

Article

The Influence of Digital Skills on Farm Households' Vulnerability to Relative Poverty: Implications for the Sustainability of Farmers' Livelihoods

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Abstract: Improving farmers' digital skills is instrumental in reducing the risk of farmer households reverting to poverty and in fostering sustainable livelihood development. This study investigated the impact of digital skills on the relative vulnerability of farm households to poverty and explored the mediating role of social capital. Based on 2022 field survey data from 917 rural households in Yunnan Province, China, we employed a probit model to evaluate how digital skills influence the likelihood of poverty reversion among farm households. The findings indicated that enhancing digital skills significantly reduced households' vulnerability to poverty, thereby mitigating the risk of poverty recurrence. The heterogeneity analysis revealed that the impact of digital skills was more pronounced among low-income households. Among various digital skills, social digital skills exerted the strongest effect in reducing poverty vulnerability. Further analysis demonstrated that enhanced digital skills strengthened social capital, which subsequently reduced the risk of poverty reversion. To ensure sustainable poverty alleviation and prevent widespread poverty relapse, accelerating the development of digital skills among rural populations in western China is essential. This will create new development opportunities and contribute to long-term livelihood sustainability.

Keywords: poverty vulnerability; digital skills; social capital; poverty alleviation; sustainable livelihoods



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1. Introduction

Poverty reduction remains a central issue on the global development agenda, especially in developing nations. As the world's largest developing country, China has eradicated absolute poverty and is now focused on addressing relative poverty. Despite this progress, ethnic minority regions, historically impacted by geographic, environmental, and economic challenges, remain vulnerable to a resurgence of poverty. Although these populations have escaped poverty, they continue to face significant livelihood vulnerabilities and possess resilience to risks, making them susceptible to poverty reversion [1–4]. As global digitalization accelerates, digital technology offers new avenues for addressing relative poverty. Digital technology not only helps raise farmers' incomes and reduce the likelihood of poverty reversion but also plays a critical role in promoting employment, entrepreneurship, and agricultural modernization [5–11]. Consequently, research and policy should prioritize enhancing farmers' digital technology capabilities, thereby strengthening their intrinsic development motivation and sustainability [12–14], improving their capacity for sustainable poverty alleviation and reducing poverty vulnerability. This approach is critical for consolidating poverty alleviation achievements and advancing rural revitalization efforts in China [15,16].

The existing literature on this topic primarily focuses on two aspects: the measurement of poverty vulnerability and its influencing factors. Three principal approaches exist for

measuring poverty vulnerability: vulnerability as expected utility (VEU), vulnerability as expected poverty (VEP), and vulnerability as uninsured risk (VER). Of these (see Table 1), the VEP method is widely recognized for its logical clarity and forward-looking perspective, and it has been applied in numerous studies [17–23]. However, the poverty thresholds employed in these studies are relatively narrow, and the data sources are outdated, limiting their applicability to the current context. Moreover, most studies examining the determinants of poverty vulnerability focus on traditional forms of livelihood capital, such as labor health, agricultural insurance, and land ownership [24–28], while paying limited attention to emerging livelihood capital in the digital economy, such as digital skills. Although some scholars have explored new forms of financial capital, such as digital finance, the role of digital skills—considered a form of new human capital—in alleviating household poverty vulnerability remains underexplored [29–31].

Table 1. Measurement for poverty vulnerability.

Category	Definition	Advantages	Disadvantages	References
VEU	The gap between the utility of a non-vulnerable consumption level and the utility of current consumption.	This approach is rooted in utility theory, assessing risk and uncertainty by maximizing individual utility. Additionally, it accounts for individuals' risk preferences, acknowledging that varying risk tolerance can result in different vulnerability levels under identical conditions.	First, estimating individual risk preferences and utility functions requires detailed data, which poses challenges for empirical applications. Second, the method's complexity in calculation, particularly when handling large datasets, limits its practical applicability.	Ligon et al. (2003) [17]; Gallardo et al. (2020) [32,33]
VEP	The risk of falling below the poverty line or, for those already impoverished, remaining in or deepening poverty.	First, it estimates the likelihood of a household falling into poverty in the future, providing critical insights for policy interventions. Second, its clear logic and compatibility with traditional poverty thresholds have led to VEP's widespread use in empirical research. Third, compared with VEU, VEP is less data intensive, making it more feasible in contexts with limited data availability.	First, VEP depends on predictive models of income or consumption, with the accuracy of the results contingent on the model's quality. Second, unlike VEU, VEP does not consider individual risk preferences, instead assuming that all individuals are equally vulnerable under similar conditions.	Chaudhuri et al. (2002) [18]; Ji et al. (2024) [21]; Li et al. (2023) [22]; Wang et al. (2020) [23]
VER	The approach that estimates welfare losses by assessing negative shocks experienced after an event.	First, VER directly measures a household's exposure to economic and environmental risks, making it particularly suitable for assessing the impact of short-term shocks on poverty. Second, it can be applied to a variety of risks, including climate, health, and economic shocks, demonstrating its versatility across diverse contexts.	First, VER primarily focuses on short-term shocks and risks, rather than long-term poverty trends, which limits its capacity for forward-looking analysis. Second, defining and measuring risk exposure is often ambiguous, making it challenging to accurately quantify the specific risks faced by households.	Gaiha et al. (2008) [19]; Azeem (2008) [34]

To address these research gaps, this study drew on micro-survey data from Yunnan Province, a multi-ethnic region in China, to examine the impact of digital skills on the relative vulnerability of rural households to poverty under different poverty thresholds

and to explore the underlying mechanisms. First, the study employed the vulnerability as expected poverty (VEP) method to evaluate households' relative poverty vulnerability using the OECD income median thresholds of 40%, 50%, and 60%, along with the World Bank's relative poverty benchmarks for daily per capita consumption of USD 2.15, USD 3.65, and USD 6.85. Second, from a new human capital perspective, the study explores the critical role of digital skills in reducing households' risk of poverty reversion, providing key policy insights for managing relative poverty in the digital age. Additionally, the study incorporates social capital to analyze how digital skills can mitigate relative poverty vulnerability by strengthening households' social networks. Finally, the study investigates the heterogeneous effects of different income levels and types of digital skills, broadening the research perspective on digital skills and poverty alleviation. This provides theoretical support and policy guidance for poverty reduction efforts within the digital economy context, contributing to preventing large-scale poverty reversion and promoting sustainable development.

2. Theoretical Framework

2.1. The Impact of Digital Skills on Farmers' Relative Poverty Vulnerability

Poverty vulnerability refers to the probability that an individual's or household's future well-being may fall below a socially acceptable level due to a shock, especially for those already susceptible to poverty. This group typically has weak and unsustainable livelihoods, making it challenging to withstand risks. Livelihood capital is a key factor element in achieving sustainable livelihoods [35,36]. The sustainable livelihoods theory posits that livelihoods are a comprehensive system encompassing natural, physical, human, financial, and social capital. Livelihood improvement focuses not merely on short-term economic growth or aid but on an integrated approach to long-term development, capacity building, social participation, and resource management. In the context of poverty governance in China, the primary goal is to strengthen the rural population's capacity for earning a living and support farm households in establishing sustainable livelihoods.

