

Article

Digital Literacy and Rural Household Economic Vulnerability: Evidence from China

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Abstract

Enhancing the risk-coping capacity and economic resilience of rural households is of great significance for consolidating the foundation of household development and improving people's well-being. As a core form of human capital in the digital era, digital literacy opens up a new pathway for addressing the economic challenges faced by rural households. Using data from the 2022 China Family Panel Studies (CFPS), this paper empirically examines the association between digital literacy and rural household economic vulnerability, as well as its underlying mechanisms. The findings reveal that: (1) Digital literacy is significantly negatively associated with rural household economic vulnerability, and this conclusion is consistently validated across different model specifications and measurement approaches, supporting Hypothesis 1; (2) Mediation analysis shows that employment quality and social trust mediate the negative association between digital literacy and rural household economic vulnerability, supporting Hypotheses 2 and 3; (3) Moderation analysis shows that education level moderates the association, and the negative association between digital literacy and rural household economic vulnerability is stronger among less-educated households, supporting Hypothesis 4b, while Hypothesis 4a is not supported; (4) Heterogeneity analysis indicates that the negative association between digital literacy and rural household economic vulnerability varies significantly across different characteristics of household heads, household endowments, and regions. It should be noted that, based on cross-sectional data, the above findings reflect correlations rather than causal relationships. Accordingly, this paper proposes policy recommendations including accelerating the construction of rural digital infrastructure, prioritizing digital literacy training for less-educated rural households, and adopting targeted policies tailored to different conditions, so as to comprehensively enhance rural households' digital literacy and inject sustainable endogenous momentum into the modernization of agriculture and rural areas.



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1. Introduction

Strengthening the ability of households to withstand risks is a crucial foundation for maintaining stable social functioning and fostering long-term economic prosperity. However, rural households, constrained by both their own development conditions—such as the characteristics of agricultural production, weak infrastructure, insufficient social protection, and small-scale operations—and the complex and volatile external environment,

are more likely to fall into a state of economic volatility and income–expenditure imbalance when facing market fluctuations, natural disaster shocks, and policy adjustments. This not only restricts the improvement of rural residents' quality of life but also hinders the sustainable and healthy development of the rural economy.

The rapid diffusion and deep application of digital technologies have gradually made digital literacy a key capability for individuals to adapt to modern society and engage in economic activities. For rural households, digital literacy not only helps them more efficiently access agricultural technologies, market information, and various resources but also plays a positive role in optimizing production decisions, reducing transaction costs, and diversifying income sources, thereby strengthening their capacity to cope with external shocks. However, research on how digital literacy is associated with rural household economic vulnerability and contributes to their ability to withstand economic shocks remains relatively limited. Meanwhile, due to multiple factors such as unbalanced regional development, disparities in the allocation of digital resources, and differences in educational endowments, there exists significant differentiation among rural households in digital awareness, willingness to adopt, and learning application. This may, to some extent, attenuate the potential association between digital literacy and rural household economic vulnerability. Therefore, exploring whether and how digital literacy is associated with rural household economic vulnerability, and examining the heterogeneous manifestations of this association across different groups, is of great significance for deepening the understanding of the intrinsic value of digital literacy in improving rural household economic conditions.

Digital literacy, as an important field of research, was first proposed by Gilster [1] in his book *Digital Literacy*, where it was defined as an individual's ability to access and utilize digital information. Eshet-Alkalai [2] further expanded this concept, emphasizing that digital literacy is not only a manifestation of survival skills but also a comprehensive capability framework required to adapt to the digital era, particularly the ability to apply digital technologies in learning and daily life. Martin [3] pointed out that digital literacy serves as the foundation for learning and information processing, encompassing the effective use of digital tools and resources. A growing body of evidence suggests that digital literacy confers multiple economic advantages to rural households. For instance, it enhances production resilience under external shocks [4], significantly promotes the enthusiasm and success rate of rural youth participating in e-commerce work [5], improves household economic mobility [6], increases the probability of household participation in commercial insurance and strengthens risk management capabilities [7], and significantly promotes rural households' entrepreneurial willingness and success rates [8]. That is, higher digital literacy enables rural households to more effectively access market information and utilize digital tools to optimize resource allocation, thereby enhancing their entrepreneurial capacity and reducing entrepreneurial risks. These studies indicate that digital literacy plays a crucial role in rural development, not only enhancing individuals' economic capabilities but also making important contributions to overall social well-being.

