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ADBI Working Paper, No. 1452

Provided in Cooperation with: Asian Development Bank Institute (ADBI), Tokyo

Suggested Citation: Chen, Ying; Chen, Ziqi (2024) : Does digitalization alleviate rural clean energy poverty?, ADBI Working Paper, No. 1452, Asian Development Bank Institute (ADBI), Tokyo, https://doi.org/10.56506/KMAF6819

This Version is available at: https://hdl.handle.net/10419/301957

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ADBI Working Paper Series

DOES DIGITALIZATION ALLEVIATE RURAL CLEAN ENERGY POVERTY?

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No. 1452 June 2024

Asian Development Bank Institute

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Suggested citation:

Chen, Y. and Z. Chen. 2024. Does Digitalization Alleviate Rural Clean Energy Poverty?. ADBI Working Paper 1452. Tokyo: Asian Development Bank Institute. Available: <u>https://doi.org/10.56506/KMAF6819</u>

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Abstract

This research investigates the impact of digital village development on clean energy poverty (CEP) in rural areas within the context of energy and digitalization transition in the People's Republic of China (PRC). Utilizing the Index of Digital Rural County (IDRC) and China Family Panel Studies (CFPS) statistical data from 2020, our findings suggest that the establishment of digital villages has a positive effect on alleviating CEP in rural households. Furthermore, our analysis reveals the mechanisms through which this occurs, including the enhancement of wealth and the acceleration of awareness transformation among rural households. Even when accounting for the influence of peers, the alleviating effect of digital villages on rural household CEP remains evident. Heterogeneity analyses demonstrate that households with younger members, higher levels of education, digital access, and those located in central areas experience greater benefits from digital dividends. Subindex analyses indicate that digital governance plays a particularly critical role in mitigating rural household CEP. Lastly, our results offer policy implications for other developing nations seeking to address CEP through digitalization.

Keywords: digital village, rural household CEP, wealth, awareness, ordered probit model

JEL Classification: Q56, R11

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1. INTRODUCTION

According to the Tracking SDG 7: The Energy Progress Report 2023, led by the World Health Organization, approximately 675 billion people still do not have access to electricity, and 2.3 billion people continue to use unhealthy and environmentally harmful fuels for cooking, highlighting the widespread prevalence of energy poverty (EP) in many households worldwide. Under the trend of the global shift towards renewable energy, the issue of EP in developing countries has become more critical. The World Investment Report 2023, released by the United Nations Conference on Trade and Development (UNCTAD), points out that international investment in renewable energy has grown rapidly since the adoption of the Paris Agreement in 2015, but the majority of investments are concentrated in developed countries. Conversely, developing countries are struggling to attract more investment in renewable energy, posing even greater challenges for their energy transition. Furthermore, World Bank research also indicates that some developing countries are trapped in a cycle of "EP" where economic development becomes increasingly difficult as they become poorer. The ability of developing countries to undergo energy transition is pivotal to achieving climate goals by 2030. And energy transition serves as a critical underpinning for their sustainable development. Consequently, a thorough examination of energy issues in developing countries holds significant academic and practical implications.

In addition to its crucial role in achieving climate goals, rural energy also plays a significant part in accomplishing rural revitalization, through enhancing the quality and efficiency of agriculture and lifting farmers out of poverty. However, it is noteworthy that rural areas have the weakest energy development. The 2022 World Energy Investment Report from the International Energy Agency (IEA) shows that clean energy spending in developing countries, except for the PRC, has remained at the 2015 level of the Paris Agreement. The PRC's leading position in energy transition can be attributed to its efforts toward rural revitalization, including the introduction of digital village construction as part of its strategy. Has this initiative alleviated EP in rural areas? Can the PRC's practical efforts in promoting energy transition through digitalization serve as a model for other developing countries? To answer the above questions, this paper focuses on the PRC to investigate the issue of rural household energy poverty (HEP), analyzing historical development, existing challenges, and pathways to alleviate EP through digitalization, and offering insights for other developing countries to address this issue.

Reviewing the related literature, the research has provided evidence on the effect of digitalization on energy (Wang, J. et al. 2022; Xin, Chang, and Zhu 2022), and the adverse effect energy poverty has brought to rural households (Xie et al. 2022). While these findings offer valuable insight, they have focused less on microlevel factors. Furthermore, the purchasing power of consumers is affected by income: When income is low or the cost of clean energy is high, rural households may find clean energy unaffordable and opt for nonclean energy sources. Moreover, the energy usage behavior of rural households is influenced by their level of awareness. As is often said, "[b]ehavior is determined by consciousness." The entrenched traditional energy dependence of rural households is partly shaped by their low level of energy-using awareness. Additionally, "[b]ehavior has a contagious effect," which means household energy-using behavior can be influenced by surrounding households. Yet, there is little literature that focuses on the effect of awareness, and the peer effect on energy using. Moreover, these studies define EP as the "[I]ack of fair access and safe use of energy, especially adequate, affordable, high-quality, and environment-friendly energy (Dogan et al. 2022)," which is not appropriate in the current situation of the PRC.

In addition, to address this deficiency, the initial step is to consider the energy poverty situation in rural PRC within the analysis framework. Although the traditional EP (lack of access to, and unaffordable, clean energy) in rural PRC has been eradicated, the focus should shift to the heavy reliance on nonclean energy and the limited affordability of clean energy in rural PRC (He, Hou, and Liao 2018). Hence, this study proposes a new definition of "clean energy poverty" (CEP) as "[a] phenomenon characterized by using nonclean energy due to internal factors (traditional energy-using pattern, unaffordable clean energy) or external factors (insufficient energy infrastructure)," which can better explain the current situation of rural household CEP in the PRC. Secondly, this study contributes to enriching the existing literature on energy poverty and digitalization. A lot of studies have analyzed the effects of digitalization on energy consumption (Xue et al. 2022), energy efficiency (Goldbach et al. 2018), and energy management (Yu et al. 2022). Nevertheless, there is a research gap between digitalization and rural HEP. Besides, the question of whether digitalization affects rural HEP and what the influence mechanism between them is remains a "black box" issue that needs to be resolved. We further exploit the underlying mechanism of the wealth and awareness effect. Finally, based on the analytical framework of the PRC, this study sheds light on eliminating rural HEP from a digitalization perspective, and it will also enlighten other developed countries in Asia and have reference value for them as they strive to cope with CEP issues.

