase in carbon dioxide emissions. With the continuous improvement
of the digital village construction, the CO2 emission rate is lower than that of CO2 treatment. The
in-depth development of digital village construction has gradually revealed positive externalities
such as technology spillover and knowledge sharing, which has brought about the optimization of
the agricultural structure. Changes in the structure of the original energy-intensive and highly
polluting heavy industries have significantly reduced carbon emissions.

**Hypothesis 1 (H1):** When other conditions remain unchanged, there is an "inverted U" curve
relationship between digital rural construction and carbon emission.

**Path analysis of the impact of digital village construction on carbon emission**

First, by adjusting the planting structure, the digital village construction can improve the carbon
sink capacity of the land and reduce the carbon emission per unit of land. In the process of
digitization of the agricultural chain, the structure of construction land has been continuously
adjusted. At this time, the structure has shifted from the high energy consumption and high
pollution emissions to the tertiary industry with low energy consumption and low pollution
emissions. The optimization of this structure effectively reduces the carbon emissions per unit of
construction land (Dong et al. 2020). At the same time, with the emergence of modern
technologies such as big data and cloud computing in rural areas, agricultural machinery has
begun to integrate with modern information technology. It is manifested in the improvement of the
intelligence level of traditional agricultural machinery and the improvement of the level of
large-scale agricultural operation. In addition, food crops require fewer agricultural chemicals
such as pesticides, fertilizers, and plastic films than commercial crops. Therefore, the increase in
the grain planting area is beneficial to reducing the carbon emission per unit area and improving
the land carbon sink capacity (Balsalobre-Lorente et al. 2019).

Secondly, digital village construction uses data as the input of production factors, which
improves the efficiency of agricultural technology. Through the scale of agricultural production,
promote the transformation of agriculture to green and low-carbon. The application of digital
technology in rural resource development and production activities enables farmers to analyze
production decisions through big data. This has greatly changed the traditional
high-energy-consumption production methods and realized the intensification and refinement of
the supply of agricultural resources. This also avoids the problems of inefficient energy use and
large input of pollutants in rural development. The scientific arrangement of agricultural seeding
and fertilization is conducive to promoting changes in soil organic matter and improving soil
carbon sequestration capacity (Govaerts et al. 2009). At the same time, improvements in
fertilization technology and farming methods have reduced the fertilizer input per unit of land,
improved soil carbon sink capacity, and reduced plant carbon emissions (Ogada et al. 2014).

Finally, digital village construction is conducive to the optimization of resource allocation
and promotes the digital transformation of agriculture. The application of digital technology can
effectively improve dynamic monitoring analysis. By promoting the key layout of carbon
reduction areas such as livestock and poultry manure and crop straw recycling, the recycling of waste can be realized and the increase in carbon emissions caused by random burning of waste can be reduced (Xashimxodjayev and Sadinov 2021). In addition, digital village construction can help alleviate information asymmetry. By reducing the energy consumption caused by intermediate links, efficient agricultural product information matching from "field " to "table" is realized. This greatly reduces the carbon emissions of transportation at the point of sale.

**Hypothesis 2 (H2):** The improvement of the planting structure helps to strengthen the carbon emission reduction effect of the digital village construction.

**Hypothesis 3 (H3):** The improvement of agricultural technology efficiency helps to strengthen the carbon reduction effect of the digital village construction.

### Methods and data

#### Measurement model settings

This paper aims to examine the impact of digital village construction on carbon emission. The basic empirical model is shown in Eq.(15):

$$\ln C_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 s_{it}^2 + \sum \beta_j cov_{it} + \mu_i + w_i + \epsilon_{it}$$  \hspace{1cm} (15)