Economic vulnerability, as a key concept for understanding household poverty dynamics and risk-coping capacity, was first systematically proposed by Chambers [9]. Chambers pointed out that vulnerability differs from poverty—poverty emphasizes a state of deprivation, while vulnerability emphasizes defenselessness, insecurity, and exposure to risks, shocks, and stress [9]. This conceptual distinction shifted the research perspective from static poverty identification to dynamic risk warning. In terms of measurement approaches, the academic community has gradually developed three mainstream pathways [10]: Vulnerability as Expected Utility (VEU), Vulnerability as Expected Poverty (VEP), and Vulnerability as Uninsured Risk (VER). The VEU approach measures vulnerability by comparing the gap between the utility of current consumption and the utility

of a non-vulnerable consumption level [11]. However, this method requires detailed data on individual risk preferences and utility function estimation, which limits its application in large-sample studies [12,13]. The VEP approach focuses on estimating the probability of households falling into poverty in the future [14]. Due to its clear logic, relatively low data requirements, and compatibility with traditional poverty thresholds, it has become the most widely used vulnerability measurement method in empirical research [15–17]. The VER approach measures vulnerability by assessing welfare losses after households experience negative shocks [18,19]. It is suitable for short-term shock assessment but struggles to capture long-term poverty trends. Dercon [20] further pointed out that vulnerability depends not only on income levels but also on households' risk exposure and their capacity to cope with risks, offering a more comprehensive analytical framework for understanding the determinants of vulnerability.

Building on this foundation, the VEP approach has been widely applied in vulnerability research owing to its data feasibility. Existing studies have systematically examined the drivers of economic vulnerability across four main dimensions, yielding a broadly consistent picture. First, at the level of individual and household endowments, limited human and financial capital are consistently identified as key risk factors. Low labor market participation, low education attainment [21], insufficient savings [22], and credit constraints [23] have all been shown to heighten household economic vulnerability by restricting income-generating capacity and limiting liquidity buffers. Second, at the level of livelihood strategies and capabilities, digital economic participation emerges as a protective factor, though with nonlinear effects. Empirical evidence indicates that the digital economy significantly reduces rural household financial vulnerability [24], while digital financial inclusion lowers poverty vulnerability only after reaching a certain developmental threshold [25]. Third, at the level of institutional safeguards and external shocks, social protection mechanisms can mitigate vulnerability, whereas financial leverage tends to amplify it. For instance, basic medical insurance reduces economic risk by lowering medical expenditure burdens [26], yet high household debt leverage exacerbates the adverse impact of external shocks, making highly leveraged households more susceptible to financial distress [27]. Fourth, at the level of environmental and exposure risks, climate hazards, geographical constraints, and pandemic shocks all impose significant vulnerability burdens. Extreme weather undermines coastal livelihoods by damaging productive assets [28]; low-income residents in disaster-prone areas face compounding disadvantages [29]; resource-dependent households are particularly sensitive to environmental fluctuations [30]; and migrant populations experienced disproportionate financial strain during the COVID-19 pandemic [31]. Moreover, these vulnerability patterns are not spatially uniform—food insecurity and economic vulnerability show significant regional clustering, as demonstrated in the Bangladesh context [32].

It can be observed that existing studies have largely focused on the impact of digital literacy on household economic conditions, with few directly linking it to rural household economic vulnerability. Meanwhile, although the literature on economic vulnerability has recognized that digital technologies have a certain mitigating effect, most studies have treated digital technology as an exogenous and singular tool, and in-depth discussions of its underlying transmission mechanisms remain relatively limited. Against this backdrop, this study utilizes data from the 2022 China Family Panel Studies (CFPS) to construct a composite digital literacy index and empirically examine the association between digital literacy and rural household economic vulnerability, as well as its underlying mechanisms, thereby offering new empirical evidence for understanding the livelihood resilience and risk-coping capacity of rural households in the digital era. The main contributions are as follows. First, it establishes the association between digital literacy and rural household

economic vulnerability. Second, by analyzing the employment quality and social trust of rural households, this paper further explores the transmission mechanisms through which digital literacy affects rural household economic vulnerability from the dual pathways of economic resources and social capital. Third, from the perspective of human capital, this paper examines the moderating role of education level in the relationship between digital literacy and rural household economic vulnerability. Fourth, through subsample regressions by gender, age, income level, and region, this study examines the heterogeneous patterns of the association between digital literacy and rural household economic vulnerability across different groups.

