Economics and Data Science 1 (2025) 251111

Economics and Data Science

journal homepage: https://www.innoviair.cn/journal/EDS

The Impact Effect and Value Path of Farmers' Digital Literacy on Reducing Rural Relative Poverty: An Empirical Analysis Based on the Initial Stage of Rural Digitalization

Zewei Zhang[a,*], Yuxuan Tong[b], Qinqi Zou[c]

[a]Agricultural Bank of China Co. LTD, Ningbo, Zhejiang 315000, China

[b]State Grid Zhejiang Electric Power Co. LTD, Cixi, Zhejiang 315300, China

[c]China Agricultural University, Beijing 100193, China

A R T I C L E I N F O

Keywords:
Digital Rural Areas
Digital Literacy
Rural Relative Poverty
Logistic Regression Model
Random Forest Model
SHAP Explainability Analysis

A B S T R A C T

In the process of reducing rural relative poverty, the construction of digital rural areas in China has developed rapidly. In response to the core contradiction of the digital divide evolving from an "access gap" to a "capacity gap", this study utilizes the data from the initial stage of rural digitalization in China in 2017 to explore the impact of digital literacy in different dimensions on the economic conditions of farmers. The research finds that after controlling for observable individual characteristics, farmers with higher levels of digital skills are more likely to reside in households above the relative poverty threshold. Although digital capabilities and attitudes do not show statistical significance, regional differences are obvious. The role of digital skills among farmers in North China, Northeast China, Northwest China, Southwest China and East China is prominent, while in Central South China, digital attitude is the key driving force. This historical perspective analysis helps to understand the root causes of the current digital divide in rural areas and provides historical experience for formulating differentiated strategies to enhance digital literacy.

1.Introduction

In the process of China's modernization, the goal of reducing rural relative poverty is confronted with practical tensions in the dual dimensions of "growth and distribution". From the perspective of the vertical development trajectory, the problem of absolute poverty in our country has been historically resolved. However, the horizontal distribution pattern is significantly unbalanced, and the income gap between urban and rural areas remains high. Against the backdrop of the rapid development of the digital economy, how to build a sustainable mechanism for increasing farmers' income has become a key bottleneck that must be broken through on the road to alleviate from rural relative poverty.

Although digital technology has brought many benefits, there are regional differences in the progress of rural Internet infrastructure and the level of Internet usage among farmers, which has prevented the benefits from being realized. Instead, to a certain extent, it has given rise to the phenomenon of the digital divide. With the continuous improvement of digital infrastructure, the once significant "access gap" has gradually been alleviated. Currently, the issue of the digital divide is more prominently manifested as a "capability gap". In the era of vigorous development of the digital economy, digital literacy has become a key driving force for farmers to continuously increase their income and move towards reducing rural relative poverty. From a practical perspective, digital literacy is a new driving force for reducing rural relative poverty among farmers. The "Key Points of Digital

* Corresponding author.
E-mail address: m15503605648@163.com.
https://doi.org/10.65455/3hxgp649
Received 16 November 2025; Received in revised form 16 December 2025; Accepted 18 December 2025; Available online 30 December 2025

Rural Development Work in 2023" clearly states the implementation of the "Digital Literacy Enhancement Project". By establishing a three-level cultivation system of "county-level digital schools - township training bases - village-level service stations", the improvement of farmers' digital literacy and skills has promoted the phased progress of digital rural development. Therefore, enhancing the digital literacy of farmers is an effective way to narrow the digital divide and an important means to prevent a return to poverty and consolidate the achievements of poverty alleviation.

At present, scholars have explored the connection between farmers' digital literacy and reducing rural relative poverty from different perspectives, but there are certain limitations. Most of the existing research focuses on the qualitative analysis of farmers' digital literacy on reducing rural relative poverty. Wang Dan and others conducted an in-depth analysis of the internal mechanism and specific paths of digital empowerment for reducing rural relative poverty in rural areas. They provided theoretical explanations from the perspectives of enhancing development capabilities, sharing the dividends of social development, and sustainable development, offering a theoretical framework for understanding the role of digital technology in reducing rural relative poverty in rural areas[1]. However, this study lacks in-depth quantitative analysis and is difficult to accurately measure the specific extent to which farmers' digital literacy affects various dimensions of reducing rural relative poverty. Sun Yinglian et al. believe that the two have achieved value coupling in strategic goals, and the construction of digital villages has formed new quality productivity in agriculture, providing the possibility for reducing rural relative poverty for farmers and rural areas. However, there is also a lack of quantitative research[2]. In the construction of the evaluation system for farmers' digital literacy, the academic circle has not yet formed a widely recognized, scientific, comprehensive and highly universal evaluation system. Some studies are highly subjective in the selection of indicators and fail to comprehensively cover all the key factors that affect farmers' digital literacy. The methods for determining weights are also not scientific enough, resulting in the evaluation results being difficult to accurately reflect the real digital literacy level of farmers. In terms of research methods, most studies adopted simple statistical models. Yang Ningze et al. used the Probit model to analyze the impact of digital literacy on reducing rural relative poverty of farmers[3]. Kong Fanbin et al. comprehensively employed fixed-effect models, instrumental variable methods, and moderating effect models, among others[4]. Comparatively, these methods were enriched, and although they could draw preliminary conclusions, However, simple statistical models have limitations when dealing with complex data relationships and are difficult to fully mine the complex information hidden behind the data.

The period from 2015 to 2017 was the initial stage of digital development in rural China. At this stage, digital infrastructure began to extend to rural areas, but there were significant differences in farmers' ability to use digital technologies. In the initial stage of the popularization of digital technology, which groups of farmers have a first-mover advantage in digital skills, how this advantage is transformed into economic benefits, and what are the differences in the responses of farmers in different regions to digitalization? By looking back at this crucial historical juncture, we can better understand the root causes of the current digital divide in rural areas and provide a historical mirror for formulating more targeted policies to enhance digital literacy.