This paper proceeds as follows. The second part comprises the background and hypotheses and discusses details on the background of the HEP issues and digital village development, analyzes, and presents the hypotheses of this paper. The third part covers the data and method used, including data and variables, and the empirical strategy. The fourth part presents results, including the main results, robustness checks, and heterogeneity analysis. The fifth part provides further analysis, examines the awareness and wealth effect of digital village on rural HEP, and discusses the peer effect of digital village on rural HEP. The last part concludes, summarizes the research results of this paper, and makes policy recommendations.

2. BACKGROUND AND HYPOTHESIS

2.1 Research Background

In examining the Chinese government's efforts regarding energy poverty alleviation, Ma and Shi (2020) propose that the policy evolution can be divided into four stages: from "Energy accessibility" (1980–1993) to "Having access to electricity" (1994–2005) to "Affordable and quality electricity access" (2006–2012) to "Optimizing electricity utilization" (2013–present). Through unremitting efforts, the PRC had already achieved "Nationwide electrification" in 2015. Subsequently, to further solve the energy needs in rural areas, the PRC has incorporated EP as a crucial component of its targeted poverty alleviation strategy and elevated it to a national strategic priority. Simultaneously, the PRC has issued a series of policy documents related to CEP alleviation. These policies are aimed at expanding the clean energy supply in rural areas, strengthening the self-development "hematopoietic function" of rural households in terms of cash income, and transforming the deeply rooted reliance on traditional energy sources among rural households. Considering the achievements and current status in EP alleviation, the PRC has without doubt gained remarkable achievements in the fight against EP over the past 4 decades, but actually, the country still faces enormous challenges in energy transition now, especially in rural areas, which aligns with the CEP issues this paper discusses. To be specific, the PRC has experienced increasing CEP problems due to insufficient clean energy (Wang, B. et al. 2017). Compared with urban areas, rural areas tend to have more clean energy but face greater CEP. The reason for this is that due to the difficulty in constructing energy infrastructure and its low popularity, rural areas are facing higher clean energy prices relatively; that is, they have difficulty making clean energy payments. Meanwhile, it is hard for traditional rural households to change their concept of energy use immediately, so they tend to choose nonclean energy spontaneously (because they are not aware of the adverse impact of traditional fuels on the environment and health). To sum up, the issue of CEP is more significant in rural areas, especially in terms of energy-using type inequality (Rao et al. 2022) and clean energy unaffordability (Chen, Qiu, and Zhang 2022).

At the same time, the PRC has incorporated the digital village development strategy into rural rejuvenation and has carried out the digital village construction focusing on the digital infrastructure, digital economy, digital governance, and digital lifestyle. The construction of digital villages is a crucial driving force for rural and agricultural modernization, as well as rural economic development. In 2019, the General Office of the Central Committee of the Communist Party of the PRC and the General Office of the State Council issued the "Outline of the Digital Rural Development Strategy," which mainly includes the following aspects: digital infrastructure, digital economy, digital governance, and digital life. The above aspects have a more profound impact on "the improvement and the digitalization of information and energy infrastructure, the emergence of new service models like online sales of agricultural products and digital cultural tourism, exploration of rural green and healthy development." With the increase in employment opportunities, these factors may alter the energy-using patterns of rural households; that is, digital village may be a potential catalyst for alleviating rural household CEP, which needs to be further discussed.

2.2 Research Hypothesis

2.2.1 Digital Village and Rural Household CEP

The key to assessing the mitigation of rural household CEP by digital village is to identify the factors that affect the energy choice of rural households, analyzing the impact of digital village construction on the above factors and how it further affects rural household CEP. Specifically, the factors that affect rural household CEP can be attributed to energy affordability, energy accessibility (Hou et al. 2017), energy-using awareness (i.e., traditional energy-using pattern; Wu and Zheng 2022), and energy supply (i.e., energy market; Qiu et al. 2015), including convenience and stability of energy supply. Thus, the impact of the digital village on CEP in rural households can be analyzed from these perspectives.

First of all, the construction of digital villages can improve the rural household income level and reduce the price of clean energy, thus alleviating rural household CEP. On the one hand, under digital development, the emergence of rural e-commerce (Yin and Choi 2022), the adoption of agricultural digitalization, and nonagricultural employment (Chen, Qiu, and Zhang 2022) have further improved the level of rural household income. According to the energy ladder hypothesis, with the improvement of farmers' income level and socioeconomic status, households will gradually switch to using clean energy (Kroon, Brouwer, and Van Beukering 2013). On the other hand, with the

continuous construction and upgrading of energy infrastructure, the price of clean energy has gradually decreased, and thus the affordability has increased.

Secondly, digital village construction can essentially promote energy transformation and alleviate CEP by changing the traditional energy-using awareness of rural households. Online education and energy information dissemination have deepened rural households' awareness and understanding of low-carbon clean energy, making them aware of the hazards to environment and health brought by traditional biomass energy, thus helping to cultivate their switch to clean energy initiatively.

Moreover, the construction of a digital countryside can promote the integrated utilization of rural renewable energy. The construction of a digital countryside focuses on energy conservation and clean energy utilization, large-scale access to distributed energy, full integration of renewable energy in rural areas, and the realization of "[s]ource locally use materials nearby," which greatly improves the energy accessibility of rural households and provides more energy options for rural households. It has greatly improved the energy accessibility of rural households, thereby giving these households more energy options.

The energy infrastructure in rural areas used to be weak, with outdated and obsolete network equipment, resulting in issues such as an inadequate and unstable energy supply (Guo et al. 2022). At the same time, there was the issue of the low efficiency of the energy supply. However, under the construction of the digital village, the transformation and upgrading of power grids have achieved remarkable results, and the reliability rate of the power supply in all provinces has exceeded 99.8%, while the service level of the power supply has been significantly improved¹. The introduction of digital technologies such as digital systems and community power grid systems has also simplified the complexity of energy payment, which makes rural households gradually more inclined to choose clean energy with its greater convenience and stability.

The analytical framework is illustrated in Figure 1 below:



Figure 1: Analysis Framework of Digital Village and Rural Household CEP

¹ Link to: https://www.moa.gov.cn/xw/zwdt/202011/P020201129305930462590.pdf.