2. Theoretical Analysis and Research Hypothesis

As an important capability endowment, digital literacy is profoundly reshaping the economic behaviors and decision-making of rural households [33]. Existing studies have shown that a household's overall level of digital literacy not only determines the efficiency and quality of information acquisition but also affects its capacity for resource allocation and risk management [34]. Specifically, rural households with higher levels of digital literacy can more efficiently utilize digital platforms to access market price information, expand sales channels for agricultural products, and optimize production and business decisions through digital means, thereby enhancing their overall household income level and stability [35]. At the same time, improving digital literacy helps rural households better understand and utilize digital financial tools, achieve diversification of asset allocation, and enhance the contribution of property income [36]. Moreover, from an intra-household perspective, improving digital literacy can also promote family members' learning and adaptation in digital skills, facilitate intergenerational information transfer and gender equality, and enhance the household's collaborative coping capacity in the face of external shocks [37]. Conversely, insufficient digital literacy places households at a structural disadvantage in information acquisition, risk early warning, and financial participation, making them more likely to fall into economic distress when responding to external shocks. Accordingly, this paper proposes Hypothesis 1:

H1. *Digital literacy is negatively associated with rural household economic vulnerability.*

Employment quality, as a core indicator measuring workers' job stability, income level, and career development prospects, plays a key role in improving individual economic status and promoting household economic stability. For rural households, laborers with higher levels of digital literacy typically possess stronger skill matching capabilities, enabling them to more effectively utilize digital technologies to access employment information and adapt to emerging industries, thereby obtaining higher-quality employment opportunities [38,39]. At the same time, the popularization and application of digital technologies have promoted the transformation and upgrading of rural industrial structures, expanding more high-quality employment spaces for laborers who are proficient in digital tools and technologies [40]. With the improvement of employment quality, laborers not only achieve higher income levels but also gain substantial enhancements in job stability and career advancement prospects, thereby driving overall improvements in household economic conditions [41]. When individuals enjoy more stable employment status, better labor protection, and more substantial income returns, their households' capacity to withstand income fluctuations and external shocks is also strengthened, thereby effectively reducing the risk of falling into economic distress. Accordingly, this paper proposes Hypothesis 2:

H2. *Employment quality mediates the negative association between digital literacy and rural household economic vulnerability.*

Social trust is an individual's subjective judgment of the predictability and reliability of the behavior of others or social members under conditions of incomplete information, and it serves as an important informal institutional arrangement that sustains social interaction and economic operation [42]. As a malleable social cognition, the formation and accumulation of social trust largely depend on an individual's information acquisition ability and social interaction experience, and digital literacy is precisely a key factor in shaping these core characteristics. On the one hand, improving digital literacy helps individuals expand their information acquisition channels, reduce information asymmetry, and increase the frequency and experience of contact with strangers through online social interaction, e-commerce, and platform-based interactions [43]. At the same time, the credit evaluation and transaction guarantee mechanisms embedded in digital platforms, to some extent, replace traditional interpersonal trust with institutional trust, reducing individuals' uncertainty and risk perception when dealing with strangers, thereby promoting the formation and enhancement of generalized social trust [44]. On the other hand, as an important form of social capital, social trust can positively influence household economic stability by reducing transaction costs, facilitating factor exchange, and strengthening risk-sharing mechanisms [45]. Accordingly, this paper proposes Hypothesis 3:

H3. *Social trust mediates the negative association between digital literacy and rural household economic vulnerability.*

Education level is an important reflection of an individual's knowledge reserve and technological application capability, determining both the basic conditions for accessing economic opportunities and the core capacity to participate in economic activities. For rural residents, individuals with higher education levels tend to possess more substantial knowledge and skill accumulation, have a competitive advantage in the labor market, and are more likely to obtain stable income and diverse economic sources [46]. Furthermore, these capability advantages embedded in education may also profoundly influence the relationship between digital literacy and rural household economic vulnerability. On the one hand, a solid educational foundation helps individuals better master digital technologies and capture online income-generating opportunities, making the positive association between digital literacy and rural household economic risk-coping capacity more pronounced. On the other hand, higher-education households have already accumulated substantial human capital and social resources through formal education channels, and their information acquisition capacity, risk perception, and ability to seize economic opportunities are relatively strong, with a lower initial level of economic vulnerability. The marginal contribution of digital literacy may therefore be relatively limited for this group. Accordingly, this paper proposes Hypothesis 4:

H4a. *Education level positively moderates the relationship between digital literacy and rural household economic vulnerability.*

H4b. *Education level negatively moderates the relationship between digital literacy and rural household economic vulnerability.*