The subscript $i$ represents the province. The subscript $t$ represents the year. $C_{it}$ is the carbon emission. $s_{it}$ is the digital village construction. $cov_{it}$ is the control variables. $\mu_i$, $w_i$, and $\epsilon_{it}$ are the individual fixed effects, time fixed effects, and random disturbance terms. Respectively. When $\alpha_1 > 0$ and $\alpha_2 < 0$, there is an "inverted U-shaped" relationship between digital village construction and carbon emission. When $\alpha_1 < 0$ and $\alpha_2 > 0$, there is a "U-shaped" relationship between digital village construction and carbon emission. Secondly, to test the mechanism of the effect of digital village construction on carbon emission. This paper builds the following econometric model :

$$\ln c_{it} = \alpha_0' + \alpha_1' s_{it} + \alpha_2' s_{it}^2 + \gamma_1' M_{it} + \gamma_2' M_{it} \times s_{it} + \sum \beta_j' cov_{it} + \mu_i' + w_i' + \epsilon_{it}'$$  \hspace{1cm} (16)

$M_{it}$ are possible conduction paths. In this paper, crop planting structure and agricultural technical efficiency are used as proxy variables of $M$, respectively . If $\alpha_1'$ is significantly greater than 0, $\alpha_2'$ is significantly less than 0, and $\gamma_2'$ is significantly negative, it means that $M$ inhibits the promotion of carbon emissions in the initial stage of digital village construction.

#### Variable description

**CO2 emissions (CE)** We discuss the carbon emission factors in rural areas based on the carbon emissions factors. Specifically, we divide rural carbon emission factors into living carbon sources, ecological carbon sources and production carbon sources. The living carbon sources mainly include the living conditions of rural residents and the consumption of durable goods needed in daily life, with rural housing, electricity, gasoline, and natural gas as the main emission factors. The ecological carbon sources include the improvement of transportation infrastructure and the improvement of air quality, etc., with roads, public buildings, productive buildings, and coal as the main emission factors. Production carbon sources include diesel fuel consumed by agricultural machinery and chemical fertilizers and pesticides in the agricultural production process, with diesel, pesticides, chemical fertilizers, and agricultural film as the main emission factors. The coefficients related to carbon emissions are as follows:

<table>
<thead>
<tr>
<th>First-level indicator</th>
<th>Secondary indicators</th>
<th>Coefficient</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>living carbon source</td>
<td>rural housing</td>
<td>0.0076</td>
<td>tons/square meter/year</td>
</tr>
<tr>
<td></td>
<td>electricity</td>
<td>0.8560</td>
<td>kg/degree</td>
</tr>
</tbody>
</table>
gasoline\hspace{0.2cm}2.9251\hspace{0.2cm}ton/ton
natural gas\hspace{0.2cm}2.1622\hspace{0.2cm}ton/ton

ecological carbon source\hspace{0.2cm}the way\hspace{0.2cm}0.0047\hspace{0.2cm}tons/square meter/year
public building\hspace{0.2cm}0.0076\hspace{0.2cm}tons/square meter/year
productive building\hspace{0.2cm}0.0076\hspace{0.2cm}tons/square meter/year
coal\hspace{0.2cm}1.9003\hspace{0.2cm}ton/ton

production carbon source\hspace{0.2cm}diesel fuel\hspace{0.2cm}3.0959\hspace{0.2cm}ton/ton
pesticide\hspace{0.2cm}18.0800\hspace{0.2cm}ton/ton
fertilizer\hspace{0.2cm}3.3000\hspace{0.2cm}ton/ton
Agricultural film\hspace{0.2cm}18.9900\hspace{0.2cm}ton/ton

Digital village construction (DVC) In this paper, the index system is constructed based on the existing literature (Cui and Feng 2020; Qi et al. 2021). We plan to build an indicator system from four dimensions: digital village infrastructure construction, financial infrastructure construction, innovation capability, and service platform construction. In the digital village infrastructure construction, we consider the two dimensions of broadband Internet foundation and mobile Internet foundation, and select rural broadband access households and the average number of rural households per 100 mobile phones as the underlying indicators. In the financial infrastructure construction, we characterize the coverage and depth of digital inclusive finance. In the innovation capability, we consider the support of digital innovation elements and the output level of digital innovation and select the local financial science and technology expenditure and the penetration of digital high-tech applications in listed companies as urban indicators. In the service platform construction, we used two indicators: the length of rural delivery routes(km) and the number of Taobao villages. The evaluation system of the digital village construction level is shown in Table 2.