The widespread adoption of information technology, coupled with the development of a digital infrastructure, presents new opportunities to reduce the poverty vulnerability of farm households. The digital infrastructure mitigates poverty vulnerability by expanding Internet access, strengthening social capital, and boosting non-farm income. This is evidenced by the information effect, communicative effect, and employment effect [37–39]. According to Schultz's human capital theory, among the various factors driving economic development, human capital is the most critical. In the digital era, digital skills represent a new form of human capital and are essential for enhancing farmers' livelihood capital [40,41]. Digital skills are multifaceted, encompassing photo-visual, reproduction, branching, information, and socio-emotional skills [42]. For individuals, digital skills include work and learning skills and online business, as well as entertainment and social skills [43,44]. Enhancing digital skills allows farm households to more effectively apply advanced technologies, access market information, expand sales channels, and increase opportunities in non-farm employment and entrepreneurship. This leads to significant income growth, reduces the risk of falling back into poverty, and mitigates poverty vulnerability [38]. We propose the following research Hypothesis 1:

H1. *Digital skills have a significant negative effect on the relative poverty vulnerability of farm households.*

2.2. Heterogeneous Impact of Digital Skills on Farmer Vulnerability to Relative Poverty

The information poverty theory posits that limited access to information and insufficient channels for acquiring it are key factors contributing to rural household poverty [45,46]. As digital village construction accelerates, digital skills play a pivotal role in enabling farmers to access information, increase income, and reduce risks, yielding what is known as the "digital dividend". However, a significant disparity in digital skills exists between income

groups. Low-income populations typically have weaker digital transformation capabilities compared with higher-income groups, exacerbating inequality and contributing to the “digital divide”. This divide not only reflects inequalities in access to digital resources but also further widens the income gap, undermining efforts to prevent the risk of falling back into poverty [47,48]. For low-income groups, limited access to digital resources and skills exacerbates income inequality and perpetuates broader social disparities. Thus, targeted improvements in the digital skills of low-income populations can not only prevent poverty relapse but also effectively narrow this gap, directly enhancing the role of digital technology in mitigating the risk of poverty recurrence [49,50].

In addition, mastering various types of digital skills, such as work and learning skills, online business skills, and entertainment/social skills, positively impacts overall income levels and significantly lowers the risk of poverty recurrence [51–53]. However, the effectiveness of different types of digital skills in reducing poverty vulnerability varies. Digital learning skills enhance human capital by improving farmers’ adaptability to market changes and enabling them to earn higher incomes, thereby reducing the risk of poverty. Digital social skills expand social networks and social capital, enabling farmers to access additional resources and support, thereby strengthening their ability to manage risks. Digital information-seeking skills enable farmers to acquire critical information, enhancing the precision of their production decisions and reducing economic uncertainty. Overall, these three types of digital skills reduce farmers’ vulnerability to relative poverty, although they operate through different mechanisms, and their effects may vary.

Based on the above, we propose the following research Hypothesis 2:

H2. *Digital skills have a heterogeneous effect on the relative poverty vulnerability of farm households*

H2a. *Digital skills have heterogeneous effects on the relative poverty vulnerability of farm households with different incomes*

H2b. *Different digital skills have heterogeneous effects on the relative poverty vulnerability of farm households.*

2.3. The Mediating Role of Social Capital in the Impact of Digital Skills on Farmers’ Relative Poverty Vulnerability

The vicious cycle of poverty theory emphasizes that this cycle stems from the rigid structure of society, which is significantly shaped by the social networks in which families are embedded [54,55]. Socially disadvantaged environments often fail to provide the critical information and opportunities necessary for upward mobility [56,57]. In rural China, traditional social capital—rooted in kinship, blood relations, and geographic ties, such as family, clans, neighborhoods, and villages—has played a positive role in reducing the vulnerability of poor farm households, despite the closed nature of information shared within these networks [58].

The widespread adoption of modern digital technologies has expanded farmers’ social networks in unprecedented ways. Digital technology provides farmers with convenient real-time communication channels, reducing both time and communication costs, while reinforcing existing strong relationships. It also creates opportunities for establishing new, weaker social ties [59,60]. This new social capital accelerates information sharing, allowing farmers to rapidly access information, communicate, learn, and support one another in times of risk, thereby reducing their vulnerability to poverty [61]. Consequently, enhancing the digital skills of farm households can further expand their social networks, thereby reducing the risk of future poverty (see Figure 1). We propose the following research hypothesis:

H3. *Social capital is a mediating channel through which digital skills reduce the relative poverty vulnerability of farm households.*

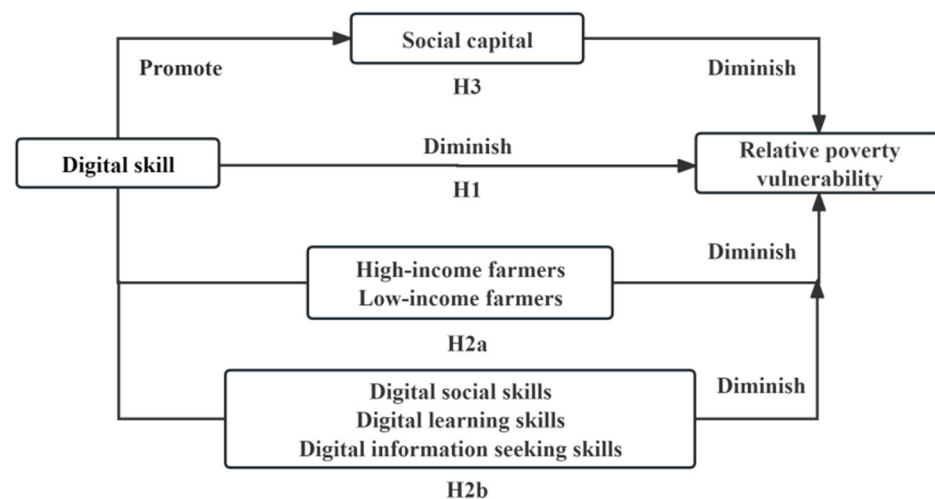


Figure 1. Theoretical analysis framework. Source: conceptual framework designed by the authors.

3. Materials and Methods

3.1. Data Sources

Yunnan Province, located in southwest China, is renowned for its diverse terrain and unique geographical features. Although its gross domestic product (GDP) is not among the lowest in the country, the province has long faced significant poverty challenges, particularly in minority regions and remote mountainous areas. By 2019, the year before China's elimination of absolute poverty, Yunnan had made substantial progress in poverty reduction; however, its poverty rates remained above the national average and consistently ranked among the top ten in the country. Economic vulnerabilities and the risk of poverty relapse persist due to the imbalanced development in rural areas and the widening digital divide. With its rich ethnic diversity and complex socio-economic and environmental dynamics, Yunnan serves as an ideal case for studying poverty vulnerability and resilience, particularly in minority regions.

From November to December 2022, our research team conducted a field survey across 16 cities and prefectures in Yunnan Province, covering 42 rural counties and collecting data from 1042 rural households. After excluding 125 invalid questionnaires, we retained 917 valid samples. To ensure the sample's representativeness, we employed a random sampling method, selecting households according to the proportions of different household types. Detailed information on household size, living conditions, income, expenditure, and fixed assets was gathered during the survey through interviews and questionnaires (see Table 2). Additionally, we held in-depth discussions with village leaders and other relevant personnel to verify and supplement the information provided by the farmers. This process enriched the field research data and further strengthened the reliability of the finding.

Table 2. The descriptive statistics of the variables.

Variable	Variable Name	Definition	Mean	SD
Explained variable	Is not a vulnerable family (40% median)	The likelihood that the household will fall into relative poverty in the future (vulnerable = 1, non-vulnerable = 0)	0.12	0.33
	Is not a vulnerable family (50% median)	The likelihood that the household will fall into relative poverty in the future (vulnerable = 1, non-vulnerable = 0)	0.21	0.41
	Is not a vulnerable family (60% median)	The likelihood that the household will fall into relative poverty in the future (vulnerable = 1, non-vulnerable = 0)	0.34	0.47

Table 2. Cont.