Thus, the first hypothesis is proposed as follows:

H1: Digital village is positively associated with rural household CEP.

2.2.2 Mechanism Analysis

According to the energy ladder theory, family income is the most important factor that decides household energy use (Li et al. 2024; Tenaw 2022). In addition, other literature provides evidence on the influential effect of awareness on energy (Chodkowska-Miszczuk et al. 2022; MacDonald et al. 2020). Based on these factors, this paper considers the effect of the digital village on rural HEP mainly in regard to two aspects: family income and environmental awareness.

The first channel is the effect of family income. The digital village improves family income in three ways. First, digital infrastructure construction can increase the labor demand of enterprises (Zhou et al. 2022), absorbing surplus rural employment and thereby raising the income level of farmers, thus enhancing their capacity to afford clean energy. Second, the digital village construction has promoted the advance of rural e-commerce. With the rapid development of rural e-commerce, the technology of "Internet+" in agricultural product sales can effectively increase agricultural income (Tang, Xiong, and Zhang 2022), thereby affecting their power to purchase clean energy. In the past, rural areas have struggled to improve agricultural productivity with digital equipment due to the lack of access to electricity and stable electricity coverage (Liu et al. 2021). However, the construction process of the digital village emphasizes the deep integration of digital technology and agricultural production. With the gradual development of energy infrastructure and the increased level of digital technology, farmers can use digital technology to make better production and management decisions (Klerkx, Jakku, and Labarthe 2019), which has greatly enhanced the efficiency of agricultural production and reduced its cost, and made households' income increase significantly. Correspondingly, the increase in the disposable income of rural households has raised the maximum price level of clean energy they can afford.

The second channel is the effect of environmental awareness. Under the digital village construction, energy infrastructure continues to be built and popularized. In this process, impacted by the surrounding environment, rural households' awareness and understanding of clean energy have also increased under the subtle influence, and the type of energy they use has gradually transformed into renewable energy with low-carbon emissions. On the other hand, based on digital governance and the construction of rural information platforms, rural information related to clean energy can be propagated through digital display (Lv and Shi 2022), which plays a crucial role in the energy-using awareness transformation among households. Furthermore, socialist sharing (Liu, Gao, and Li 2022) can also transform the awareness formation of clean energy significantly. Moreover, the enhancement of rural access to networks, and the level of digitalization of education, strengthen the environmental awareness of rural households. When they receive higher education, households are more sensitive to environmental issues (He, Hou, and Liao 2018). Above all, the digital village accelerates the environmental awareness transformation of rural households, which makes them tend to actively choose clean energy spontaneously, thereby enhancing their energy-using level and mitigating rural HEP.

After analyzing the impact of the digital village on household income and environmental awareness, we believe that the influence of digital village on household income will outweigh its impact on farmers' energy-using awareness. This is based on the principle that rational economic agents make decisions to maximize profit. Under income

constraints, rural households will make choices among different energy combinations. Research has shown that households with higher incomes are more likely to use clean energy (Zhu et al. 2022). Therefore, faced with limited income, low-income households are inclined to choose nonclean energy sources with lower costs to gain higher utility, even if they have greater environmental and energy-using awareness. Based on the above analysis, this paper takes the view that, compared to environmental awareness, household income plays a more crucial role in the reduction of CEP promoted by digital villages.

Figure 2 shows the analysis framework of the wealth and awareness mechanism.



Figure 2: Analysis Framework of Effect Mechanism

Based on the above analysis, we propose the second hypothesis:

H2-1: Digital village reduces the rural household CEP by promoting family income.

H2-2: Digital village reduces the rural household CEP by enhancing environmental awareness.

H2-3: Compared with environmental awareness, family income plays a more vital role in rural household CEP alleviation of the digital village.

3. DATA AND METHOD

3.1 Data and Variables

The data in this study are matching data regarding three aspects. The first data comprise the county-level digital village index in 2020, which comes from the IDRC released by the Institute of New Rural Development of Peking University. The index selects 33 specific indicators from the four dimensions of rural digital infrastructure, rural economy digitalization, rural governance digitalization, and rural life digitalization for index calculation. The county-level digital village indicator system

covering 2,843 county-level units in the PRC, which is more in line with the reality of the PRC's "three rural areas," becomes a more comprehensive indicator system for assessing the level of rural digital development currently. The second aspect of data comes from CFPS data in 2020, which was organized and implemented by the PRC Center for Social Survey of Peking University, using multistage equal probability sampling, covering 2,481 counties in 28 provinces. We match and unify the above two aspects' data into the cross-sectional data at the household level, and the matched data are processed as follows: (1) according to the urban and rural classification data of the National Bureau of Statistics, excluding urban samples and only retaining rural samples; (2) keeping household samples and matching characteristics information about household head; (3) eliminating invalid and missing data, and limiting the household head's age range to 18–80.

The core explained variable of this paper is CEP, based on the research of Zhang, Li, and Han (2019) and Luan, Zou, and Huang (2023). This paper further considers CEP from three perspectives: energy-using level (EP_1), energy-using cost (EP_2), and multidimensional (EP_3). Combined with CFPS questionnaire survey data, we measure the rural household energy-using level (EP_1) by cooking fuel; the rural household energy-using level (EP_1) by cooking fuel; the rural household energy-using level, and the energy-using level. Finally, we construct a multidimensional index (EP_3) by combining the energy-using level and energy-using cost. The specific measurement methods of CEP indicators are shown in Table 1 below:

Variable		Label	Definition
Clean Energy poverty	Energy-using level	EP ₁	Nonclean fuels (firewood and coal) for cooking = 1; Clean fuels (canned gas/liquefied gas, natural gas/pipeline gas/solar energy/biogas, electricity) for cooking = 0.
	Energy-using cost	EP ₂	$EP_2 = 1$ if $(EP_1 = 1$ and household total income below the medium level), or $(EP_1 = 0$ and the ratio of energy-using fee to total income > 10%); $EP_2 = 0$ if $(EP_1 = 1$ and household total income above the medium level), or $(EP_1 = 0$ and the ratio of energy-using fee to total income <= 10%).
	Multidimensional	EP₃	$EP_3 = 0$ if $(EP_1 = 0$ and $EP_2 = 0$); $EP_3 = 1$ if $(EP_1 = 1$ and $EP_2=0$) $(EP_1 = 0$ and $EP_2 = 1$); $EP_3 = 2$ if $(EP_1 = 1$ and $EP_2 = 1$).