Table 2  Index system of digital rural construction

<table>
<thead>
<tr>
<th>First-level indicator</th>
<th>Secondary indicators</th>
<th>Underlying indicator</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>digital village infrastructure construction</td>
<td>Broadband Basics</td>
<td>rural broadband access users</td>
<td>million households</td>
</tr>
<tr>
<td>financial infrastructure construction</td>
<td>Mobile Basics</td>
<td>the average number of mobile phones per 100 people in rural households</td>
<td>department</td>
</tr>
<tr>
<td>innovation capability</td>
<td>Breadth of coverage</td>
<td>the coverage of digital financial inclusion</td>
<td>index</td>
</tr>
<tr>
<td>service platform construction</td>
<td>Depth of use</td>
<td>depth of digital financial inclusion</td>
<td>index</td>
</tr>
<tr>
<td>innovation capability</td>
<td>Digital innovation element support</td>
<td>fiscal science and technology expenditure</td>
<td>billion</td>
</tr>
<tr>
<td>innovation capability</td>
<td>Digital innovation output level</td>
<td>penetration of digital high-tech applications in listed companies</td>
<td>index</td>
</tr>
<tr>
<td>service platform construction</td>
<td>freight miles</td>
<td>rural delivery route length</td>
<td>kilometer</td>
</tr>
<tr>
<td>service platform construction</td>
<td>E-commerce business development</td>
<td>number of Taobao Villages</td>
<td>individual</td>
</tr>
</tbody>
</table>

Control Variables To control the impact of regional economic development and other factors on carbon emission, the following indicators are selected as control variables: (1) GDP per capita (lg) – According to the environmental Kuznets theory, the increase in carbon emissions is caused by economic growth by-product. With the improvement of the level of economic development, carbon emissions show a downward trend. Therefore, this paper takes the primary term lg and quadratic term slg of the logarithm of GDP per capita as control variables. (2) Energy consumption structure (energy) – This paper measures the proportion of coal consumption to total consumption. Coal consumption is the main source of fossil energy consumption. When the proportion of clean energy is larger, the carbon emission per unit of GDP is also lower. (3) Level of economic agglomeration (ln jiju) – We refer to the research of Ciccone and Hall (1996), taking the labor force per unit of land area as a proxy variable of the level of economic agglomeration. Economic agglomeration can reduce carbon dioxide emissions through technological spillovers and economies of scale. (4) degree of opening to the outside world (open) – We measure by the ratio of FDI to GDP. The reason for considering this variable is mainly due to the FDI polluting
paradise hypothesis.

Endogenous mitigation and selection of instrumental variables This paper tries to control some key variables as much as possible. However, it is always difficult to prevent the occurrence of omitted variables and lead to possible estimation errors. Some estimation problems may arise. For example, in areas with a high level of digital village construction, the use of clean energy and rural governance capabilities are inherently high, so it is impossible to effectively identify whether digital village construction has an important impact on rural carbon emissions. Secondly, digital village construction will affect rural carbon emissions, but rural carbon emissions will also limit the development of digital village construction, so there may be a reverse causality problem. Given this, we attempt to alleviate the endogeneity problem through the instrumental variable method. We consider the number of fixed telephones per 100 people and the volume of postal and telecommunications services per 100 people as instrumental variables for digital village construction.

Considerations for selecting instrumental variables are as follows. First of all, the popularization of Internet technology is an important prerequisite for the construction of digital villages. One step forward, the application of Internet technology began with the popularization of landlines. Therefore, the construction of digital villages is closely related to the popularization of fixed-line telephones. That is to say, the areas with a high fixed-line penetration rate are very likely to be areas with better development of digital village construction. At the same time, the post office, as a directly related department of fixed-line installation, is also closely related to the construction of digital villages. This paper uses the post and telecommunications information indicators of several years before as an instrumental variable. This processing assumes that the past post and telecommunications layout of a region will indirectly affect the current digital village construction by affecting the current Internet development, but it has little impact on today’s carbon emissions. Therefore, using the number of fixed-line telephones in 1984 (Iv1) and the volume of postal and telecommunications services in 1984 (Iv2) as instrumental variables, the "correlation" and "exclusiveness" assumptions of effective instrumental variables are satisfied. Second, if the cross-sectional data is directly used as an instrumental variable, it will be difficult to measure due to the application of the fixed-effect model. Therefore, this paper uses the intersection between the Internet penetration rate and the number of fixed telephones per 10,000 people, and the number of postal and telecommunications services per 100 people in 1984 as the instrumental variables for the current digital village construction.