Variable	Variable Name	Definition	Mean	SD
Core explanatory variables	Digital skills	Level of mastery of digital skills	3.76	1.49
	Digital learning skills	Frequency of Internet learning	3.13	2.35
	Digital social skills	Internet socialization frequency	4.51	2.17
	Digital information search skills	Internet access to information	3.63	1.12
Mediating variables	Social capital	The logarithm of the amount of favor gifts in 2022	5.19	3.72
	Age	Age of head of household in 2022	47.69	11.95
	Sex	Male = 1; female = 0	1.26	0.44
	Nation	Ethnicity of head of household	4.33	4.64
Control variables	Marital status	Married = 1; unmarried = 2; widowed = 3; divorced = 4	1.26	0.70
	Actual family population count	Actual household size	4.50	1.61
	Number of people over 60 years old	Number of persons over 60 years of age in the household	0.73	0.90
	The normal number of labor force	Number of regular laborers in the household	2.74	1.24
	The number of weak workers	Number of weak workers able to perform simple tasks	0.93	1.32
	Government's monitoring	Yes = 1; no = 0	0.19	0.39
	Homestyle	Households with special difficulties = 1; unstable out of poverty = 2; marginal households vulnerable to poverty = 3; stable out of poverty = 4; relatively well-off households = 5; general farming households = 6	4.83	1.37
	Highest education	Highest education in the family.	3.04	1.54
	The highest degree for a family decision-maker	The highest level of education for families as decision-makers	1.67	1.07
	Basic medical insurance	Whether everyone in the family is enrolled in basic health insurance for urban and rural residents (yes = 1; no = 0)	0.96	0.19
	Chronic diseases	Several members of the family suffer from chronic diseases	0.28	0.55
	Financial products	The logarithm of the amount received for financial products	0.31	1.79

Source: authors' own research.

3.2. Variable Selection

3.2.1. Explained Variable

The key explanatory variable in this study was the relative poverty vulnerability of farm households. We measured this vulnerability using Chaudhuri's vulnerability as expected poverty (VEP) method. The model assumed a relative poverty line for rural residents and that the per capita income of rural households followed a lognormal distribution. Using the feasible generalized least squares (FGLS) method, we estimated the expected value and variance of future per capita income. We then calculated the probability that future per capita income would fall below the relative poverty line using the distribution function. A fixed probability threshold of 50% defined relative poverty vulnerability. Households with probabilities exceeding this threshold were classified as vulnerable, while those below it were not.

First, we estimated the income equation. The squared residuals from the regression were log-transformed to represent income fluctuations for the ordinary least squares (OLS) estimation. The estimated equation is given by

$$\ln y_{it} = \alpha_0 + \beta x_{it} + \varepsilon_i \quad (1)$$

In Equation (1), y_{it} represents the per capita household income of farm household i in period t ; x_{it} is the individual and household characteristic variables of farm household i in period t , specifically including the five categories of natural capital, financial capital, human capital, physical capital, social capital, etc. (Table 1); α_0 is the parameter to be estimated; and ε_i is the residual term.

In the second step, weights were constructed for FGLS estimation using the fitted values obtained in the first step to derive the expectation and variance of log income:

$$\hat{E}(\ln y_{it}|x_{it}) = x_{it}\hat{\beta}_{FGLS} \quad (2)$$

$$\hat{V}(\ln y_{it}|x_{it}) = \sigma^2 \varepsilon_i \quad (3)$$

In the third step, the relative poverty line $\ln z_i$ was selected to calculate the relative poverty vulnerability of the farm household for the next period:

$$Vul_i = Pr(\ln y_{it} \leq \ln z_i | x_{it}) = \Phi\left(\frac{\ln z_{it} - x_{it}\hat{\beta}_{FGLS}}{\sigma^2 \varepsilon_i}\right) \quad (4)$$

Using the VEP method, we assigned a value of 1 to farm households experiencing relative poverty vulnerability and 0 otherwise. As indicated in Equation (4), the choice of the relative poverty line $\ln z_i$ influenced this measurement. We adopted two approaches to determine the poverty line: one based on income and the other on consumption. From the income perspective, we used 40%, 50%, and 60% of the median per capita income as the low, middle, and high relative poverty lines, respectively. For robustness, we also considered per capita consumption, using the World Bank's poverty standards for low-, middle-, and high-income economies. Specifically, we used per capita consumption thresholds of USD 2.15, USD 3.65, and USD 6.85 as the low, middle, and high relative poverty lines. Stata18 software was utilized for this analytical task.

3.2.2. Explanatory Variables

In this study, the core independent variable represented the primary factor of interest to the researcher. The explanatory variables were digital skills. Based on DiMaggio P and Bonikowski B. [62], digital skills were defined as the average of digital learning skills, social skills, and information-seeking skills. Among them, digital learning skills referred to the ability of rural households to acquire and learn new knowledge or skills through the Internet; digital social skills referred to their ability to engage in social interactions via the Internet, including communication with family, friends, colleagues, or rural networks; and digital information-seeking skills were defined as the ability to search for useful information online, such as market trends, agricultural product prices, government policies, and weather forecasts. The process of quantification was as follows:

Digital skills were quantified using three metrics: the frequency of using the Internet for learning, socializing, and obtaining information. These metrics respectively reflected digital learning, social, and information-seeking skills. By summing and averaging these variables, we constructed an aggregate digital skills index. Higher values on this index indicated greater mastery of digital skills.

First, this study categorized the frequency of Internet use for learning and socializing among farmers on a scale from 0 to 6. Non-users were assigned a value of 0, reflecting "very low digital learning and socializing skills". Those using the Internet once every few months received a 1, denoting "low mastery of digital skills". Monthly usage was rated as

2, indicative of “low mastery”, while 2–3 times per month was scored as 3, representing “average mastery”. Usage of 1–2 times per week was assigned a 4, suggesting “higher mastery”, and 3–4 times per week was a 5, reflecting “high mastery”. Daily users scored a 6, denoting a “high level of digital skills mastery”.

Second, this study measured the importance attributed by farmers to the Internet for obtaining information on a scale of 1 to 5. Farmers who deemed the Internet as very unimportant were assigned a value of 1, indicating a “low level of digital information searching skills”. A rating of 2 indicated a “relatively low level of digital information searching skills”. A moderate importance was scored at 3, indicating an “average level of digital information searching skills”. Those who regarded it as important received a 4, indicating a “relatively high level of digital information searching skills”. Finally, a value of 5 was assigned to farmers who viewed the Internet as very important, indicating “high digital information searching skills”.

3.2.3. Mediating Variables

Based on the previous analysis, digital technology was found to mitigate the risk of re-entering poverty by enhancing the social capital of farm households. Referring to the study of Liu and Xu [15], this paper took the logarithm of income and selected the logarithm of household expenditure on favor gifts as a measure of social capital.

3.2.4. Control Variables

Control variables were included to ensure the accuracy and reliability of the results by accounting for potential confounders. These variables, selected based on their potential influence on the vulnerability of farm households to relative poverty, included demographic and socioeconomic characteristics of the household head and family. Specifically, the study considered age, sex, ethnicity, the highest education of the household head and the main decision-maker, household size, number of dependents under one week old, number of able-bodied and weak labor force members, marital status, government monitoring status, family type, coverage under the basic medical insurance for urban and rural residents, and the number of people suffering from chronic diseases. Descriptive statistics for these variables are shown in Table 2.