3. Materials and Methods

3.1. Data Sources

The main data source for this paper is the China Family Panel Studies (CFPS) conducted by the Institute of Social Science Survey (ISSS) of Peking University. The survey covers 25 provinces, autonomous regions, and municipalities directly under the central government across China, encompassing 95% of the national population. The survey

content includes demographic characteristics, employment status, economic information, and subjective well-being of residents, providing a comprehensive data foundation for analyzing the association between digital literacy and rural household economic vulnerability. The CFPS project has been formally approved by the Peking University Institutional Review Board (PU IRB) with the unified ethical approval code (IRB00001052-14010) for all survey waves. The dataset is publicly available at the Peking University Open Research Data Platform with the DOI: <https://doi.org/10.18170/DVN/45LCSO>, accessed on 7 March 2025. This study employs the 2022 wave of the CFPS data (Version 45.1), merging the household economic database with the individual database. The analysis focuses on rural households, with the household head as the unit of analysis. The sample selection procedure is as follows: (1) retaining rural household heads with one household head per family yielded 3806 observations; (2) selecting household heads aged between 18 and 80 yielded 3759 observations; (3) winsorizing household per capita income at the 1st and 99th percentiles to mitigate the influence of outliers, with the sample size remaining 3759 after winsorization; and (4) employing listwise deletion to handle observations with missing values on key variables, which resulted in a loss of 638 observations. The final analytical sample consists of 3121 households.

3.2. Variable Selection

3.2.1. Explained Variable

The explained variable is rural household economic vulnerability measured by the VEP (Vulnerability as Expected Poverty) approach. It is defined as the likelihood and extent to which a household, when facing external risk shocks, finds it difficult to maintain its original economic level, withstand financial distress, and experiences deterioration in economic conditions due to unreasonable income structure, insufficient liquidity, and weak risk diversification capacity [47].

As early as 1989, scholars had introduced the concept of vulnerability into economic research [9]. Early research on vulnerability primarily focused on household poverty [47], with its measurement typically based on the volatility of household income or consumption, calculated in conjunction with poverty line standards. Drawing on the study of Chaudhuri [14], this paper employs the forward-looking VEP approach to assess the likelihood of rural households experiencing adverse outcomes in the future from an income perspective, thereby measuring their economic vulnerability. The specific formulas are as follows:

Step 1: Estimate the income model based on OLS regression:

$$\ln Y_i = \alpha X_i + e_i \quad (1)$$

In Equation (1), Y_i represents household per capita income, and X_i denotes the covariates affecting income levels, including gender, age, education level, marital status, health status, household size, child dependency ratio, elderly dependency ratio, household savings, government subsidies, household debt, and housing conditions. It should be noted that digital literacy is not included in the first-stage income model; it enters only in the second-stage vulnerability regression (Equation (5)) as the core explanatory variable. Although the covariates overlap across the two stages, their roles differ: the first stage estimates income levels and their volatility, while the second stage incorporates them as control variables directly affecting vulnerability. This specification follows the standard VEP approach [14]. Given that the vulnerability outcome is derived from a transformation of the first-stage covariates, the coefficients on the second-stage controls should be interpreted with this mechanical dependence in mind. The digital-literacy coefficient is unaffected by this concern, as digital literacy is excluded from the first-stage income model.

Step 2: Estimate the expected value and variance of the logarithm of income:

This paper adopts the three-stage Feasible Generalized Least Squares (FGLS) method proposed by Amemiya [48]. Based on Step 1, weighted regression is conducted to obtain unbiased estimators $\hat{\alpha}_{FGLS}$ and $\hat{\beta}_{FGLS}$. Using these FGLS estimators, the expected value μ and variance $\sigma_i^2 = \beta X_i + \omega_i$ of the future logarithm of per capita income for rural households are estimated as follows:

$$\hat{\mu} = \hat{E}[\ln Y_i | X_i] = X_i \hat{\alpha}_{FGLS} \quad (2)$$

$$\hat{\sigma}_i^2 = \widehat{Var}[\ln Y_i | X_i] = X_i \hat{\beta}_{FGLS} \quad (3)$$

Step 3: Assuming that the logarithm of per capita net income follows a normal distribution, estimate rural household economic vulnerability:

$$\widehat{VUL}_i = \widehat{Pr}(\ln Y_i \leq \ln Poor) = \Phi \left(\frac{\ln Poor - X_i \hat{\alpha}_{FGLS}}{\sqrt{X_i \hat{\beta}_{FGLS}}} \right) \quad (4)$$

Currently, there is no unified consensus in the academic community on the identification criteria for welfare thresholds. Considering China's actual national conditions and drawing on the studies of Jolliffe and Prydz [49], Han et al. [50], and Yang et al. [51], this paper adopts two types of thresholds as poverty lines: the \$3.2/day standard and 50% of the median per capita income of rural households. The vulnerability line is the key criterion for determining whether a household is in a state of economic vulnerability—when a household's vulnerability probability exceeds the designated threshold, it is classified as economically vulnerable. Following the approach of Günther [52], this paper sets the baseline vulnerability line at 29%, while also using 50% as an alternative vulnerability line for robustness tests to ensure the reliability of the research findings [53]. The specific settings are presented in Table 1.