Handling of the indicator system In this paper, the entropy method is used to assign values to the index system. To ensure the comparability of each index data, this paper carries out dimensionless normalization processing on the original data.

Forward normalization: $X' = \frac{x_y - x_{\min}}{x_{\max} - x_{\min}} + 0.01$

Negative normalization: $X' = \frac{x_{\max} - x_y}{x_{\max} - x_{\min}} + 0.01$

$x_y$ is the value after standardization of each indicator. $x_y$ is the original value of the indicator. $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the original data, respectively.

The proportion of each indicator: $\beta_y = \frac{X_y}{\sum_{i=1}^{m} X_i}$

Index entropy value: $e_y = -\frac{1}{\ln m} \sum_{i=1}^{m} \beta_y \ln \beta_y$

Reverse entropy conversion: $p_i = 1 - e_i$

The indicator weights: $w_j = \frac{p_j}{\sum_{j=1}^{n} p_j}$

The time factor is added on the basis of the traditional entropy method. The proportion of
each index becomes \( \beta_{p2i} = \frac{X_{ij}}{\sum_{p=1}^{P} \sum_{i=1}^{m} X_{p2i}} \), and the entropy value of the index changes as

\[ e_{p2i} = -\frac{1}{\ln m} \sum_{p=1}^{P} \sum_{i=1}^{m} \beta_{p2i} \ln \beta_{p2i}. \]

Based on this, the comprehensive index score of each province based on the time series can be obtained.

**Data Sources**

This paper takes 30 provinces in China from 2011 to 2020 as the research sample. The data mainly comes from the "China Rural Statistical Yearbook", "China Energy Statistical Yearbook" and "China Urban and Rural Construction Statistical Yearbook". We deflated and adjusted various currency volume indicators with 2011 as the base period to eliminate the impact of price factors. The descriptive statistics of each variable are shown in Table 3.

**Table 3** Descriptive statistics of each variable

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
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<td>0.0104</td>
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</tr>
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<td>0.0248</td>
<td>2.4609</td>
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<td>-5.3537</td>
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<tr>
<td>open</td>
<td>300</td>
<td>0.0267</td>
<td>0.0301</td>
<td>0.0028</td>
<td>0.1417</td>
</tr>
</tbody>
</table>

**Empirical results analysis**

**Benchmark regression**

Table 4 shows the regression results using random effects, fixed effects, and two-stage least squares, respectively. Hausman's test shows that it is more reasonable to use a fixed-effects model. Column (2) of Table 4 is the double fixed effect regression with the addition of control variables. The results show that the linear coefficient of digital rural construction is significantly positive, and the quadratic coefficient is significantly negative. Columns (3)-(5) show the regression results using instrumental variables. After considering endogeneity, the elastic coefficients of the primary and quadratic terms of digital villages increase, and both are significant at the 1% level, indicating that the estimated coefficients of digital villages have a downward bias when endogeneity is not considered. In order to verify the validity of instrumental variables, Kleibergen-Paaprk LM test, Kleibergen-Paaprk Wald F test and Hansen J test were carried out. The choice of variables is appropriate.

So far, we can consider that hypothesis 1 holds. That is to say, there is a significant "inverted U-shaped" relationship between digital village construction and carbon emissions. In addition, the primary term of economic development level is significantly positive at the 5% level, and the quadratic term is significantly negative at the 10% level. It shows that with the growth of the economic level, carbon emissions will first show a trend of increasing first and then decreasing. This is consistent with the environmental Kuznets hypothesis. The overall conclusion shows that the hypothesis about Kuznets also occurs in the context of digital economic activity. This is similar to the conclusion of Meng and Zhao (2022). Next, this paper will further discuss the internal mechanism of the impact of digital village construction on carbon emission.