3.3. Methods

3.3.1. Baseline Regression Model

The probit model is commonly employed for the analysis of binary dependent variables and was especially well suited for examining “relative poverty vulnerability” as a binary outcome in this study. Compared with alternative models, the probit model effectively captured changes in the probability of binary outcomes through maximum likelihood estimation, particularly when poverty vulnerability was not appropriately represented by a continuous variable. This feature enabled the probit model to yield more accurate estimates of marginal effects, facilitating a more in-depth investigation of the complex relationship between digital skills and the relative poverty vulnerability of rural households.

In our analysis, the micro-level data consisted of discrete variables, where the dependent variable denoted poverty vulnerability. The dependent variable was assigned a value of 1 if a household was considered vulnerable to poverty and 0 otherwise. By employing this regression model, we not only strengthen the robustness of our findings but also offer novel insights into the role of digital skills in influencing poverty vulnerability. This innovative application adds value by providing empirical evidence to inform policy-makers in designing more effective interventions aimed at reducing the poverty vulnerability of rural households. Accordingly, the following regression model was constructed:

$$Pr(Vul_i) = \beta_0 + \beta_1 DIG + \beta_2 X_i + \varepsilon_i \quad (5)$$

where Vul_i denotes the relative poverty vulnerability of farm households, DIG is the

mastery of digital skills by farm households, X_i is a control variable, β_1 is a parameter to be estimated, and ε_i is an error term.

3.3.2. Mediating Effect Model

The mediation effect model analyzes how digital skills indirectly impact poverty vulnerability through variables like social capital. This model reveals how digital skills influence rural households' poverty vulnerability through intermediary mechanisms. It helps understand both the direct effects of digital skills and their indirect effects through mediating variables. This insight aids policy-making by identifying specific intervention points for addressing poverty vulnerability. Thus, the mediation effect model offers a comprehensive framework, revealing underlying causal mechanisms beyond surface-level effects. This study used mediation analysis to explore how digital skills indirectly affected farm households' relative poverty vulnerability. Social capital was identified as the mediating variable to assess its role in this relationship. The following models investigated this mediating effect:

$$Pr(Vul_i) = \beta_0 + \beta_1 DIG + \beta_2 X_i + \varepsilon_i \quad (6)$$

$$SC = \alpha_1 + \alpha_2 DIG + \alpha_3 X_i + \varepsilon_i \quad (7)$$

$$Pr(Vul_i) = \omega_1 + \omega_2 DIG + \omega_3 SC + \omega_4 X_i + \varepsilon_i \quad (8)$$

where Vul_i represents the relative poverty vulnerability of rural households; DIG denotes digital skills; SC represents the social capital of rural households; X_i are the control variables; α_2 , ω_2 , and ω_3 are the parameters to be estimated; and ε_i is the random error term.

In Equation (7), we analyze the effect of digital skills improvement on rural households' social capital. Equation (8) assesses the combined impact of digital skills and social capital on their relative poverty vulnerability. Integrating Equations (3) and (7) with Equation (6) allows us to verify the mediating effect of social capital. Equation (6) shows that coefficient β_1 represents the total effect of digital skills on relative poverty vulnerability. Equation (8) shows that the coefficient represents the direct effect of digital skills on this vulnerability. The product of the coefficients from Equations (7) and (8) represents the mediating effect of social capital on the relationship between digital skills and relative poverty vulnerability.

If coefficient β_1 in Equation (6) was significant, it indicated a substantial impact of digital skills on poverty vulnerability. Next, we verified the coefficients in Equations (7) and (8). If both were significant, this confirmed the mediating effect of social capital, with the impact degree indicated by the product of these coefficients. If the coefficient in Equation (8) was not significant, social capital was a full mediator. If it was significant but smaller than β_1 in Equation (6), social capital was a partial mediator.

4. Results

4.1. Model Estimation

Table 3 presents the benchmark regression results analyzing the effect of digital skills on the relative poverty vulnerability of farm households, using 40%, 50%, and 60% of the median per capita income as relative poverty thresholds. The estimated coefficients for the impact of digital skills on poverty vulnerability were -0.208 , -0.191 , and -0.147 , significant at 1% level. These findings supported Hypothesis H1, demonstrating that enhancing digital skills can reduce the vulnerability of farm households to relative poverty and lower the risk of re-entering poverty.

Furthermore, the marginal effect of digital skills varied non-linearly with the poverty threshold, exhibiting initial increases followed by slight decreases, with values of -0.027 , -0.032 , and -0.028 . This pattern may reflect the interplay between digital skills and income levels, where digital technology fosters opportunities in rural industries and non-farm employment, enhancing income growth. However, as the poverty threshold increased, the emerging "digital divide" among different income groups became more pronounced, potentially influencing the efficacy of digital skills in reducing poverty vulnerability.

Table 3. Benchmark regression and marginal effects results.

Variable Name	40% Median	50% Median	60% Median
Digital skills	−0.208 *** (0.047)	−0.191 *** (0.043)	−0.147 *** (0.040)
Age	−0.019 (0.006)	−0.023 (0.006)	−0.029 * (0.005)
Sex	−0.948 *** (0.146)	−1.071 *** (0.138)	−1.385 *** (0.140)
Nation	0.026 * (0.015)	0.054 *** (0.013)	0.038 *** (0.013)
Highest education	−0.021 (0.050)	−0.084 * (0.045)	−0.077 * (0.042)
The highest degree for a family decision-maker	0.261 *** (0.063)	0.343 *** (0.062)	0.308 *** (0.059)
Actual family population count	0.476 *** (0.063)	0.526 *** (0.055)	0.605 *** (0.054)
Number of people over 60 years old	−0.197 ** (0.093)	−0.107 (0.080)	−0.151 ** (0.077)
The normal number of labor force	−0.581 *** (0.077)	−0.644 *** (0.070)	−0.728 *** (0.068)
The number of weak workers	−0.104 * (0.058)	−0.074 (0.051)	0.060 (0.049)
Marital status	−0.446 *** (0.156)	−0.481 *** (0.126)	−0.529 *** (0.110)
Government's monitoring	0.306 (0.196)	0.780 *** (0.171)	0.874 *** (0.166)
Homestyle	−0.151 *** (0.055)	−0.214 *** (0.049)	−0.252 *** (0.049)
Financial products	−0.118 (0.362)	−0.079 (0.333)	−0.110 (0.313)
Basic medical insurance	−0.593 * (0.274)	−0.681 ** (0.257)	−0.606 * (0.248)
chronic diseases	0.366 *** (0.112)	0.516 *** (0.107)	0.670 *** (0.107)
Constant	−0.246 (0.612)	0.153 (0.549)	0.506 (0.524)
R ²	0.3475	0.4169	0.4605
Wald	233.79 (0.000)	390.11 (0.000)	540.25 (0.000)
Dy/dx	−0.027 *** (0.006)	−0.032 *** (0.007)	−0.028 *** (0.007)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels. Source: authors' own research.

We also analyzed the impacts of control variables on the relative poverty vulnerability of rural households. It was found that the sex, education level, marital status, family type, and medical insurance of the household head had significant negative effects on poverty vulnerability. Conversely, the actual number of household members and the number of individuals with chronic diseases had significant positive effects on poverty vulnerability. Households with male heads, higher education levels, marital status, and medical insurance had stronger risk management capabilities and lower risks of falling back into poverty [63]. In contrast, households with larger family sizes and more members with chronic illnesses were more likely to experience poverty. This was consistent with the findings of Liu et al., who concluded that larger family sizes exacerbated household expenses on education, healthcare, etc., thereby increasing the likelihood of falling back into poverty [64].