In view of the problems existing in the depth of quantitative analysis, the scientificity of the evaluation system and the diversity of research methods in the current studies, this paper, based on theoretical analysis and research hypotheses, constructs a measurement and evaluation index system for farmers' digital literacy. By combining statistical learning models and machine learning models, this paper constructs a multidimensional index of farmers’ digital literacy grounded in theoretical frameworks. By integrating statistical and machine learning models, we empirically examine the association between digital literacy dimensions and farmers’ relative poverty status, and further uncover region-specific patterns during the early phase of rural digitalization.

2.Materials and methods

2.1.Theoretical analysis and research hypotheses

Digital literacy has a multi-dimensional empowering effect on the rural household group. Through the dual path of strengthening the willingness to participate in rural governance and stimulating entrepreneurial momentum, it has established an innovative practical mechanism for reducing rural relative poverty.

According to Amartya Sen's theory of capacity, the endogenous development capacity of low-income groups is continuously weakened due to the limited accumulation of human capital, forming a "capacity poverty trap" in the process of reducing rural relative poverty[5]. The cultivation of digital literacy can specifically address the predicament of ability deprivation - optimizing the quality of individual decision-making at the micro level. At the meso level, reconstruct the allocation of production factors and ultimately narrow the income distribution gap by enhancing the set of feasible capabilities, thus forming a sustainable poverty alleviation development path[6]. From a theoretical perspective, based on the theories of farmers' behavior, human capital, and information economy, digital literacy, on the one hand, serves as a key ability for farmers to process and utilize information, reducing information asymmetry, enhancing farmers' cognitive and decision-making levels regarding economic activities, optimizing their own decisions to achieve the rational allocation of production factors, and increasing their likelihood of seizing new technological and information opportunities. Enhance integration into the digital society and market competitiveness. On the other hand, as a special form of human digital capital, it can enhance the development momentum and skills of low-income farmers, alleviate income inequality caused by a lack of capabilities, and ultimately reduce rural relative poverty. Figure 1 shows the theoretical framework of the impact of digital literacy on reducing rural relative poverty of farmers.

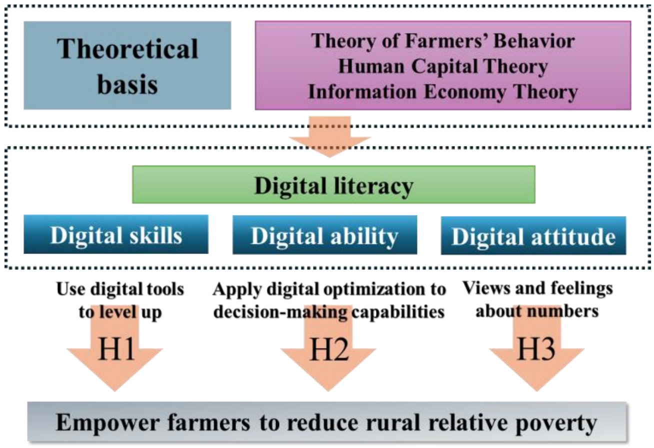

Fig 1. The theoretical framework of the impact of digital literacy on reducing rural relative poverty of farmers

Firstly, enhancing digital skills helps improve farmers' application level of digital payment tools and financial service channels, effectively alleviates the exclusion effect of the traditional financial system, helps farmers better adapt to the development needs of the digital society, and at the same time, objectively promotes the narrowing of economic gaps among different groups of farmers by optimizing the efficiency of financial resource allocation and market participation[7,8]. Propose research hypotheses:

H1: Promoting the improvement of digital skills has a significant positive impact on reducing rural relative poverty of farmers.

Secondly, farmers' production and operation decisions are formed based on a comprehensive consideration of cost control, income expectations, risk tolerance and resource endowment[9]. By enhancing digital application capabilities, farmers can optimize data-driven decision-making mechanisms, effectively integrate market information and technological resources, and thereby build multi-dimensional income-increasing models, achieving sustainable growth in agricultural operation benefits[10]. Propose research hypotheses:

H2: Promoting the improvement of digital capabilities has a significant positive impact on reducing rural relative poverty of farmers.

Thirdly, digital literacy narrates the development gap between urban and rural areas by enhancing the accuracy of poverty governance, and it transforms the traditional notion that entertainment is useless[11,12]. Digital cognition optimizes production decisions, safety awareness ensures the reliability of technology application, and ethical norms avoid social risks. Enhance farmers' resilience in responding to risks, achieve the coordinated development of economic efficiency and humanistic care, and form a sustainable poverty reduction path[13]. Propose research hypotheses:

H3: Promoting the improvement of digital attitudes has a significant positive impact on reducing rural relative poverty of farmers.

2.2.Construction of data sources and index evaluation systems

The data in this article is derived from the "Chinese General Social Survey" (CGSS) project. This survey adopted a stratified multi-stage probability sampling method, covering 28 provincial administrative regions in China. It formed the most representative database of individual Internet usage under the background of reducing rural relative poverty among farmers in the country at present, providing reliable data support for exploring the influencing factors of farmers' digital literacy.

The concept of Chinese digital literacy is defined by the "Action Plan for Enhancing the Digital Literacy and Skills of All Citizens (2021)" as the skills, abilities and attitudes of individuals to adapt to the demands of the information age and comprehensively apply digital technologies to solve problems. Its connotation is composed of three core dimensions: digital skills, digital abilities and digital attitudes[14]. By consulting the literature included in important domestic and foreign databases such as Web of Science, Google, and China National Knowledge Infrastructure (CNKI), and sorting out the research on related topics of digital literacy of rural residents at home and abroad, it provides a theoretical basis for the design of the index system of digital literacy of rural residents in China. Based on this, while taking into account the availability of data, a digital literacy evaluation system is constructed. The specific index contents of the evaluation system are shown in Figure 2.