**Table 4** Impact of digital economy development on rural carbon emission

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) RE</th>
<th>(2) FE</th>
<th>(3) The first stage</th>
<th>(4) The first stage</th>
<th>(5) Second stage</th>
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<td></td>
<td>9.4004***</td>
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<tr>
<td></td>
<td>(1.3068)</td>
<td>(1.4213)</td>
<td></td>
<td></td>
<td>(1.3718)</td>
</tr>
<tr>
<td>sz²</td>
<td>-3.6536***</td>
<td>-3.8895**</td>
<td></td>
<td></td>
<td>-9.7546***</td>
</tr>
</tbody>
</table>
Fractional test

Table 5 reports the impact of digital village construction on sub-dimension carbon emissions. The results in columns (1) and (2) of Table 5 show that there is an obvious "inverted U-shaped" relationship between digital village construction and living carbon sources and ecological carbon sources. This shows that the construction of digital villages will increase the domestic carbon emissions and ecological carbon emissions in rural areas in the short term. But after a certain period, the opposite happens. The possible reason is that the construction of digital villages has increased the demand for infrastructure such as electricity and roads in rural areas, resulting in a rapid rise in carbon emissions from electricity, roads, and public buildings. This is similar to the conclusion of Li et al. (2021). Therefore, in the initial stage, digital village construction will lead to the increase of living carbon sources and ecological carbon sources in rural areas. With the development of digital village construction, residents' digital literacy and environmental awareness are gradually enhanced. The use of coal and gasoline has gradually declined. Clean energy is gradually replacing coal, and traditional vehicles are gradually being replaced by new energy vehicles. These have greatly eased the pressure of carbon emission reduction in rural areas, thereby reducing domestic carbon emissions and ecological carbon emissions. Therefore, there is an "inverted U-shaped" relationship between digital village construction and domestic carbon emissions, and ecological carbon emissions.

The results in column (3) of Table 5 show that the impact of digital village construction on production carbon emissions is not significant. The possible reason is that for areas with high population density and weak infrastructure construction, the carbon reduction effect of digital technology in the production field is limited, and the scale effect is not obvious. Therefore, the effect of digital village construction on production carbon emissions is not obvious. This is similar to the conclusion of Balsalobre-Lorente et al. (2019).

Table 5  The impact of digital villages on carbon emissions in various dimensions

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>living carbon source</td>
<td>ecological carbon source</td>
<td>production carbon source</td>
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<td></td>
<td>(1.3445)</td>
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<td>(0.0578)</td>
</tr>
</tbody>
</table>

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. The values in brackets are robust standard errors.
Conduction Mechanism Test

Conduction path of crop planting structure In this paper, the ratio of food crop cultivation area and agricultural land area is used as the measurement variable of the planting structure. The results in column (1) of Table 6 show that the cross-product of digital rural construction and planting structure is significant at the 10% level, indicating that the larger proportion of grain crop area restrains the increase in carbon emissions in the early stage of digital rural construction. The results in column (2) of Table 6 show that the optimization of crop planting structure promotes the earlier arrival of the "inverted U-shaped" inflection point between digital village construction and rural carbon emission. Therefore, Hypothesis 2 is established.

Conduction path of agricultural technical efficiency We use DEAP2.1 software to measure agricultural technical efficiency. The capital input selects three indicators: the effective irrigation area, the total power of agricultural machinery, and the number of agricultural chemical fertilizers. The labor input selects two indicators such as the area of arable land and the number of laborers. The output indicator is the gross agricultural product. The results in columns (3) and (4) of Table 6 show the impact of the improvement of agricultural technical efficiency on the carbon emission reduction effect of digital villages. The results in column (3) of Table 6 show that the interaction term between digital villages and agricultural technical efficiency is significant at the level of 5%, indicating that the improvement of agricultural technical efficiency has shortened the range of positive effects of digital village construction on carbon emissions. The results in column (4) of Table 6 show that the interaction term between the quadratic term of digital rural construction and agricultural technical efficiency is significant at the 5% level. Moreover, the regression results are consistent with the benchmark regression, indicating that the improvement of agricultural technical efficiency has strengthened the carbon emission reduction effect of digital village construction. Therefore, Hypothesis 3 is established.