4.2. Heterogeneity Analysis

4.2.1. Heterogeneity of Household Income

This paper examines the differential impacts of digital skills on the relative poverty vulnerability of farm households across income levels. We divided the sample into low-income (below median) and high-income (above median) groups and ran separate regressions. As shown in Table 4, digital skills significantly reduced poverty vulnerability in low-income households, while the effect was not significant for high-income households, supporting Hypothesis H2a. This suggested that enhancing digital skills was particularly effective for low-income groups, highlighting a “digital dividend” effect that varied across income levels.

Table 4. Tests for heterogeneity in household income.

Variable Name	40% Median		50% Median		60% Median	
	High Income	Low Income	High Income	Low Income	High Income	Low Income
Digital skills	−0.068 (0.088)	−0.227 *** (0.067)	−0.109 (0.077)	−0.177 *** (0.060)	−0.038 (0.071)	−0.147 *** (0.055)
Control variables	Control	Control	Control	Control	Control	Control
Constant	−2.278 ** (1.133)	1.313 (0.925)	−1.265 (0.944)	0.788 (0.764)	−1.085 (0.928)	0.951 (0.725)
R ²	0.437	0.397	0.489	0.412	0.562	0.432
Wald	110.53 *** (0.000)	160.49 *** (0.000)	179.65 *** (0.000)	222.46 *** (0.000)	283.58 *** (0.000)	270.26 *** (0.000)
Dy/dx	−0.005 (0.007)	−0.034 *** (0.001)	−0.012 (0.009)	−0.034 *** (0.011)	−0.005 (0.009)	−0.032 *** (0.012)

Note: *, **, and *** indicate significance at the 5%, and 1% statistical levels. Source: authors’ own research.

4.2.2. Heterogeneity of Digital Skills

This study examined how different types of digital skills affected the relative poverty vulnerability of farm households, as detailed in Table 5.

Table 5. Heterogeneity test for digital skills.

Variable Name	40% Median			50% Median			60% Median		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Digital learning skills	−0.060 ** (0.030)			−0.072 *** (0.027)			−0.047 * (0.025)		
Digital social skills		−0.150 *** (0.032)			−0.137 *** (0.029)			−0.098 *** (0.027)	
Digital information search skills			−0.082 (0.057)			−0.048 (0.054)			−0.117 ** (0.052)
Control variables	Control	Control	Control	Control	Control	Control	Control	Control	Control
Constant	−0.735 (0.609)	−0.370 (0.621)	−0.768 (0.612)	−0.302 (0.544)	0.043 (0.558)	−0.431 (0.549)	0.102 (0.517)	0.363 (0.528)	0.239 (0.530)
R ²	0.366	0.393	0.363	0.431	0.447	0.424	0.469	0.478	0.471
Wald	246.08 *** (0.000)	264.34 *** (0.000)	244.06 *** (0.000)	403.28 *** (0.000)	418.32 *** (0.000)	397.08 *** (0.000)	551.02 *** (0.000)	560.49 *** (0.000)	552.46 *** (0.000)
Dy/dx	−0.008 ** (0.004)	−0.018 *** (0.004)	−0.011 (0.007)	−0.012 *** (0.004)	−0.021 *** (0.004)	−0.008 (0.009)	−0.009 * (0.005)	−0.018 *** (0.005)	−0.022 ** (0.010)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels. Source: authors’ own research.

At the 40% median income threshold, digital learning skills significantly reduced poverty vulnerability at the 5% level with a marginal effect of −0.008, while digital social skills had a larger reduction, significant at the 1% level with a marginal effect of −0.018. Digital information search skills were not significant at this threshold. At the 50% median income threshold, both digital learning and social skills significantly reduced poverty vulnerability at the 1% level, with marginal effects of −0.012 and −0.021, respectively. Digital searching skills remained insignificant. At the 60% median income threshold, digital learning skills were significant at the 10% level with a marginal effect of −0.008, digital social skills were significant at the 1% level with a marginal effect of −0.018, and

digital socialization skills were significant at the 5% level with a marginal effect of -0.022 . These findings confirmed Hypothesis H2b, highlighting the varying impact of digital skills on poverty vulnerability.

Overall, digital social skills consistently exhibited the most substantial impact on reducing poverty vulnerability among farm households. This was likely due to the role of digital socialization in improving farmers' access to information and opportunities. These findings confirmed Hypothesis H2b, underscoring the differentiated impact of various digital skills on poverty vulnerability.

4.3. Robustness Test

4.3.1. Replacement of Explanatory Variables

To assess the robustness of our findings, we redefined and re-estimated the relative poverty vulnerability of farm households based on per capita consumption. Using the World Bank's poverty line standards, we set thresholds at USD 2.15, USD 3.65, and USD 6.85 per day for low, middle, and high relative poverty lines, respectively. The results in Table 6 show that digital skills consistently had a significant negative impact on the relative poverty vulnerability.

Table 6. Results of replacing explanatory variables.

Variable Name	USD 2.15 per Day	USD 3.65 per Day	USD 6.85 per Day
Digital skills	-0.201^{***} (0.041)	-0.210^{***} (0.036)	-0.169^{***} (0.057)
Control variables	Control	Control	Control
Constant	0.235 (0.570)	1.905 (0.665)	3.002 (0.680)
R ²	0.3281	0.3303	0.2961
Wald	288.47 (0.000)	419.78 (0.000)	169.46 (0.000)

Note: *** indicate significance at the 1% statistical levels. Source: authors' own research.

4.3.2. Replacement of Estimation Method

To strengthen the reliability of our findings, this study employed the Logit model to re-estimate the benchmark regression, verifying the impacts of digital skills under different relative poverty thresholds. The results confirmed that the improvement of digital skills significantly reduced the relative poverty vulnerability of farm households, demonstrating the robustness of previous findings (Table 7).

Table 7. Logit model regression results.

Variable Name	40% Median	50% Median	60% Median
Digital skills	-0.326^{***} (0.092)	-0.298^{***} (0.079)	-0.227^{***} (0.071)
Control variables	Control	Control	Control
Constant	-0.978 (1.184)	-0.345 (1.021)	0.383 (0.955)
R ²	0.3812	0.4419	0.478
Wald	256.46 (0.000)	413.55 (0.000)	560.35 (0.000)

Note: *** indicate significance at the 1% statistical levels. Source: authors' own research.

4.4. Mechanism Analysis

Theoretical analysis indicates that digital skills may indirectly influence farmers' vulnerability to relative poverty via social capital. The enhancement of social capital through digital technologies can reduce the risk of farmers falling back into poverty. Consequently,

this study employed a mediation effect model to examine this mechanism, with results shown in Table 8.

Table 8. Results of the mechanism of action tests.

Variable Name	Social Capital	40% Median	50% Median	60% Median
Digital skills	0.2211 *** (0.0833)	−0.0231 *** (0.0067)	−0.0226 *** (0.0076)	−0.0211 ** (0.0083)
Social capital		−0.0121 *** (0.0027)	−0.0142 *** (0.0031)	−0.0139 *** (0.0033)
Control variables	Control	Control	Control	Control
N	917	917	917	917
R ²	0.1219	0.2605	0.3828	0.4673

Note: **, and *** indicate significance at the 5%, and 1% statistical levels. Source: authors' own research.

Table 8 summarizes the regression results. Column (1) shows Model (6) results, with a 0.2211 coefficient for digital skills on social capital, significant at the 1% level. This indicated that a one-unit increase in digital skills increased social capital by 0.2211. Columns (2) to (4) present the results for Model (7), indicating negative and significant marginal effects of both digital skills and social capital on relative poverty vulnerability at thresholds of 40%, 50%, and 60% of median per capita income. The marginal effects of digital skills were −0.0231, −0.0226, and −0.0211, while those for social capital were −0.0121, −0.0142, and −0.0139, all significant at the 1% level.