 Table 1: Definitions of Clean Energy Poverty

The core explanatory variable of this paper is the digital village index (*Digital_village*), resourcing from the IDRC (2020), which was released by the Institute of New Rural Development of Peking University². It should be noted that, due to the limited availability of CFPS data at the provincial level, we aggregate and average the digital rural development indices of counties within each province, finally getting the provincial-level digital village index (*Digital_village*).

For control variables, individual and household characteristics have a small impact on the explanatory variables, but they have a high correlation with the explained variables. Based on studies by Luan, Zou, and Huang (2023) and Wang, P. et al. (2022), this paper selects control variables at both the individual and household levels, which may affect rural HEP. The individual-level variables include age (*Age*), gender (*Gender*),

² The detailed calculation method of digital village can be seen at: https://www.moa.gov.cn/xw/zwdt/ 202011/P020201129305930462590.pdf.

education level (*Edu*), employment status (*Employ*), health status (*Health*), and marital status (*Mar*) of the household head, and the household-level variables include family size (*Fam_num*). To alleviate the problem of omitted variables at the provincial level, we controlled provincial fixed effects.

The descriptive statistical results of the above variables are shown in Table 2 below. According to the descriptive statistics, it can be seen that there is a large gap in the degree of CEP in different rural areas. CEP is more reflected in the energy-using level than energy-using cost. The minimum value of the digital village development variable is 42.897, and the maximum value is 82.575, indicating that the development level of digital village in different counties is quite different. At the same time, control variables, such as individual characteristics like age, education level, and health of household heads, also have great differences.

Variables	Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
EP ₁	3,561	0.402	0.490	0	1
EP ₂	3,561	0.268	0.443	0	1
EP ₃	3,561	0.671	0.794	0	2
Independent variables					
Digital_village	3,580	56.229	8.196	42.897	82.575
Control variables					
Age	3,580	50.989	13.561	18	80
Gender	3,580	0.618	0.486	0	1
Edu	3,534	6.823	4.087	1	16
Employ	3,521	0.859	0.348	0	1
Health	3,541	3.045	1.269	1	5
Mar	3,482	0.950	0.218	0	1
Fam_num	3,580	4.032	2.037	1	15
Channel variables					
Fam_digital	3,418	282.008	363.258	0	6,344.792
Envir_digital	3,419	337.260	178.959	0	825.749

Table 2 : Statistical Description of Variables

3.2 Empirical Strategy

This paper focuses on the impact of digital village development on rural household CEP. Specifically, the explained variable is rural household CEP, represented by EP_1 , EP_2 , and EP_3 , where EP_1 is 0 to 1, EP_2 is 0 to 1, and EP_3 is 0 to 2, which are sequential data, and OLS estimation is not applicable in this situation. Therefore, referring to the research of Lian and Li (2015), this paper uses the extended model of the probit model, that is, the Oprobit model, for estimation. The construction model is as follows:

$$EP_{i} = F(\alpha_{0} Digital village_{i} + \beta_{0} X_{i} + \varepsilon_{ii}), \qquad (1)$$

where EP_i is the explained variable, which represents the CEP index of rural households i *Digital_village_i* is the core explanatory variable in this paper, represents the development level of the digital village in province j; X_i is a series of control variables, including variables such as household characteristics and household head

characteristics. ε_{ij} represents the random disturbance term. $F(EP_i^*)$ is a nonlinear function with the following relation:

$$F(EP_{i}^{*}) = 0 \quad EP_{i}^{*} < \mu_{1}$$

$$F(EP_{i}^{*}) = 1 \quad \mu_{1} < EP_{i}^{*} < \mu_{2}$$

$$F(EP_{i}^{*}) = n \quad EP_{i}^{*} > \mu_{n-1},$$

where EP_i^* is the discrete array of {0,1,...n}, which represents the CEP level of i rural household; $\mu_1 < \mu_2 < K < \mu_{n-1}$ is called the tangent point and all parameters are estimated. After replacing the explained variable with EP_i^* , the Oprobit model is constructed as follows:

$$EP_{i} = \alpha_{0} Digital village_{j} + \beta_{0} X_{i} + \varepsilon_{ij}$$
⁽²⁾

4. RESULTS

4.1 Main Results

Combined with the Oprobit model, we verify the relationship between digital village development and rural household CEP. It should be noted that before regressing the Oprobit model, it is necessary to test the parallel hypothesis of the model first. If the parallel hypothesis is satisfied, the Oprobit model can be selected for estimation. The result of the parallel hypothesis test shows that the p-value is significantly greater than zero, which satisfies the parallel hypothesis and can be estimated by the Oprobit model. Therefore, in accordance with Model (2), this paper conducts regression analysis on EP_1 , EP_2 , and EP_3 . The baseline regression results are shown in Table 3 below:

	(1)	(2)	(3)	(4)	(5)	(6)
	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit
Variables	EP ₁	EP ₂	EP ₃	EP ₁	EP ₂	EP ₃
Digital_village	-0.075***	-0.017***	-0.050***	-0.074***	-0.022***	-0.052***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Control	No	No	No	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Ν	3,561	3,561	3,561	3,411	3,411	3,411

Table	3	:	Baseline	Results
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Note: Standard errors in parentheses. The other variables include age, gender, edu, mar, health, employ, and fam_num. *** p < 0.01, ** p < 0.05, * p < 0.1, the same below.

Table 3 shows the regression results of the digital village on energy-using level, energy-using cost, and multidimensional energy poverty. Columns (1)–(3) in Table 3 present the estimates with no control variables. We find that digital village alleviates the energy poverty of rural households at the 1% significance level. Columns (4)–(6) show the estimates with control variables besides household head, household, and province

fixed effects. The results also show that digital village eases the rural household CEP, which draws a similar conclusion to Columns (1)–(3). In summary, the effect of the digital village on rural household CEP is positive, which accelerates the eradication of CEP in rural areas. To explain: On the one hand, the construction of digital infrastructure accelerates the energy transition in rural areas, which improves the clean energy access of rural households; on the other hand, digital village development with digital economy, digital governance, digital life, which raises the clean energy affordability and changes the energy-using awareness of rural households, thus alleviates the rural household CEP, which confirms the first hypothesis, H1, we proposed.