Table 6 Conduction mechanism test

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</tr>
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</table>
Heterogeneity Analysis

Analysis based on the degree of economic development From the factual point of view, the level of economic development is an important factor affecting the carbon emission. In regions with relatively high levels of economic development, the carbon emission reduction mechanisms are relatively more complete, and the driving force for reducing pollution emissions through innovative emission reduction technologies is stronger. And a higher level of economic development is often accompanied by a higher level of digital supervision. Therefore, we will discuss the differential impact of digital village construction on carbon emission reduction under different economic development levels. The regions with the median value in the top 1/3 of the sample period were defined as high levels, the cities with per capita GDP in the lower 1/3 were defined as low levels, and the middle regions were defined as medium regions, and sub-sample regression was performed.

The sub-sample regression results are shown in Table 7. The estimation results in columns (1) and (2) in table 7 show that in the regions with high economic development levels, the coefficients of the first and quadratic terms of digital village construction are 11.8224 and -11.9876 respectively, which are significant at the 1% level is positive. In areas with a moderate level of economic development, the primary and quadratic coefficients of digital village construction are 11.4682 and 13.3287, which are significant at the level of 1% and 10%, respectively. The results in column (3) of table 7 show that the coefficient of the first order of digital village construction is 8.0387 at the 5% level, but the coefficient of the second order is not significant. The results show that the impact of digital village construction on carbon emission reduction in areas with high economic development level is stronger than that in areas with low economic development level. This is similar to the conclusion of Salahuddin et al. (2016).

Analysis based on the intensity of environmental regulation The effectiveness of China's carbon emission reduction system is affected by environmental regulation. Strong environmental regulations provide a certain guarantee for the effective operation of emission reduction work. We take environmental protection tax as a proxy variable for environmental regulation and use resource tax, urban construction tax, land tax, consumption tax, etc. as the main object of environmental protection tax. The estimated results are shown in columns (4) to (6) of Table 7.

Column (4) in Table 7 shows that in areas with a relatively high degree of environmental regulation, the carbon emission reduction effect of digital village construction is not obvious. The possible explanation is that generally speaking, areas with strong environmental regulations, often face greater environmental pressures. This will also have a greater incentive effect on energy conservation and emission reduction for digital village construction. But the reality is that the effect of environmental regulation depends not only on the intensity of environmental regulation but also on the form of environmental regulation. When the form of regulation is unreasonable, even if the government and society pay more attention to the carbon emission problem in agriculture and rural areas, the desired effect may not be achieved, thus reducing the significance of the "U-shaped" curve trend. The results in columns (5) and (6) of Table 7 show that in areas with a moderate degree of environmental regulation, the primary and quadratic coefficients of digital village construction are 6.8592 and -17.0715, which are significant at the level of 5% and 1%, respectively. In areas with low environmental regulation, the primary and quadratic coefficients of digital village construction are 5.3152 and -4.2475, which are significant at the level of 1% and 5%, respectively. Through comparison, it is found that, compared with areas with low environmental regulation, the impact of digital village construction on carbon emission reduction in areas with medium environmental regulation is more obvious. This is similar to the findings of Hashmi and Alam (2019).

Table 7 Heterogeneity analysis

<table>
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<tr>
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<tr>
<td>R-squared</td>
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</table>
Further robustness check

Excluding the municipalities takes into account the obvious political, economic, and cultural advantages of the municipalities directly under the Central Government. To eliminate the influence of this institutional factor on the regression results, we remove the sample of municipalities and use the remaining samples for regression. The regression results are shown in column (1) of Table 8. There is still an "inverted U-shaped" relationship between digital village construction and rural carbon emission.

In the previous analysis, we used the total amount of rural carbon emission as the explained variable. To eliminate the difference in results caused by population, we further used the rural per capita carbon emission as the explained variable to estimate the parameters. The results in column (2) of Table 8 show that the digital village construction and rural per capita carbon emission still show an "inverted U-shaped" relationship. In addition, we also use the unit GDP carbon emission as the explained variable for parameter estimation. The results in Table 8(3) show that the conclusion of the benchmark study in this paper is still valid.