The calculated indirect effects mediated by social capital amount to reductions of 0.0027, 0.0032, and 0.0031 units in relative poverty vulnerability for each unit increase in digital skills. Considering the total effects noted in Table 2 (0.027, 0.032, and 0.028), these indirect effects accounted for 9.91%, 9.81%, and 11.43% of the total effects. In conclusion, digital skills influenced the relative poverty vulnerability both directly and indirectly, with more significant direct effects. Thus, Hypothesis 3 was validated by the mediation analysis.

5. Discussion

This study established a theoretical framework to explore the impact of digital skills on the relative poverty vulnerability of farm households, providing theoretical and practical guidance for dynamic poverty governance in the context of the digital economy.

5.1. Theoretical Significance

This study highlighted the vital role of digital skills in reducing farm households' poverty vulnerability. Multiple robustness checks, including redefining poverty vulnerability and adjusting model specifications, confirmed the stability of this effect. Regardless of the changes in poverty thresholds or model adjustments, the negative impact of digital skills remained significant, consistent with prior research [16,63]. Improved digital skills reduced poverty recurrence by promoting employment, entrepreneurship, and production efficiency [6–9], ultimately increasing income and lowering the risk of falling back into poverty. Thus, digital skills are key to poverty reduction strategies.

Second, digital skills had a varying impact on farmers' vulnerability to relative poverty. Specifically, they had a more pronounced effect in alleviating low-income farmers' vulnerability compared with that of high-income farmers. Low-income farmers often faced challenges in accessing information and converting it into actionable outcomes, limiting their market and employment opportunities. Enhanced digital skills enabled them to engage in activities like e-commerce, remote work, and digital agriculture, which significantly reduced their vulnerability to relative poverty. Conversely, the impact on high-income farmers was less significant. This shift not only lowered the risk of poverty recurrence but also helped bridge the “digital divide”.

On the other hand, compared with other digital skills, digital social skills were especially effective in reducing farmers' vulnerability to relative poverty compared with other

digital skills. While digital learning skills enhanced market competitiveness over the long term and digital information-seeking skills provided passive information, digital social skills directly expanded farmers' networks and interactions, enabling them to actively seek opportunities and resources [54]. This was particularly beneficial in isolated areas like Yunnan with limited information access. Digital social skills enhanced economic opportunities, risk management, and social capital accumulation, making them significantly more effective in poverty alleviation.

Third, this study confirmed that social capital mediated the reduction in poverty vulnerability through digital skills. Enhanced digital skills improved farm households' economic capacity and helped them build new forms of social capital via digital platforms. This social capital accelerated information sharing, enabling quick access to valuable information and community support during risks. The rapid flow of information and resources allowed households to respond more flexibly to economic, health, or disaster-related challenges, reducing the risk of falling back into poverty. For households with limited traditional resources, digital skills facilitated the creation of supportive virtual networks, crucial during crises [61,63]. Thus, by fostering social capital, digital skills enhanced both immediate risk response and long-term sustainable development, supporting economic growth and stability.

Finally, the analysis of the control variables revealed that the sex, education level, marital status, family type, and medical insurance of the household head significantly reduced poverty vulnerability, while larger household sizes and more individuals with chronic illnesses increased it. Families with male heads, higher education, stable marital status, and medical insurance were better at managing risks and had a lower poverty risk [63]. In contrast, larger families and those with more chronic illnesses faced higher expenses in education and healthcare, increasing their poverty risk [64]. These findings highlighted the need for targeted policies, such as medical coverage and education subsidies, to alleviate financial burdens and improve the long-term quality of life [65].

5.2. Practical Significance

This study explored the impact and mechanisms of digital skills on the relative poverty vulnerability of farm households, providing insights for consolidating poverty alleviation achievements and promoting the sustainable development of farm households.

First, the government should increase investment in rural digital infrastructure to ensure universal Internet access and enhance farmers' digital literacy through systematic training. Collaborations with local institutions and enterprises could provide free or low-cost training on smart device usage and practical skills like e-commerce. A digital skills assessment system should be established to tailor training based on farmers' existing skill levels. Additionally, policy-makers should introduce incentives, such as financial support and tax breaks, to attract local digital talent and young entrepreneurs to return, promoting rural digital transformation.

Second, the government should develop targeted policies to enhance digital skills among low-income farmers, ensuring they benefit from digitalization. Systematic training programs should focus on improving their digital literacy and access to online information. A shared digital skills platform integrating online and offline resources would provide flexible learning opportunities. Additionally, "online + offline" and "theory + practice" models should be adopted to enhance training effectiveness. Fixed training centers and mobile services can offer flexible learning options, with personalized programs tailored to farmers' skill levels and needs to ensure practical relevance.

Last, the government should encourage farmers to use digital technology to expand their social networks. Subsidies or preferential policies for digital devices, such as smartphones and tablets, can help farmers access the Internet. Digital knowledge dissemination through local communities, village committees, or cooperatives can raise awareness and motivate farmers to use digital tools. Additionally, promoting the sharing of production experiences, market information, and collaboration opportunities on digital platforms

would create a resource-sharing rural digital community. Establishing regional digital alliances and hosting regular online and offline events would further enhance farmers' social networks and cooperation.

5.3. Limitations

This study contributed significantly to the existing literature on digital skills and poverty by making four key advancements. First, it applied the vulnerability as expected poverty (VEP) method to measure relative poverty vulnerability and incorporated multiple international relative poverty standards (OECD and World Bank benchmarks), enhancing the scientific rigor and global applicability of the research. Second, from the perspective of contemporary human capital theory, this study used micro-survey data to assess how digital skills influenced the relative poverty vulnerability of rural households. A review of the literature revealed that few studies have explored this issue from this angle. Furthermore, the study offered a fresh perspective on poverty prevention, particularly in the unique context of Yunnan Province, a multi-ethnic region in China, thereby addressing a regional research gap in the existing literature. Third, the study integrated social capital analysis to uncover the mechanisms through which digital skills alleviated poverty vulnerability by strengthening households' social networks. This provided new intervention pathways and practical guidance for policy-makers. Finally, the study examined the varying effects of digital skills across income groups, proposing targeted anti-poverty strategies and providing theoretical support for precision poverty alleviation in the digital economy.

Although this study provides valuable insights, several limitations remain. First, the cross-sectional data limited our ability to establish causality between digital skills and poverty vulnerability. Future research using longitudinal data could offer better causal inference and reveal the dynamic impact of digital skills over time. Second, the reliance on self-reported survey data may introduce measurement errors and bias. Incorporating objective data, such as digital behavior tracking, would enhance the result accuracy. Third, while Yunnan Province is a representative area, its unique conditions may limit the generalizability of the findings. Future studies in other regions would help validate and expand these results. Last, this study examined how different digital skills affected poverty vulnerability but did not explore their specific impact on household economics. Further research should address this gap to fully understand the role of digital skills in poverty reduction.

6. Conclusions

Our study emphasized the critical role of digital skills in reducing the vulnerability of rural households to relative poverty. Enhanced digital capabilities were shown to lower the risk of falling back into poverty, confirming their importance in poverty alleviation strategies. Notably, the impact of digital skills varied by income level and skill type, with a notably stronger effect on low-income households and in the use of digital social skills.