4.2 Robustness Checks

4.2.1 Endogeneity: Instrumental Variable Strategy

In the baseline regression part, the above model setting may face potential endogeneity problems. As a result, this paper further considers introducing instrumental variables for testing, referring to the practice of Liu and Ma (2020) and other scholars, taking the spherical distance from the provincial capital city to Hangzhou (Sph dis) as an instrumental variable to solve possible endogeneity problems in this paper. The selection of this instrumental variable is motivated by two aspects. Firstly, the spherical distance from the provincial capital city to Hangzhou is directly correlated with the level of digital rural development, thereby satisfying the assumption of instrumental variable relevance. Secondly, the spherical distance from the provincial capital city to Hangzhou does not have a direct relationship with rural household CEP, meeting the assumption of instrumental variable exogeneity. Specifically, the IV-Oprobit model is used to retest the relationship between digital village and rural household CEP, and the test results are shown in Table 4 below. Column (1) in Table 4 is the first-stage regression result of the IV-Oprobit. The result shows that the farther the spherical distance from the provincial capital city to Hangzhou, the lower the development level of digital village, which is in line with our expectations. Columns (2) to (4) in Table 4 show the results of the IV-Oprobit second-stage estimation. The coefficient between the indicators of digital village development and rural household CEP is negative at the 1% significance level, which is consistent with the above, indicating that the conclusion that digital village development can help alleviate rural household CEP has strong robustness.

	IV-Oprobit First Stage	IV-Oprobit Second Stage					
	(1)	(2)	(3)	(4)			
Variables	Digital_village	EP₁	EP ₂	EP ₃			
Digital_village		-0.090*** (0.004)	-0.023*** (0.006)	-0.053*** (0.003)			
Sph_dis	-15.818*** (0.201)						
Control	Yes	Yes	Yes	Yes			
Province FE	Yes	Yes	Yes	Yes			
Ν	3,545	3,578	3,578	3,578			
F	6,176.43						
Adj-R ²	0.635						
Wald chi2		45,519.83	2,136.08	20,060.37			

Table 4 : IV-Oprobit Results

4.2.2 Change Calculation Method

Referring to the study of Luan, Zou, and Huang (2023), we employ the change calculation method of CEP to further verify the conclusion we draw above. The indicator of the "10% energy poverty line" is widely used in the research on measuring energy poverty (Fry, Farrell, and Temple 2022), but it may not be applicable to the PRC (Luan, Zou, and Huang 2023). Therefore, we use the 15% and 20% thresholds to recalculate the CEP. The results of changing the calculation method are shown in Table 5 below. It can be seen that digital village reduces the energy-using cost and lowers the CEP of rural households, at the 1% significance level, which is consistent with the conclusions above; hence, the baseline estimation conclusions are still robust.

	(1)	(2)	(3)	(4)
	15%	15%	20%	20%
Variables	EP ₂	EP ₃	EP ₂	EP ₃
Digital_village	-0.029***	-0.056***	-0.030***	-0.057***
	(0.006)	(0.005)	(0.006)	(0.005)
Control	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Ν	3,411	3,411	3,411	3,411

Table 5 : Results of Changing Calculation Method

4.2.3 Replace Regression Method

Since the explained variable in this paper is ordered data, we choose the more appropriate model of Oprobit in the benchmark regression part. In the robustness check part, this paper selects the robustness check method of replacing the benchmark regression method and adopts the traditional OLS regression method and Ologit method to conduct the robustness checks. The regression results are shown in Table 6 below. It can be seen that EP_1 , EP_2 , and EP_3 are all negative; that is, the conclusions we draw from Table 3 are the same as for Table 6, and the only difference between them is the coefficient size. Therefore, after changing the regression method, the conclusions obtained are consistent with the previous ones and still pass the robustness test.

				•		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reg	Reg	Reg	Ologit	Ologit	Ologit
Variables	EP ₁	EP ₂	EP ₃	EP₁	EP ₂	EP ₃
Digital_village	-0.026***	-0.007***	-0.033***	-0.122***	-0.038***	-0.087***
	(0.002)	(0.002)	(0.003)	(0.010)	(0.010)	(0.008)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Ν	3,411	3,411	3,411	3,411	3,411	3,411
R ²	0.181	0.092	0.155			

Table 6 : Results of Replacing Regression Method

4.3 Heterogeneity Analyses

4.3.1 Geographical Location

Existing literature studies have found that there are significant differences in CEP among different regions of the country, as shown by the lower level in the economically developed provinces along the southeast coast and the higher level in the less economically developed provinces in the central and western regions (Cai, Zhao, and Xu 2021). Based on this, this paper attempts to further investigate the impact of the digital village on different CEP-level areas. According to the geographical location of rural households, we divide the samples into eastern, central, and western regions for grouping regression. The regression results are shown in Table 7 below:

	(1) Eastern	(2) Eastern	(3) Eastern	(4) Central	(5) Central	(6) Central	(7) Western	(8) Western	(9) Western
Variables	EP1	EP ₂	EP ₃	EP1	EP ₂	EP ₃	EP1	EP ₂	EP ₃
Digital_village	-0.034***	-0.006	-0.023***	-0.049***	-0.023***	-0.039***	-0.056***	-0.010	-0.037***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.012)	(0.013)	(0.011)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ν	1,054	1,054	1,054	958	958	958	1,340	1,340	1,340

 Table 7 : Results of Geographical Heterogeneity Analysis

The regression results of the eastern region show that (Column (1) to Column (3) in Table 7) the digital village has a positive effect on the improvement of rural household energy-using levels and the alleviation of comprehensive CEP, but it has no significant impact on energy-using cost. The regression results of the central region show (Column (4) to Column (6) in Table 7) that digital village contributes to the improvement of rural household CEP alleviation in all aspects, and the effect is higher than that of the eastern region. The regression results of the western region show (Column (7) to Column (9) in Table 7) that digital village has significantly improved the energy-using level and decreased the comprehensive CEP, but it has no significant impact on the energy-using cost. Generally, the digital village can reduce rural household CEP, especially in the central region. Specifically, the positive impacts of the digital village on CEP in the eastern, central, and western regions are mainly reflected in the improvement of energy-using levels, mostly in the western areas.