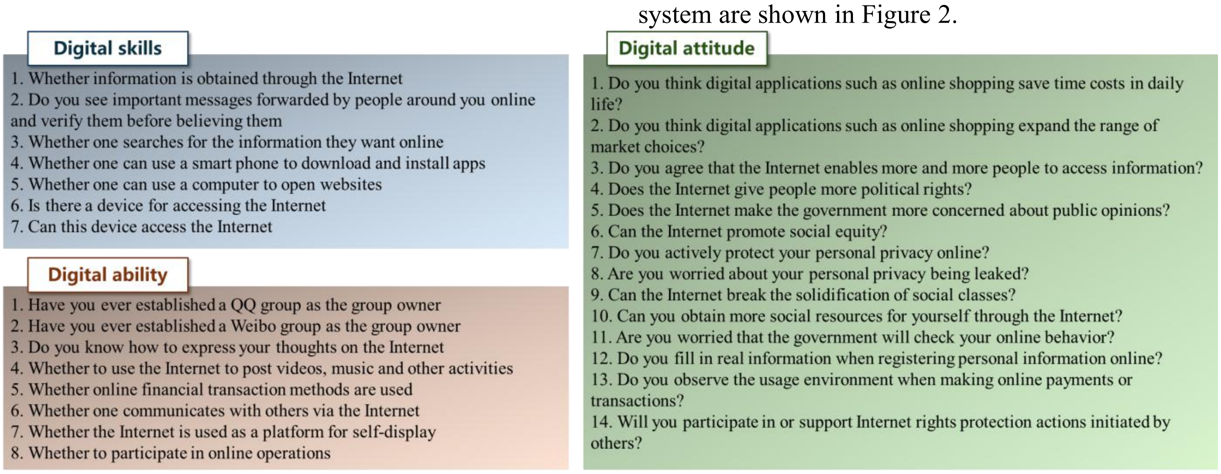

Fig 2. Measurement index system for digital literacy of rural residents

From the perspective of technological empowerment, digital skills are the fundamental threshold for farmers to integrate into the digital society and then use digital tools to increase family income. Digital skills are measured from basic operational capabilities and information acquisition capabilities, including seven items. Mastering basic operations such as device Internet access and software installation is a prerequisite for integrating into digital life. Whether farmers can search for the required information online (JN3), download and install apps by themselves (JN4), and open websites using a computer (JN5), etc., these basic skills affect whether they can smoothly access the digital world. Obtaining information through the Internet is a fundamental ability in the digital age. Whether farmers can search for information on the Internet, browse news, and verify before believing when they see forwarded messages on wechat Moments (JN1) reflects their ability to screen and distinguish information.

The construction of digital capabilities places greater emphasis on systematicness and innovation, and it is a core element for farmers to achieve sustainable development in the digital environment. Digital capabilities are measured from social operation capabilities, network application capabilities, and rights protection capabilities, including eight items. As a group owner, establishing chat groups and wechat groups (NL1 and NL2) reflects farmers' ability to organize, manage social circles and share information by using digital social tools. How to express ideas on the Internet (NL3), use the Internet to release videos and music (NL4), conduct financial transactions (NL5), and other operations demonstrate the application level of diverse network functions by farmers. Using the Internet as a platform for self-display, such as Posting on Moments and participating in online activities to safeguard their own rights and interests (NL7), reflects farmers' awareness and ability to expand their social circle and protect their rights and interests through the Internet, which is conducive to enhancing their participation and say in the digital space.

Digital attitude, as a soft indicator for measuring the digital literacy of rural residents, is related to the healthy and sustainable development of the digital society. Digital attitudes are measured from privacy and security awareness, social impact cognition and online behavior participation, including 14 items. Paying attention to personal privacy protection and worrying about privacy leakage (TD7) reflects the security awareness of rural residents in the digital environment. The views on whether the Internet can break the solidification of social classes (TD9), enable people to access more social resources (TD10), and promote social equity (TD6) reflect rural residents' recognition of the social value of digital technology. Observing the usage environment during online payments and transactions (TD13), and participating in or supporting others' rights protection actions (TD14) reflect the rational behavior and social responsibility awareness of rural residents in the digital space, promoting the healthy and orderly development of the digital environment in rural areas.

2.3.Model construction

Based on the digital literacy index system, this section deeply analyzes the impact of digital literacy (including digital skills, digital capabilities, and digital attitudes) on reducing rural relative poverty of farmers by constructing a Logit regression model and a random forest model integrating SHAP interpretability analysis. The former explores the influence mechanism of different digital literacy capabilities on reducing rural relative poverty of farmers, while the latter assesses the significance of digital literacy characteristics. The method that combines the proposed statistical model with the machine learning model can not only accurately quantify the causal relationships among various variables and mine hidden patterns in the data, but also effectively overcome the possible limitations when using a single type of model.

2.3.1.Statistical model based on Logit regression

Logit regression is a generalized linear model (GLM) and a commonly used method for dealing with binary dependent variables. The core is to represent the log-odds of the dependent variable as a linear combination of the independent variables. The model form is:

$$p_i(y_i=1)=\frac{exp(\beta_0+\sum_{i=1}^{n}\beta_i x_i)}{1+exp(\beta_0+\sum_{i=1}^{n}\beta_i x_i)}+\varepsilon_i \tag{1}$$

Among them, $y_i=1$ indicates that farmers have alleviated from rural relative poverty; p_i is the probability of alleviating from rural relative poverty, x_i is the sample characteristic variable, β_0 is the constant term, β_i is the regression coefficient of x_i, and ε_i is the error term. After conversion, the following can be obtained:

$$\ln\frac{p_i}{1-p_i}=\beta_0+\sum_{i=1}^{n}\beta_i x_i+\varepsilon_i \tag{2}$$

$$Y_i=\beta_0+\beta_1 X_d+r_{ij}X_{ij}+\varepsilon_i \tag{3}$$

$$d=1, 2, 3; i=1, 2, 3\ldots,n; j=1, 2, 3,\ldots, m$$

Among them, $Y=1$ indicates that farmers have alleviated from rural relative poverty, β_0 is the intercept term of the regression model, X_d is the digital literacy situation of farmers, $d=1$ is digital skills, $d=2$ is digital ability, $d=3$ is digital attitude, X_{ij} is other influencing factors, including the gender, age and educational level of farmers in this paper, β_i is the regression coefficient of X , γ_{ij} is the regression coefficient of X_{ij}, and ε_i is the random error term. The parameter estimation of the Logit regression model adopts the maximum likelihood estimation method, which estimates the model parameters by maximizing the likelihood function of the sample observations. The likelihood function represents the probability of the occurrence of observed data under given parameters. By maximizing the likelihood function, the parameter values that best explain the data can be found.