Our findings showed that improved digital skills enhanced social capital, reducing households' poverty vulnerability and mitigating the risk of poverty recurrence. This highlighted the importance of digital skills in sustaining poverty alleviation efforts and strengthening the resilience of economically disadvantaged groups. In the digital era, enhancing farmers' digital skills is crucial to preventing poverty relapse. Policy-makers should recognize the role of digital technologies in addressing relative poverty, especially in western China, and implement targeted, effective measures.

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References

1. Wang, S.; Zhou, Y. Build effective mechanisms and policies to prevent large-scale return to poverty. *Agric. Econ. Issues* **2022**, *6*, 12–22. [CrossRef]
2. He, Y.; Ahmed, T. Farmers' livelihood capital and its impact on sustainable livelihood strategies: Evidence from the poverty-stricken areas of Southwest China. *Sustainability* **2022**, *14*, 4955. [CrossRef]
3. He, L.; Zhang, X. The impact of the epidemic in the first century, the global scale of the return to poverty and China's response. *Shanghai Econ. Res. Study* **2022**, *7*, 84–102. [CrossRef]
4. Akter, S.; Mallick, B. The poverty–vulnerability–resilience nexus: Evidence from Bangladesh. *Ecol. Econ.* **2013**, *96*, 114–124. [CrossRef]
5. Qin, T.; Wang, L.; Zhou, Y.; Guo, L.; Jiang, G.; Zhang, L. Digital technology-and-services-driven sustainable transformation of agriculture: Cases of China the, E.U. *Agriculture* **2022**, *12*, 297. [CrossRef]
6. Xie, L.; Luo, B.; Zhong, W. How are smallholder farmers involved in digital agriculture in developing countries: A case study from China. *Land* **2021**, *10*, 245. [CrossRef]
7. Khan, N.; Ray, R.L.; Zhang, S.; Osabuohien, E.; Ihtisham, M. Influence of mobile phone and internet technology on income of rural farmers: Evidence from Khyber Pakhtunkhwa Province, Pakistan. *Technol. Soc.* **2022**, *68*, 101866. [CrossRef]
8. Li, F.; Zang, D.; Chandio, A.A.; Yang, D.; Jiang, Y. Farmers' adoption of digital technology and agricultural entrepreneurial willingness: Evidence from China. *Technol. Soc.* **2023**, *73*, 102253. [CrossRef]
9. Mora-Rivera, J.; García-Mora, F. Internet access and poverty reduction: Evidence from rural and urban Mexico. *Telecommun. Policy* **2021**, *45*, 102076. [CrossRef]
10. Jiang, S.; Zhou, J.; Qiu, S. Digital agriculture and urbanization: Mechanism and empirical research. *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121724. [CrossRef]
11. Yang, C.; Ji, X.; Cheng, C.; Liao, S.; Obuobi, B.; Zhang, Y. Digital economy empowers sustainable agriculture: Implications for farmers' adoption of ecological agricultural technologies. *Ecol. Indic.* **2024**, *159*, 111723. [CrossRef]
12. Jia, J.; Liu, J. Preventing the return of poverty on a large scale: Theoretical logic, key issues and realization mechanism. *Agric. Econ. Issues* **2024**, *3*, 128–144. [CrossRef]
13. Deng, Q.; Li, E.; Zhang, P. Livelihood sustainability and dynamic mechanisms of rural households out of poverty: An empirical analysis of Hua County, Henan Province, China. *Habitat Int.* **2020**, *99*, 102160. [CrossRef]
14. Bebbington, A. Capitals and capabilities: A framework for analyzing peasant viability, rural livelihoods and poverty. *World Dev.* **1999**, *27*, 2021–2044. [CrossRef]
15. Liu, Y.; Liu, Z. Internet embeddedness, social capital and poverty vulnerability of rural residents. *J. Yunnan Univ. Financ. Econ.* **2023**, *39*, 85–100. [CrossRef]
16. Zhang, G.; Wu, X.; Wang, K. Research on the impact and mechanism of internet use on the poverty vulnerability of farmers in China. *Sustainability* **2022**, *14*, 5216. [CrossRef]
17. Ligon, E.; Schechter, L. Measuring vulnerability. *Econ. J.* **2003**, *113*, C95–C102. [CrossRef]
18. Chaudhuri, S.; Jalan, J.; Suryahadi, A. *Assessing Household Vulnerability to Poverty from Cross-Sectional Data: A Methodology and Estimates from Indonesia*; Columbia University: New York, NY, USA, 2002; pp. 1–25. [CrossRef]
19. Gaiha, R.; Imai, K. Measuring Vulnerability and Poverty Estimates for Rural India. Helsinki: UNU-WIDER. 2008. Available online: <https://hdl.handle.net/10419/45160> (accessed on 1 January 2020).
20. Mahanta, R.; Das, D. Flood induced vulnerability to poverty: Evidence from Brahmaputra Valley, Assam, India. *Int. J. Disaster Risk Reduct.* **2017**, *24*, 451–461. [CrossRef]
21. Ji, X.; Wang, Z.; Shen, X. Can land transfer reduce relative poverty vulnerability of farm households?—An empirical analysis based on CFPS micro panel data. *J. Hunan Agric. Univ. (Soc. Sci. Ed.)* **2024**, *25*, 25–34. [CrossRef]
22. Li, S.; Liao, Q. Impact of rural female labor participation on household poverty vulnerability—An empirical study based on CHFS micro data. *Agric. Technol. Econ.* **2023**, *2*, 20–44. [CrossRef]