4.3.2 Individual Characteristics

In addition to the geographical differences in CEP, there are also some characteristic differences between household heads, such as individual differences in age, education level, and digital access, which make the development of a digital village have a heterogeneous effect on different characteristics of households. Existing literature shows that there exists a "digital divide" between the older and younger groups (Wang, Zhang, and Zhao 2023), the less educated and the more educated groups (Wang, Yin, and Jiang 2023), and groups with and without access to digital. Moreover, scholars also found that individual characteristics like age (Mensah and Adu 2015), gender (Behera and Ali, 2016), and education (Özcan, Gülay, and Üçdoğruk 2013) are influencing factors in energy-using decisions (Khan et al. 2022). Based on this, this paper groups according to age, education level, and digital access of household heads to test the impact of the digital village on rural households with different ages, education levels, and digital access. The regression results are shown in Table 8 below:

		(1)	(2)	(3)
		Oprobit	Oprobit	Oprobit
Variables	Group	EP ₁	EP ₂	EP ₃
Age	Young	-0.107*** (0.017)	-0.033** (0.015)	-0.081*** (0.015)
	Middle	-0.077*** (0.008)	-0.018** (0.008)	-0.052*** (0.006)
	Old	-0.043*** (0.011)	–0.016 (0.011)	-0.030*** (0.010)
Edu	Low level	-0.069*** (0.006)	-0.017*** (0.006)	-0.046*** (0.005)
	High level	-0.088*** (0.014)	-0.054*** (0.017)	-0.081*** (0.014)
Dig_access	No access	-0.061*** (0.008)	-0.017** (0.008)	-0.040*** (0.007)
	Access	-0.085*** (0.008)	-0.028*** (0.008)	-0.065*** (0.007)
Control		Yes	Yes	Yes
Province FE		Yes	Yes	Yes

Table 8 : Results of Individual Heterogeneity Analysis

Note: In accordance with the practice of Luan, Zou and Huang (2023), we divide household head age into three groups: young group (18 to 35 years old), middle group (35 to 60 years old), and old group (60 to 80 years old); we divide the education level of household head into two groups: low level (below high school) and high level (high school and above); and we divide the digital access of household head into two groups: no access (no mobile Internet access) and access (mobile Internet access).

The regression results of different age groups in Table 8 show that, for the young group, digital village development improves the energy-using level and eases the CEP degree of rural households at the 1% significance level. However, the CEP reduction effect is even lower in the middle group, and the lowest in the old group. Based on the above analysis, it can be seen that the development of the digital village is more obvious for the alleviation of CEP in rural households of young people; that is, there is a "digital divide" between different age groups. According to the regression results of different education levels in Table 8, the alleviation effect on the low education group is lowest, but higher on the high education group. Based on the above analysis, it can be seen that the reduction effect of rural household CEP by digital village is more obvious in the group with a high education level; that is, there is a "digital divide" between groups with different education levels. Finally, results of different digital access groups show that groups with digital access benefit more from digital village development, which presents a higher alleviation effect on CEP.

4.3.3 Dimensional Effect

To explore which aspects contribute most to rural household CEP alleviation in the process of digital village construction, this paper considers using the subindicators for constructing a subindex of digital village, namely rural digital infrastructure, rural economy digitalization, rural economy digitalization, rural governance digitalization, and rural life digitalization, to conduct the subindex regression. The regression results of the dimensional effect are shown in Table 9 below. Columns (1)–(3) in Table 9 present the effect of digital infrastructure on rural household CEP, which indicates that digital infrastructure has a positive effect on alleviating rural household CEP, but the coefficient between digital infrastructure and the energy-using cost is not significant; Columns (4)–(6) in Table 9 show the effect of digital economy on rural household CEP, with the development of digital economy contributing more to rural household CEP.

alleviation; Columns (7)–(9) in Table 9 show that the positive impacts of digital governance on rural household CEP are higher than those of digital economy; and Columns (10)–(12) in Table 9 present the effect of digital life on rural household CEP, with the effect being less than that of digital governance. Taken together, the alleviation of rural household CEP by rural digital development is mostly due to the improvement of rural digital governance, then rural digital life, rural digital infrastructure, and rural digital economy.

	(1)	(2)	(3)	(4)	(5)	(6)
	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit
Variables	EP ₁	EP ₂	EP ₃	EP ₁	EP ₂	EP ₃
Dig_fra	-0.072***	-0.022***	-0.051***			
	(0.006)	(0.006)	(0.005)			
Dig_eco				-0.056***	-0.017***	-0.039***
				(0.004)	(0.004)	(0.004)
Dig_gov						
Dig_life						
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,411	3,411	3,411	3,411	3,411	3,411
	(7)	(8)	(9)	(10)	(11)	(12)
	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit	Oprobit
Variables	EP ₁	EP ₂	EP ₃	EP ₁	EP ₂	EP ₃
Dig_fra						
Dig_eco						
Dig_gov	-0.180***	-0.054***	-0.128***			
	(0.014)	(0.014)	(0.012)			
Dig_life				-0.105***	-0.032***	-0.075***
				(0.008)	(0.008)	(0.007)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Ν	3,411	3,411	3,411	3,411	3,411	3,411

Table 9	:	Results	of	Dimensional	Effect
	•	i toounto	U 1	Dimensional	LIICOL

5. FURTHER ANALYSES

Based on the main results we gave before, in this section, this paper further reveals the effect channels through which digital village alleviates CEP, from the perspective of awareness and wealth, and explores the peer effect on energy using of rural households within the village.

5.1 Mechanisms

5.1.1 Awareness Effect

One potential mechanism is that digital village development may strengthen the environmental awareness of rural households, which can accelerate the transition of energy. The research found that environmental awareness plays a crucial role in rural household decision-making (Zhu, Liao, and Zhou 2023), and awareness of the detrimental effect of traditional fuels is closely linked to household energy-using choice (Imran, Özçatalbaş, and Bakhsh 2019); therefore, among rural households using energy, there may be awareness that barriers exist (MacDonald et al. 2020). To investigate the effect mechanism of awareness, we introduce environmental awareness to reflect the energy-using perception of rural households. To be specific, we standardize the environmental awareness, interact it with the digital village, form the variable of *Envir_digital*, and put it into Model (2) to examine the effect mechanism of awareness.