Although this study enhances result robustness by controlling for observable individual characteristics—such as gender, age, and educational attainment—and cross-validating estimates across Logit, Probit, and OLS models, the cross-sectional nature of the data inherently limits our ability to fully address endogeneity arising from unobserved confounders. Of particular concern is individual ability endowment—including cognitive flexibility, learning initiative, and social adaptability—which may simultaneously facilitate the acquisition of digital skills and improve economic outcomes. Consequently, the measured "digital skills" variable may partially act as a proxy for such latent heterogeneity. This phenomenon is well-documented in human capital literature as "ability bias" by Heckman.

Given that the CGSS 2017 dataset lacks exogenous variation suitable for constructing valid instrumental variables—such as village-level broadband rollout timing or county-level coverage of digital literacy programs—this paper cannot establish a causal effect. Therefore, the reported "significant positive association between digital skills and relative poverty alleviation" should be interpreted more precisely as follows: during the initial phase of rural digitalization (2015–2017), farmers with higher levels of digital skills were more likely to reside in households above the relative poverty threshold. The value of this finding lies not in demonstrating that skill acquisition causes poverty escape, but in revealing the early distributional pattern of digital dividends.

Historically, this association highlights which farmer groups gained a first-mover advantage after the "access gap" began to narrow, thereby offering empirical guidance for designing differentiated digital literacy enhancement policies today.

2.3.2.Machine learning model based on random forest

The Random Forest model is a classifier based on ensemble learning methods, which is suitable for dealing with and analyzing the complex influence mechanism of variables in multi-class classification problems. Random forest is an extended variant of Bagging. Based on the construction of a Bagging ensemble with decision trees as the base learner, it further introduces random feature selection in the training process of decision trees. The random sample selection process is the same as Bagging, and the Bootstraping self-sampling method is adopted. The implementation principle of the random forest model is shown in Figure 3.

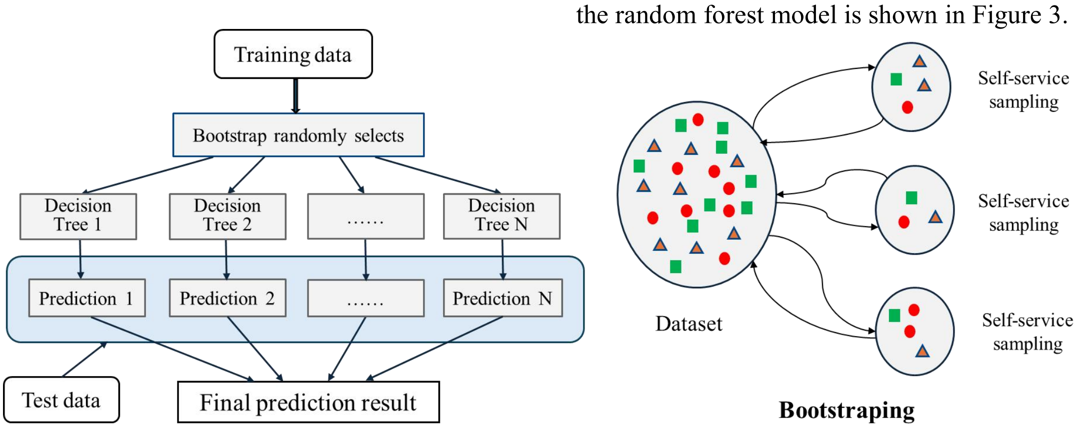

Fig 3. Schematic diagram of the random forest model

During the random forest training process, the greater the influence of each index variable on the heterogeneity of observations at each node of the classification tree, the more important the variable is. In this paper, the error rate index of out-of-pocket Data (OOB Data) of the random forest algorithm is used to evaluate the importance of digital literacy characteristics.

$$VI_j^{(OOB)}=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i^o}\left(\sum_{p=1}^{m_i^o} I\left(Y_p=Y_p^i\right)-\sum_{p=1}^{m_i^o} I\left(Y_p=Y_{p,\pi_j}^i\right)\right) \quad (4)$$

Among them, $VI_j^{(OOB)}$ represents the significance of the indicator; m_i^o is the number of observed cases in the tree OOB data; $I_{(g)}$ is a characteristic function. When the two values are equal, take 1. Y_p is the true result of the observation; Y_p^i is the prediction result of the pre-perturbation tree on the observation of OOB data; Y_{p,π_j}^i is the prediction result of the perturbed tree on the observation of OOB data.

2.3.3.SHAP interpretability analysis model

SHAP is an interpretability model based on game theory, which can quantify the contribution of each feature to the evaluation model of reducing rural relative poverty in random forests. SHAP is an additive interpreter that can decompose the predicted values of a model into the sum of the pivot values and the contributions of all features. At the same time, SHAP and the random forest model can be converted into each other. By taking advantage of the structural features of the tree model (such as path segmentation and leaf node scores), the Shapley value can be efficiently calculated, as shown in the following formula.

$$\ln\frac{\hat{y}}{1-\hat{y}}=\phi_0(x)+\sum_{i=1}^{M}\phi_i(x) \quad (5)$$

Among them, $\hat{y}$ is the predicted value for alleviating from rural relative poverty; $\phi_i(x)$ is the Shap Values of each feature; $\phi_0(x)$ is the benchmark value, the expected predicted value when there are no features.