23. Wang, X.; He, G. Digital financial inclusion and farmers' vulnerability to poverty: Evidence from rural China. *Sustainability* **2020**, *12*, 1668. [\[CrossRef\]](#)
24. Su, J.; Guo, S. Human capital and rural households' vulnerability to relative poverty: Evidence from China. *Discret. Dyn. Nat. Soc.* **2022**, *2022*, 3960691. [\[CrossRef\]](#)
25. Yerrabati, S. Does vulnerable employment alleviate poverty in developing countries? *Econ. Model.* **2022**, *116*, 106043. [\[CrossRef\]](#)
26. Zhang, Y.; Wang, W.; Feng, Y. Impact of different models of rural land consolidation on rural household poverty vulnerability. *Land Use Policy* **2022**, *114*, 105963. [\[CrossRef\]](#)
27. Huang, Y.; Lu, D.; Zhang, H. A study on the impact of policy agricultural insurance on the poverty vulnerability of farm households—A case study of local specialty agricultural products insurance. *Insur. Res.* **2021**, *5*, 16–32. [\[CrossRef\]](#)
28. Fraser, T.; Naquin, N. Better together? The role of social capital in urban social vulnerability. *Habitat Int.* **2022**, *124*, 102561. [\[CrossRef\]](#)
29. Koomson, I.; Villano, R.A.; Hadley, D. Effect of financial inclusion on poverty and vulnerability to poverty: Evidence using a multidimensional measure of financial inclusion. *Soc. Indic. Res.* **2020**, *149*, 613–639. [\[CrossRef\]](#)
30. Zhang, D.; Yin, Z. Financial inclusion, risk response, and poverty vulnerability of rural households. *China Rural. Econ.* **2018**, *4*, 54–73. Available online: <https://link.cnki.net/urlid/11.1262.f.20180423.1459.010> (accessed on 23 September 2024).
31. Han, J.; Wang, J.; Ma, X. Effects of farmers' participation in inclusive finance on their vulnerability to poverty: Evidence from Qinba poverty-stricken area in China. *Emerg. Mark. Financ. Trade* **2019**, *55*, 998–1013. [\[CrossRef\]](#)
32. Gallardo, M. Measuring vulnerability to multidimensional poverty. *Soc. Indic. Res.* **2020**, *148*, 67–103. [\[CrossRef\]](#)
33. Gallardo, M. Identifying vulnerability to poverty: A critical survey. *J. Econ. Surv.* **2018**, *32*, 1074–1105. [\[CrossRef\]](#)
34. Azeem, M.M.; Mugera, A.W.; Schilizzi, S. Vulnerability to multi-dimensional poverty: An empirical comparison of alternative measurement approaches. *J. Dev. Stud.* **2018**, *54*, 1612–1636. [\[CrossRef\]](#)
35. Ellis, F.; Mdoe, N. Livelihoods and rural poverty reduction in Tanzania. *World Dev.* **2003**, *31*, 1367–1384. [\[CrossRef\]](#)
36. Liu, Y.; Xu, Y. A geographic identification of multidimensional poverty in rural China under the framework of sustainable livelihoods analysis. *Appl. Geogr.* **2016**, *73*, 62–76. [\[CrossRef\]](#)
37. Cheng, C.; Gao, Q.; Ju, K.; Ma, Y. How digital skills affect farmers' agricultural entrepreneurship? An explanation from factor availability. *J. Innov. Knowl.* **2024**, *9*, 100477. [\[CrossRef\]](#)
38. Zhang, Z.; Xia, Y.; Abula, K. How Digital Skills Affect Rural Labor Employment Choices? Evidence from Rural China. *Sustainability* **2023**, *15*, 6050. [\[CrossRef\]](#)
39. Gao, Z.; Zhang, X. Digital finance and poverty vulnerability of farm households—a study based on CHFS data. *J. Xinjiang Univ. (Philos. Soc. Sci. Ed.)* **2023**, *51*, 1–10.
40. Dzator, J.; Acheampong, A.O.; Appiah-Otoo, I. Leveraging digital technology for development: Does ICT contribute to poverty reduction? *Telecommun. Policy* **2023**, *47*, 102524. [\[CrossRef\]](#)
41. Garcia-Mora, F.; Mora-Rivera, J. Exploring the impacts of Internet access on poverty: A regional analysis of rural Mexico. *New Media Soc.* **2023**, *25*, 26–49. [\[CrossRef\]](#)
42. Alkali, Y.E.; Amichai-Hamburger, Y. Experiments in digital literacy. *CyberPsychology Behav.* **2004**, *7*, 421–429. [\[CrossRef\]](#)
43. Tinmaz, H.; Lee, Y.T.; Fanea-Ivanovici, M. A systematic review on digital literacy. *Smart Learn. Environ.* **2022**, *9*, 21. [\[CrossRef\]](#)
44. Magesa, M.; Jonathan, J.; Urassa, J. Digital literacy of smallholder farmers in Tanzania. *Sustainability* **2023**, *15*, 13149. [\[CrossRef\]](#)
45. Lythreathis, S.; Singh, S.K.; El-Kassar, A.N. The digital divide: A review and future research agenda. *Technol. Forecast. Soc. Chang.* **2022**, *175*, 121359. [\[CrossRef\]](#)
46. Mariscal, J. Digital divide in a developing country. *Telecommun. Policy* **2005**, *29*, 409–428. [\[CrossRef\]](#)
47. Martin, S.P.; Robinson, J.P. The income digital divide: Trends and predictions for levels of Internet use. *Soc. Probl.* **2007**, *54*, 1–22. [\[CrossRef\]](#)
48. Mervyn, K.; Simon, A.; Allen, D.K. Digital inclusion and social inclusion: A tale of two cities. *Inf. Commun. Soc.* **2014**, *17*, 1086–1104. [\[CrossRef\]](#)
49. Lechman, E.; Popowska, M. Harnessing digital technologies for poverty reduction. Evidence for low-income and lower-middle income countries. *Telecommun. Policy* **2022**, *46*, 102313. [\[CrossRef\]](#)
50. Consoli, D.; Castellacci, F.; Santoalha, A. E-skills and income inequality within European regions. *Ind. Innov.* **2023**, *30*, 919–946. [\[CrossRef\]](#)
51. Zhang, S.; Liu, Q.; Zheng, X. Internet use and the poverty vulnerability of rural households: From the perspective of risk response. *Sustainability* **2023**, *15*, 1289. [\[CrossRef\]](#)
52. Zhou, D.; Zha, F.; Qiu, W. Does digital literacy reduce the risk of returning to poverty? Evidence from China. *Telecommun. Policy* **2024**, *48*, 102768. [\[CrossRef\]](#)
53. Cheng, Z.; Zhao, X.; Hou, Q. Do Preferences for Digital Skills Mitigate Relative Poverty? A Quantitative Analysis Based on 2019 CSS. *Mod. Manag.* **2023**, *43*, 145–155. [\[CrossRef\]](#)
54. Rosenberg, N. Capital formation in underdeveloped countries. *Am. Econ. Rev.* **1960**, *50*, 706–715. Available online: <https://www.jstor.org/stable/1812467> (accessed on 18 August 2024).
55. Cleaver, F. The inequality of social capital and the reproduction of chronic poverty. *World Dev.* **2005**, *33*, 893–906. [\[CrossRef\]](#)
56. McKenna, K.Y.A.; Bargh, J.A. Plan 9 from cyberspace: The implications of the internet for personality and social psychology. *Personal. Soc. Psychol. Rev.* **2000**, *4*, 57–75. [\[CrossRef\]](#)

57. Ellison, N.B.; Vitak, J.; Gray, R. Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes. *J. Comput.-Mediat. Commun.* **2014**, *19*, 855–870. [[CrossRef](#)]
58. Zhang, B.; Hu, J.; Yan, J.; Fan, C. Social network, information access and household entrepreneurial income—an empirical study based on the perspective of urban-rural differences in China. *Econ. Rev.* **2015**, *2*, 52–67. [[CrossRef](#)]
59. Urquhart, C.; Liyanage, S.; Kah, M.M.O. ICTs and poverty reduction: A social capital and knowledge perspective. *J. Inf. Technol.* **2008**, *23*, 203–213. [[CrossRef](#)]
60. Mandarano, L.; Meenar, M.; Steins, C. Building social capital in the digital age of civic engagement. *J. Plan. Lit.* **2010**, *25*, 123–135. [[CrossRef](#)]
61. Zhang, Y.; Zhao, W. Social capital's role in mitigating economic vulnerability: Understanding the impact of income disparities on farmers' livelihoods. *World Dev.* **2024**, *177*, 106515. [[CrossRef](#)]
62. DiMaggio, P.; Bonikowski, B. Make money surfing the web? The impact of Internet use on the earnings of US workers. *Am. Sociol. Rev.* **2008**, *73*, 227–250. [[CrossRef](#)]
63. Wu, B.; Xiao, S.; Ma, Y. The Risk of Returning to Poverty in Poor Households of Small Ethnic Minorities: Measurement Methods, Influencing Factors, and Policy Orientation. *Northwestern J. Ethnol.* **2021**, *2*, 119–135. [[CrossRef](#)]
64. Liu, S.; Zhao, X. Assessment of Vulnerability to Return to Poverty among Farmers in Ecologically Fragile Areas and Its Influencing Factors: A Case Study of Longnan Mountain Area. *Ecol. Sin.* **2024**, *44*, 1009–1023. [[CrossRef](#)]
65. Kim, Y.; LaRose, R.; Peng, W. Loneliness as the cause and the effect of problematic Internet use: The relationship between Internet use and psychological well-being. *Cyberpsychol. Behav.* **2018**, *12*, 451–455. [[CrossRef](#)] [[PubMed](#)]

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