<table>
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<tr>
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<tr>
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Conclusion and discussion

Over the past 40 years of reform and opening up, China's economic and social development has made remarkable achievements. However, it is accompanied by increasing energy demand and relatively serious environmental pollution, which greatly restricts the development of China and even other countries. China now ranks second globally in GDP, but it ranks first in terms of both pollutant emissions (CO2, SO2, PM2.5, oxynitride, etc.) and primary energy consumption. This has forced China to change modes from traditional development to green development. The three key factors in green development are economic development, resource conservation, and environmental protection. Although the existing literature has carried out a lot of research on China's energy conservation and emission reduction, in order to seek better environmental regulation measures. However, they seldom pay attention to and conduct relevant research in
agricultural and rural areas.

Therefore, this paper selects 30 provinces in China as observation samples and evaluates the impact of digital village construction on carbon dioxide emissions from 2011 to 2020. The research results show that:

First, there is a significant "inverted U-shaped" relationship between digital village construction and rural carbon emission. In the initial stage, digital village construction will increase carbon emissions. However, when its level exceeds a critical value, the opposite happens. Therefore, digital village construction has a carbon emission reduction effect. Crop planting results and agricultural technical efficiency are important ways for digital village construction to affect carbon emissions.

Second, in regions with different levels of economic development and intensity of environmental regulation, there are significant differences. In areas with a high level of economic development, the impact of digital village construction on carbon emission reduction is more obvious. In addition, compared with areas with low environmental regulation intensity, digital village construction in areas with medium environmental regulation intensity has a greater impact on carbon emission reduction.

Based on the above research conclusions, we draw the following inspirations:

First, formulate digital village development plans with high standards and accelerate the construction of digital infrastructure. Quickly formulate plans for the construction and development of digital villages in various regions, lead the construction and development of digital villages with high-standard planning, accelerate the construction of digital village information infrastructure, and promote the construction of 5G and gigabit Internet in rural areas in an orderly manner. Accelerate the digital and intelligent transformation and transformation of infrastructure such as water conservancy, roads, and electricity in rural areas, provide a foundation for application scenarios such as smart agricultural production, rural e-commerce, and digital life, and provide basic support for the realization of green, precise, and smart agriculture.

Second, while promoting the construction of digital villages, regional environmental regulations should be strengthened. In the process of promoting the construction of digital villages, the relationship between agricultural production and environmental protection should be coordinated to achieve green and low-carbon development of agriculture. At the same time, the impact of digital village construction on different carbon sources is also heterogeneous, and the emission reduction efforts of different carbon sources are also different. Therefore, reasonable emission reduction targets should be formulated, and effective emission reduction targets should be formulated according to the actual situation in rural areas, to gradually realize the harmonious coexistence of rural economic development and ecological protection.

Third, speed up the cultivation of rural digital talents. Accelerate the cultivation of rural digital talents and the popularization of digital application technologies, and enhance the digital adaptability of farmers. Through mobile phone application skills training and e-commerce training, more farmers can flexibly master information technology and digital technology. Accelerate the process of farmers' integration into the digital village construction, and drive the overall revitalization of the countryside.

However, regardless of the positive results, there are still some limitations. First, due to the vast territory of China, there are obvious differences in the resource endowment and energy consumption structure of different regions, which may distort the research conclusions. Therefore, it is necessary to conduct case studies for specific regions to enrich the empirical evidence on the impact of digital village construction on carbon emission reduction. Second, compared to the popularization of digital information technology in rural areas, we should also pay attention to how farmers' digital literacy can help achieve carbon neutrality goals. This is also an important direction for further research.

Author contribution Conception and design of the study: AH and JT. Acquisition of data: JT. Analysis and interpretation of data: YH. Drafting the manuscript: YH. Revising the manuscript critically for important intellectual content: JT.

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Data availability The datasets used during the current study are available from the corresponding
author on reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References:


Meng, F., Zhao, Y., (2022). How does digital economy affect green total factor productivity at the industry level in
China: from a perspective of global value chain. Environmental Science and Pollution Research.


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