The calculation of Shap Values is based on the Shapley value formula in game theory, as shown in the following formula:

$$\phi_i(x)=\sum_{S\subseteq F\setminus\{i\}}\frac{|S|!(M-|S|-1)!}{M!}[f_x(S\cup\{i\})-f_x(S)] \quad (6)$$

Among them, F is the set of all features; S is the feature subset; $f_x(S)$ is the model prediction value when only the feature subset is used; M is the total number of features.

3.Research design

3.1.Reliability and validity testing of the digital literacy index system

Reliability analysis was conducted via SPSS27, and Cronbach's Alpha was all greater than 0.7. Reliability analysis was conducted on each scale after deleting items. The reliability coefficients of the scales were not improved after the items were deleted. The specific results are shown in Table 1.

Analyze the significance of the KMO value of the scale and the Bartlett sphericity test. If the KMO value is greater than 0.7 and is significant at the 0.05 level, factor analysis can be conducted. The specific results are shown in Table 2.

Confirmatory factor analysis was conducted through AMOS, and the structural validity results are shown in Table 3. The validity results of each dimension are all within the reference values, indicating that the questionnaire data have good structural validity.

Table 1. Reliability analysis of the impact of digital literacy on reducing rural relative poverty of farmers

Variable	Cronbach's Alpha	Number of items
Digital skills	0.729	7
Digital ability	0.740	8
Digital attitude	0.738	14
Overall	0.859	29

***.The correlation is significant at the 0.001 level (two-tailed); The correlation is significant at the 0.01 level

Table 2. The significance results of KMO values and Bartlett's sphericity test

Variable	KMO value and significance
Digital skills	0.802***
Digital ability	0.794***
Digital attitude	0.782***
Overall	0.881***

Table 3. Results of structural validity analysis

Indicator	Result	Reference value
X^2/df	2.896	<3
RMSEA	0.046	<0.10
RMR	0.011	<0.05
GFI	0.922	>0.9
AGFI	0.906	>0.9

3.2.Descriptive statistical analysis

First, a descriptive analysis of the digital literacy index system was conducted. According to Table 4, it can be concluded that the average values of each dimension of the overall digital literacy are all around 0.6, indicating that although the general public has already laid a certain foundation in digital literacy, there is still considerable room for improvement. Among the various constituent dimensions of digital literacy, the average value of digital skills is 0.655 and the standard deviation is 0.253, indicating that the average level of digital skills is relatively high, but the differences among individuals are relatively large. The average value of digital ability is 0.632, and the standard deviation is 0.238. Its average level is slightly lower than that of digital skills, and individual differences are also relatively obvious. The mean value of digital attitude is 0.604 and the standard deviation is 0.207, which is the lowest average level among the three dimensions, and the individual differences are relatively small.

Table 4. Descriptive analysis of digital literacy evaluation indicators

Indicator	Mean	Standard deviation
Digital skills	0.655	0.253
Digital ability	0.632	0.238
Digital attitude	0.604	0.207

Based on the nature of household registration, a sample of respondents with rural household registration was screened and retained. Alleviate from rural relative poverty was measured as the dependent variable indicating whether a farmer's household is relatively poor. Following the World Bank (2018) and Ravallion & Chen (2019), we define relative poverty as household per capita annual income below 40% of the national rural median income (approximately ¥6,000 in 2017)[11]. Digital literacy is divided into digital skills, digital abilities and digital attitudes as independent variables, and different genders, ages and educational levels as control variables. After eliminating invalid questionnaires with missing values and those that refused to answer questions, a total of 901 valid samples were finally obtained. With the help of the SMOTE method, the sample was expanded to 12,000. Table 5 shows the results of descriptive statistical analysis of the variables.

Table 5. Descriptive analysis of the impact of digital literacy on reducing rural relative poverty of farmers

Variable	Indicator symbol	Variable explanation	Average value	Standard deviation
Rural relative poverty	FUY	1= The per capita annual income of the family is higher than 6,000 yuan.	0.83	0.38
Annual household income	MON	0= The per capita annual income of the family is less than 6,000 yuan	66986.75	79216.54
Digital skills	JN	Total household income in 2017	0.65	0.25
Digital ability	NL	It is derived from the indicator system	0.63	0.24
Digital attitude	TD	It is derived from the indicator system	0.60	0.21
Gender	GEN	It is derived from the indicator system	0.49	0.50
Age	AGE	1= male, 0= female	37.92	11.53
Educational attainment	ED	Actual age in 2017	2.24	0.98

3.3.Analysis of the impact of digital literacy on reducing rural relative poverty of farmers

This analysis is based on cross-sectional data from the initial stage of rural digitalization in 2017, reflecting the correlation between farmers' digital literacy and economic conditions during this specific historical period. These findings should not be regarded as a direct description of the current situation, but rather as a historical starting point for understanding the current inequality in rural digital development.

The Logit regression model is used to analyze the impact of digital literacy on reducing rural relative poverty of farmers. To avoid the influence of multicollinearity caused by variable selection, the average variance inflation factor of the independent variables in this paper is lower than the critical value of 10, and the model does not have a serious multicollinearity problem.

As shown in Table 6, regardless of whether other influencing factors are introduced into the model or not, digital skills have a significant positive impact on reducing rural relative poverty of farmers at the 1% statistical level, and the marginal effect after introducing other factors is 0.199. Digital literacy can increase the possibility of farmers alleviating from rural relative poverty by 19.9%, and Hypothesis 1 has been confirmed.