Table 10 shows the regression of the awareness effect mechanism, which demonstrates that the digital village promotes the environmental awareness of rural households, thus leading to the probability of CEP decreasing, indicating that Hypothesis H2-1 is established, despite the coefficient being small. One potential explanation for this is that the energy is consciousness determined. When the rural household environmental awareness improves, the CEP they are suffering will be eliminated.

	(1)	(2)
	Oprobit	Oprobit
Variables	EP ₁	EP ₁
Envir_digital	-0.002***	-0.001*
	(0.000)	(0.000)
Digital_village	-0.079***	-0.074***
	(0.006)	(0.006)
Control	No	Yes
Province FE	Yes	Yes
Ν	3,403	3,386

Table 10 : Mechanism Analysis: Effect of Awareness on CEP

Note: The variable of *Envir* is defined as "[h]ow important you think environmental protection is." resources from CFPS 2020.

5.1.2 Income Effect

Family income is considered to be an essential determinant of household consumption decisions by many researchers (Huang, Wu, and Zhou 2022; Yang et al. 2023). A lot of literature confirms that digitalization has a positive effect on income increase (Sun and Liu 2022). With the income increasing, rural households may turn to using clean energy as it is affordable. To explore the effect mechanism of household income, after standardizing the variable of family income, we interact it with the digital village index, obtain the channel variable of *Fam_digital*, then put it into Model (2) and conduct the regression again.

Table 11 shows that digital village increases the rural household income, thus lowering the energy-using cost of rural households. This finding is in line with the literature of Luan, Zou, and Huang (2023), which provides further evidence regarding the improvement effects of the digital village on CEP. Therefore, Hypothesis H2-2 is established. It can be explained that when rural household income increases, energy affordability will also be enhanced, thus the clean energy purchase ability of the rural household will be strengthened. However, compared with the coefficients in Table 10, the coefficients in Table 11 are significantly larger, indicating that the impact of digital villages on rural CEP alleviation is mainly achieved by promoting household income, and the increase in household income shows a stronger positive effect on CEP alleviation, which verifies Hypothesis H2-3. The explanation for this finding is that rural households are rational economic agents, under the constraints of income, and they will not choose clean energy just because of their increased clean energy-using awareness, but will choose it based on their income and purchasing power. Therefore, in the process of alleviating the CEP of rural households, governments should emphasize strengthening energy affordability, with the auxiliary of the energy-using awareness transformation.

	(1) Oprobit	(2) Oprobit
Variables	EP ₂	EP ₂
Fam_digital	-0.050***	-0.049***
	(0.004)	(0.004)
Digital_village	-0.061***	-0.057***
	(0.009)	(0.010)
Covariates	No	Yes
Province FE	Yes	Yes
Observations	3,399	3,260

Table 11 : Mechanism: Effect of Income on CE	Table 11
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Note: The variable of *Fam_income* is defined as "total household income for the past twelve months." resources from CFPS 2020.

5.2 The "Contagion": Peer Effect on Rural Household Energy Using

Previous studies found that individual behavior will be affected by the behavior of surrounding people, resulting in a "social multiplier" that makes the behavior of members within the community infect each other (Glaeser, Sacerdote, and Scheinkman 2003). Existing research also found that household energy has "contagion" in rural areas (Wen, Wang, and Nie 2021); that is, the energy and energy payments of rural households may be affected by other people around them, thus making the above estimation of CEP reduction effect on digital village biased. Therefore, based on village-level data, this paper further tests the "peer effect" of energy use and energy payment in each village, explores whether the previous conclusion that digital village can alleviate rural household CEP still holds after further considering the "peer effect". Specifically, referring to the practice of Wang, Chen, and Lu (2009), we rewrite Model (2) as:

$$EP_{i} = \alpha_{0} Digital village_{j} + \alpha_{1} \overline{EP_{ik}} + \beta_{0} X_{i} + \varepsilon_{ij}$$
(3)

The specific variables in Model (3) are consistent with those in Model (2), and $\overline{EP_{ik}}$ represent the average CEP level in village k except for household I = (sum of CEP level of all surveyed households in the village – CEP level of household i) / (Total number of surveyed households in village-1). The regression results of Model (3) are shown in Table 12 below:

	(1) Oprobit EP ₁	(2) Oprobit EP ₂	(3) Oprobit EP ₃
Variables			
Digital_village	-0.056***	-0.020***	-0.043***
	(0.006)	(0.006)	(0.005)
Aver_EP ₁	1.467***		
	(0.118)		
Aver_EP ₂		0.513***	
		(0.180)	
Aver_EP ₃			0.585***
			(0.062)
Covariates	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	3,272	3,272	3,272

Table 12 : Results of Peer Effect on Rural Household Energy Using

According to Table 12, the peer effect significantly exists in the decisions of energy using and energy payment of rural households, which is reflected in the fact that rural households in villages use more nonclean energy and pay less for energy, thus showing a higher degree of CEP. The coefficient between the explanatory variable and explained variable in Table 12 is significantly negative, which is consistent with the conclusion obtained in Table 3; that is, after considering the influence of the peer effect, the digital village is still conducive to reducing the level of rural household CEP. Comparing the coefficients in Table 12 and Table 3, it can be seen that after considering the influence of the peer effect of rural households in the village, the degree of CEP alleviation of rural households in the digital village has decreased. This shows that rural households are highly dependent on traditional energy, most of them still use nonclean energy, and the affordability of clean energy is still low, which is also consistent with the current situation of rural CEP in the PRC.

6. CONCLUSION AND POLICY RECOMMENDATIONS

As the strategic direction of the PRC's rural revitalization, digital villages are also crucial for building a digital PRC. The digital village development has permeated every aspect of rural agricultural production and farmers' lives, accelerating the process of rural digitalization, and advancing the achievement of the goals of the rural revitalization strategy. The construction of a digital village bridges the connection between urban and rural, releasing digital dividends and achieving common prosperity. To further explore from the energy-using perspective, this paper analyzes the effect of digital village on the rural energy-using level and energy-using cost, rural household CEP respectively.