Table 6. Logit analysis results on the impact of digital literacy on reducing rural relative poverty of farmers

Variable	Model 1			Model 2		
	Coefficient	Standard error	Marginal effect	Coefficient	Standard error	Marginal effect
Digital skills	1.595***	0.499	0.218	1.482***	0.527	0.199
Digital ability	0.438	0.524	0.060	0.395	0.576	0.053
Digital attitude	-0.502	0.493	-0.069	-0.498	0.495	-0.067
Gender				-0.365*	0.188	-0.049
Age				0.016	0.011	0.002
Educational attainment				0.385***	0.115	0.052
Constant term	0.632	0.283		-0.533	0.691	
pseudo R^2	0.032			0.050		
AIC	802.465			794.112		
Log lik.	-397.232			-390.056		

Digital ability and digital attitude have an impact on reducing rural relative poverty of farmers at the 1% statistical level, but it is not significant. Hypotheses 2 and 3 do not hold. One possible reason is that in 2017, the popularization and application of digital technology was limited. Although farmers had certain digital capabilities, there were few application scenarios that could be transformed into actual economic benefits or reducing rural relative poverty. Meanwhile, the construction of digital infrastructure in rural areas is still not perfect, which restricts the full play of farmers' digital capabilities. Furthermore, farmers' awareness and acceptance of digital technology are not high. Even if they have a positive attitude, they may find it difficult to transform their positive attitude into effective actions to reduce rural relative poverty due to the lack of relevant skills training and guidance.

In terms of other influencing factors, gender and educational attainment have an impact on reducing rural relative poverty at significance levels of 1% and 5% respectively. The higher the educational attainment of farmers, the higher the degree of reducing rural relative poverty. Gender has a negative and significant effect on farmers reducing rural relative poverty at a significance level of 1%, that is, women are 4.9% more likely to reduce rural relative poverty than men.

Digital literacy conducts robustness tests on the replacement of the OLS regression model and Probit regression model for reducing rural relative poverty model of farmers. The OLS and Probit regression results in Table 7 are basically consistent with those of the Logit regression model, and hypotheses 1, 2, and 3 are verified again.

Table 7. Robust analysis results of the impact of digital literacy on reducing rural relative poverty of farmers

	OLS		Probit		
	Model 3		Model 4		
	Marginal effect	Robust standard error	Coefficient	Robust standard error	Marginal effect
Digital skills	0.228***	0.073	0.858***	0.299	0.206
Digital ability	0.062	0.080	0.244	0.322	0.059
Digital attitude	-0.074	0.069	-0.308	0.283	-0.074
Control variable	Controlled		Controlled		
Constant term	0.505	0.097	-0.260	0.385	
pseudo R^2				0.050	
R^2	0.046				
AIC	763.614			793.880	
Log lik.				-389.940	

3.4.Analysis of the impact of digital literacy on reducing rural relative poverty of farmers in different regions

The previous text analyzed and proved through the Logit regression model that digital skills, digital capabilities, and digital attitudes all have an impact on the degree of reducing rural relative poverty of farmers. Given the historical background of unbalanced regional development in China, in 2017, there were significant differences among farmers in different regions in terms of access to digital technology, the level of infrastructure construction and digital application scenarios. This section, through regional comparisons, reveals the differentiated paths for the development of digital literacy among farmers in different regions during the initial stage of digitalization. This historical analysis helps to understand the root causes of the current digital divide between regions. Given that regional economic development differences may regulate the above relationship, this paper divides China into six major regions: East China, North China, Northeast China, Northwest China, Southwest China, and Central South China. It also uses random forest and SHAP methods to integrate traditional statistics and machine learning to overcome the limitations of a single method. The SHAP summary graph in Figure 4 shows the direction and intensity of the influence of the three types of variables on reducing rural relative poverty on the horizontal axis, and arranges them in order of importance from top to bottom on the vertical axis. The size of the characteristic values is indicated by the depth of color, with red representing high and blue representing low.

Longitudinal comparison reveals that, except for Central and South China, digital skills are the primary factor in all regions. The digital attitude is the most explanatory in the central and southern regions. Digital capabilities stand out in North China and Northwest China. A horizontal comparison reveals that the order of influence in East China, Northeast China and Southwest China is digital skills > digital attitude >

digital ability. In these regions, the industrial foundation or characteristic agriculture is relatively mature, and digital skills can be directly integrated into the production and circulation links, quickly transforming into income-increasing momentum. In North China and Northwest China, the order is digital skills > digital capabilities > digital attitudes. The reason is that digital capabilities are more operational and have higher resource conversion efficiency, while the lag in concept renewal makes it difficult for digital attitudes to generate immediate economic benefits. In the central and southern regions, the trend is digital attitude > digital skills > digital capabilities. The open mindset nurtured by Lingnan culture has prompted farmers to be the first to accept and apply new knowledge about the digital economy. Digital capabilities, which require long-term accumulation, lag behind relatively and thus have the weakest influence in this region.

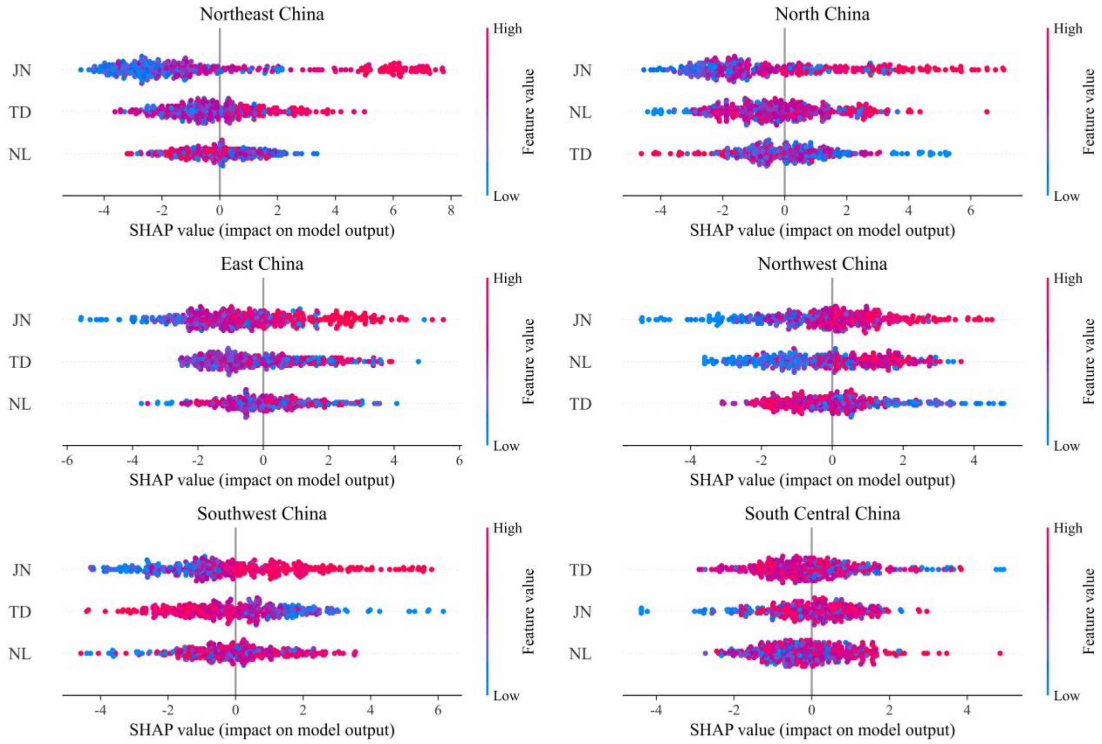

Fig 4. SHAP summary chart of the impact of farmers' digital literacy on their reducing rural relative poverty

It can be seen from the SHAP values that the characteristic values of the impact of digital skills, digital capabilities and digital attitudes on reducing rural relative poverty of farmers in the East China region and the Central South region are all concentrated in the middle. In terms of digital skills, most characteristic values are relatively large, indicating that the majority of farmers possess relatively good digital skills. This might be attributed to the development of the digital industry in this region and the promotion of related skills training, which enables it to actively reduce rural relative poverty. Some characteristic values of digital attitude and digital ability are relatively small, reflecting that some farmers do not attach enough importance to and apply digital technology, or are affected by traditional agricultural production concepts and the uneven distribution of digital educational resources.

For the North China region, the SHAP values of digital skills are mostly distributed on the right side of 0, showing a significant and relatively concentrated positive impact. The North China region, located between the North China Plain and the Loess Plateau, is a key area for grain production, with a rich variety of industrial types. Some farmers have been exposed to digital-related content relatively early. In terms of digital skills, most characteristic values are relatively large, indicating that the majority of farmers possess relatively good digital skills. This might be attributed to the advancement of industrial digital transformation in Beijing and Tianjin in this region, as well as the extensive promotion of agricultural science and technology, which have provided farmers with opportunities to learn and apply digital skills. The SHAP values of digital attitude and digital ability are distributed on both sides of 0, indicating that their impact on reducing rural relative poverty is not stable enough and it is necessary to further enhance the digital attitude and digital ability of farmers. Perhaps due to the constraints of traditional concepts and the lagging development of digital education in some rural areas, farmers' acceptance and application ability of digital technology have been affected.

For the Northeast region, the SHAP values of digital skills are mostly positive and relatively concentrated, and they have a strong positive promoting effect on reducing rural relative poverty. The Northeast region is an important agricultural production area in China, and there is a certain foundation for the large-scale development of agriculture. In terms of digital skills, many feature values are relatively large, indicating that farmers have accumulated certain skills in leveraging digital technology to assist agricultural production and the sale of agricultural products. The SHAP values of digital attitude and digital ability are relatively discrete, with both positive and negative values occurring. This indicates that it is necessary to strengthen the cultivation of farmers' digital attitude and digital ability to steadily reduce rural relative poverty. The characteristic values of digital attitude and digital ability are relatively small, which may be due to the fact that the local agricultural production methods are relatively traditional and farmers' responses to the updates and iterations of digital technology are relatively lagging behind.

In the northwest region, the SHAP values of digital skills, digital attitudes, and digital capabilities are more frequently distributed around 0 and to the left of 0, indicating that their positive impact on reducing rural relative poverty is relatively weak. It is urgently necessary to strengthen the construction of digital infrastructure and related training to enhance the digital-related level of farmers, thereby reducing rural relative poverty. The northwest region is vast in territory, yet the digital infrastructure in some areas is relatively weak. In the three aspects of digital skills, digital attitudes and digital capabilities, there are many cases where the characteristic values are relatively small, reflecting that there is considerable room for improvement in the popularization of digital skills, the enhancement of farmers' enthusiasm for digital attitudes and the cultivation of digital capabilities. This situation is constrained by multiple factors such as geographical conditions, the level of economic development, and the relatively scarce digital resources.

In the southwest region, the SHAP values of digital skills have a certain positive distribution, but the SHAP values of digital attitudes are more frequently distributed on the left side of 0. This indicates that it is necessary to improve farmers' digital attitudes and enhance their digital capabilities to contribute to reduce rural relative poverty. The terrain in the southwest region is complex, and transportation in some mountainous areas is inconvenient. A certain number of characteristic values of digital skills are relatively large, indicating that some farmers can master the corresponding digital skills, but there are many cases where the characteristic values of digital attitude and digital ability are relatively small. This might be because the terrain factors have affected the flow of information, and at the same time, the traditional production and lifestyle are deeply rooted, which to some extent hinders the application of digital technology.

4.Conclusions

This study finds that during the initial phase of rural digitalization in China (2017), digital skills significantly contribute to reducing rural relative poverty, a pattern especially pronounced in North, Northeast, Northwest, Southwest, and East China. In Central-South China, digital attitude emerges as the key differentiator. Importantly, our results do not imply that digital skills eliminate poverty per se; rather, they reflect that farmers with stronger operational and information-seeking competencies were more likely to be alleviated from relative poverty once basic digital infrastructure was in place. Therefore, current “ Digital Literacy Enhancement” initiatives should move beyond one-size-fits-all approaches. Instead, policies must be regionally tailored and targeted at vulnerable groups — such as older or less-educated farmers — to reduce their risk of falling into or remaining in relative poverty, thereby fostering more inclusive rural development.