Based on this, this paper combines CFPS and IDRC data, constructs a CEP index measurement system to analyze the relationship between digital village and rural household CEP (energy-using level, energy-using cost, comprehensive index) systematically, and performs Oprobit estimation with controlled province fixed effects. Our results show that digital village improves energy-using levels, lowers the energyusing cost, and alleviates comprehensive rural household CEP. Further investigations indicate that the effect of digital village on rural household CEP through wealth and awareness might be among the potential mechanisms, while the wealth mechanism plays a more crucial role in promoting CEP alleviation. Specifically, with the development of the digital village, the income of rural households will be increased, and the environmental awareness of rural households will be strengthened, thus alleviating the rural household CEP essentially. Heterogeneity analyses reveal that the benefits of the digital village for rural household CEP are more prominent for younger, high education level, digital access groups, which indicates that older and lower education aroups get fewer dividends from digital village: from the perspective of geographical location, in central areas, the digital village development shows a higher rural household CEP alleviation effect; moreover, the rural household CEP alleviation benefits most through digital governance in the process of digital village development.

These findings have some policy implications for other developing countries in alleviating rural household CEP and optimizing digital development in the future, thus improving the rural household welfare and narrowing the urban-rural gap essentially.

(1) Accelerate the construction speed of digital villages in rural areas.

The research results show that digital village construction can help improve the rural household energy-using level, lower the energy-using cost of rural households, and alleviate rural household CEP. Based on this, it is essential to accelerate the construction of digital villages, strengthening the digital and intelligent transformation of infrastructure, such as electricity, wind, and solar energy infrastructure in rural areas. Meanwhile, it can be found that the construction of digital villages has not yet covered all Chinese villages; hence, it is necessary to further expand the depth and breadth of the coverage of digital villages in rural PRC, and then the digital dividend can be shared by all rural households in the country. At the same time, the stability of rural power infrastructure should also be continuously improved, to ensure the power supply capacity and reliability in rural areas. In addition, implementing the energy ladder price policy, reducing the price of renewable energy, and giving appropriate subsidies to rural families that use clean energy may be considered too when the accessibility and affordability of high-quality energy for rural families are improved, and the degree of CEP in rural families is finally reduced.

(2) Adapt to local resource advantage and give more attention to digital governance

On the one hand, according to the research conclusion, it can be found that digital village plays a stronger role in promoting the improvement of rural household CEP in the eastern, central, and western regions, mostly on the energy-using level promotion in western areas. Combined with the real development situation, the renewable energy resources in eastern and central regions are insufficient, but they have a higher level of digital development and more advanced digital technology. Therefore, the government should give full play to the guiding role of digital technology in the eastern and central regions, and make full use of the advantages of abundant energy resources and low energy prices in the western region, accelerate the process of "[c]hannel more

computing resources from the eastern areas to the less developed western regions," promote the interconnection of digital energy infrastructure, and promote the on-site consumption of clean energy in western rural areas, while at the same time promoting the transformation of energy structure and supply structure in the eastern and central regions through digital development, to bridge the "digital-energy" connection between different regions.

On the other hand, our results show that the development of rural digital governance has played a crucial role in promoting the process of rural CEP reduction. Therefore, the process of digital village construction should promote rural digital governance and give full play to the role of "governance guides and lead[s] farmers to common prosperity." Digital governance can help the government understand the distribution of resources, so as to formulate policies more accurately and improve the rural governance efficiency. Meanwhile, digital governance has also played an important part in agricultural production. Based on this, the government should also combine online and offline training to help farmers improve their digital technology and digital literacy. At the same time, it should accelerate the level of agricultural digitalization, introduce agricultural intelligent monitoring and management systems, etc., and cultivate farmers' professional digital talents, to help farmers' income growth and sustainable development; then they will be able to afford clean energy and thus their CEP will be greatly alleviated.

(3) Improve the digital inclusion of the elderly, lower education, and nondigital access groups

On the one hand, the results indicate that the CEP of elderly households benefits less from the development of the digital village. Combined with objective facts, it can be seen that the elderly group has a low degree of digital integration, and there are certain difficulties in learning digital skills. At the same time, the rural elderly group has formed a fixed pattern of thinking about the energy use lifestyle of straw and fuelwood for a long time, and it is difficult to quickly change their approach to using energy. Therefore, it is crucial to strengthen the construction of information infrastructure in digitally weak areas and enhance the network accessibility of rural elderly groups, give full play to the role of communities, carry out smartphone training for rural elderly groups, and publicize the concept of green environmental protection, while at the same time mobilizing the support of family members, forming a good intergenerational interaction, and helping rural elderly groups to cross the digital divide.

On the other hand, compared with the middle and higher education groups, the digital village has a lower-degree improvement effect on CEP in poorly educated rural households. It can be seen that lower education groups often face a digital "using gap" and have a low degree of mastery of digital technology. Meanwhile, related studies have shown that education level is positively correlated with environmental awareness, so a lower education level also reduces the initiative of these households to use clean energy. Based on this, digital skills training should be carried out among rural families with low education and nondigital access households, to lower their digital threshold and improve their basic Internet-using ability, while at the same time promoting energy conservation knowledge actively, improving the awareness of energy conservation and environmental protection of poorly educated and nondigital access households, making sure the digital resources are used sufficiently, and thus helping them cross the "digital divide" and eradicate the rural household CEP.

(4) Strengthen the wealth and environmental awareness of rural households through digitalization

According to the conclusions we draw, it can be seen that the digital village can improve the income level of rural households and strengthen the environmental awareness of rural households, thus reducing the possibility of falling into the CEP trap. Meanwhile, the results of the peer effect show that energy-using levels and energy-using costs remain low in rural areas, which means the average environmental awareness of rural households still lags behind. Due to the economic and cultural level of rural households having been restricted for a long time, they are relatively inadequate in the sense of energy use and the lack of affordability of clean energy, thus facing a more severe situation of CEP. Based on this, we should strengthen the effect of "employment income increase" and "energy saving and emission reduction" in the digital village. The government should continue to promote the development of digital villages, expand farmers' employment channels, and help rural households achieve common prosperity. At the same time, the government should promote the construction of rural digital ecological civilization and publicize the concept of "energy conservation and environmental protection" in digital form in rural areas, thus realizing the awareness transformation of rural households' energy consumption through digitalization.

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