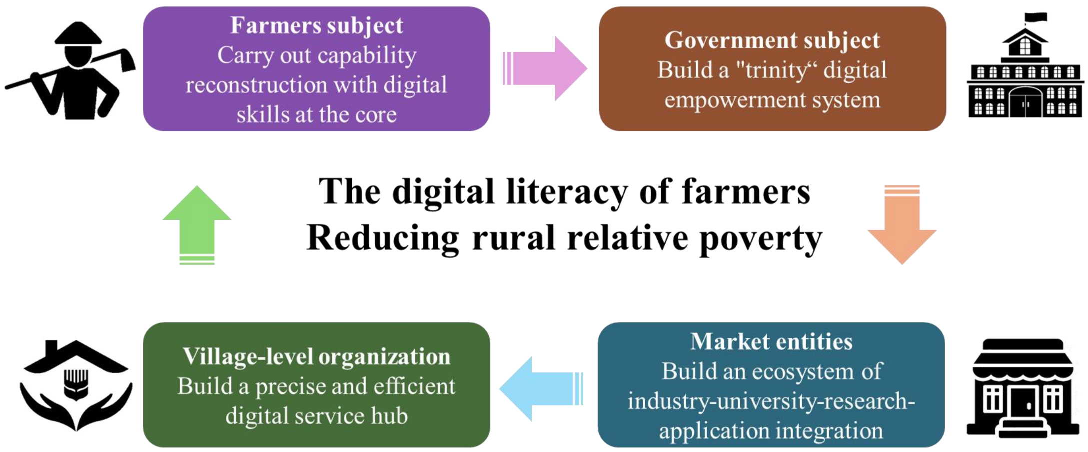

Fig 5. The digital literacy of farmers empowers the realization path of reducing rural relative poverty

This study explains which farmers were more likely to cross the digital capability threshold and escape relative poverty during the initial phase of rural digitalization in China (2015 – 2017). This historical snapshot reveals the uneven distribution of early digital dividends, offering an empirical baseline for understanding subsequent policy evolution.

Based on this historical evidence, the key insight is that rural digitalization did not unfold uniformly — pathways for crossing the “capability gap” diverged across regions. Consequently, when retrospectively evaluating the evolution of subsequent digital inclusion policies, attention could be paid to whether regional strategies have addressed the structural disparities evident at the outset. Furthermore, the study suggests that, during the initial phase of technological diffusion, certain groups may have been less able to benefit promptly due to capability constraints — a historical lesson worth considering in understanding the long-term trajectory of digital equity.

Farmers could actively respond to the digital skills training projects organized. Given that digital skills are significantly associated with non-poverty status in North, Northeast, Northwest, Southwest, and East China, while digital attitude matters only in Central-South China, training projects are more needed in Central-South China. The village committee and marketing entities could, in accordance with the policy spirit of building harmonious and beautiful villages and deepening the integrated reform of rural areas, establish dynamic archives of farmers' digital literacy and implement classified policies based on the "skill deficiency type", "equipment shortage type" and "concept lag type". Integrate

Spaces such as rural libraries and cultural halls to build digital stations, enriching farmers' digital learning experiences.

Government departments could further improve the special planning for digital infrastructure. Accelerate the full coverage of 5G networks and logistics stations in administrative villages to lay a solid foundation for the digitalization of agriculture. Establish a three-level training system of "basic - advanced - elite", and jointly develop dialect version teaching resources with universities to enhance the pertinence and practicality of the training. Referring to the emphasis on farmers' training in the "Twenty Support Policies for Rural Revitalization", the training hours are linked to the quota of small loans to encourage farmers to actively participate in training and enhance their digital skills. Establish a digital agriculture development fund and provide a 30% equipment subsidy to cooperatives that adopt Internet of Things technology in accordance with policies, guiding agricultural business entities to increase their investment in digitalization.

5.Research prospects

This article is based on the policy connotation of the "Action Outline for Enhancing the Digital Literacy and Skills of All Citizens (2021)", and constructs an evaluation system for farmers' digital literacy that includes three dimensions: digital skills, digital capabilities, and digital attitudes. It is also based on the data from the 2017 China General Social Survey (CGSS). Innovatively integrating the Logit regression model with the random forest model integrating SHAP (SHapley Additive exPlanations) explainability analysis. The former is used to identify the marginal impact and direction of different literacy dimensions on reducing rural relative poverty of farmers, while the latter reveals the relative importance of each digital literacy feature and its nonlinear effect through machine learning methods. This hybrid analysis strategy of "statistical model + machine learning" not only enhances the robustness of causal inference but also strengthens the explanatory power for complex decision-making mechanisms, providing new methodological support for understanding the micro-path of reducing rural relative poverty driven by digital literacy.

However, this study also has limitations. The primary limitation lies in the timeliness of the data. In 2017, rural areas were still in the early stage of digital transformation. The penetration rate of smart phones, mobile payment and emerging applications such as short videos had not yet been widely adopted. This might have underestimated the current actual digital literacy level of farmers and its marginal effect on reducing rural relative poverty. Secondly, due to the limitations of cross-sectional data, it is difficult for this paper to completely rule out the endogeneity problem, which poses certain challenges to the identification of causal relationships. In addition, some advanced dimensions of digital literacy (such as data analysis, the use of artificial intelligence tools, etc.) were not covered in the 2017 questionnaire, and there is still room for expansion in the indicator system. It should be noted that although this article is based on the CGSS data of 2017, that year coincides with a crucial starting point for the digital transformation of rural areas in China, which can truly reflect the initial state of digital literacy development. The evaluation system constructed closely follows the national digital literacy policy framework of 2021, demonstrating both forward-looking and theoretical continuity. Meanwhile, under the current condition of lacking more representative national microdata, CGSS 2017 remains the best choice that takes into account authority, availability and variable adaptability.

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