Table 1. Definitions and values of the poverty line and vulnerability threshold.

Concept	Definition	Value
Poverty line	Benchmark for identifying households in poverty	\$3.2/day (international standard); 50% of median income (domestic standard)
Vulnerability line	Probability cutoff for identifying vulnerable households	29% (baseline); 50% (robustness check)

The combinations of different poverty lines and vulnerability lines yield four economic vulnerability indicators in this paper: Vul1 is based on the \$3.2/day poverty line and the 29% vulnerability line; Vul2 is based on the 50% median income poverty line and the 29% vulnerability line; Vul3 is based on the \$3.2/day poverty line and the 50% vulnerability line; and Vul4 is based on the 50% median income poverty line and the 50% vulnerability line. Vul1 and Vul2 serve as the main dependent variables in the baseline model, while Vul3 and Vul4 are used for robustness checks.

3.2.2. Explanatory Variables

Digital literacy is the explanatory variable of this paper. Considering that the household head is the core agent of household economic decision-making, whose digital literacy level can more accurately reflect the overall digital capability and economic behavior characteristics of the household, this paper takes the household head as the unit of measurement. Referring to the definition of Wen and Liu [54], incorporating the seven competence areas (CA) from the Global Digital Literacy Framework [55], and drawing on the studies of Yang and Chu [56], Zhao et al. [6], and Su and Peng [57], this paper selects relevant items

from the CFPS questionnaire and divides digital literacy into three dimensions: digital general literacy, digital life literacy, and digital professional literacy, encompassing a total of 12 measurement items, including both behavioral items and attitudinal items. It should be noted that attitudinal items are included because digital awareness is a core component of digital literacy [55], and measuring digital literacy solely through usage behaviors cannot fully capture an individual's digital capability. To test the robustness of the indicator system, this paper further excludes attitudinal items and recalculates the digital literacy index using only behavioral items in the robustness checks. The specific indicators are presented in Table 2. In terms of indicator weighting, this paper employs the entropy method to assign weights to the 12 measurement items and calculate a composite digital literacy index for rural households. The entropy method determines weights based on the information entropy of each indicator, objectively reflecting the contribution of each measurement item to the overall evaluation and avoiding the bias associated with subjective weighting. To ensure the robustness of the conclusions, this paper also follows the approach of Zhang and Wang [7] by using principal component analysis (PCA) to recalculate the digital literacy composite score, which is then employed as an alternative indicator for robustness checks.

Table 2. Measurement indicators of digital literacy.

Primary Indicator (Weight)	Secondary Indicator	Measure	Direction
Digital general literacy (0.4115)	Mobile internet access	Yes = 1, No = 0	+
	Mobile internet usage duration	Hours/week	+
	Computer internet access	Yes = 1, No = 0	+
	Computer internet usage duration	Hours/week	+
	Watching short videos	Yes = 1, No = 0	+
	Online shopping	Yes = 1, No = 0	+
Digital life literacy (0.2802)	Importance of the internet for daily life	Assigned values 1–5 based on importance level: 5 = very important; 1 = very unimportant	+
	Importance of the internet for leisure and entertainment	Assigned values 1–5 based on importance level: 5 = very important; 1 = very unimportant	+
	Importance of the internet for staying connected with family and friends	Assigned values 1–5 based on importance level: 5 = very important; 1 = very unimportant	+
	Online learning	Yes = 1, No = 0	+
Digital professional literacy (0.3083)	Importance of the internet for learning	Assigned values 1–5 based on importance level: 5 = very important; 1 = very unimportant	+
	Importance of the internet for work	Assigned values 1–5 based on importance level: 5 = very important; 1 = very unimportant	+

3.2.3. Mediating and Moderating Variables

The mediating variables of this paper include employment quality and social trust. Regarding employment quality, drawing on the studies of Xu et al. [58] and Chen and Han [59], this paper constructs a composite employment quality index from four dimensions: work income, work intensity, job protection, and job stability. The specific coding of each dimension is as follows: work income is measured as the logarithm of after-tax wage income from the primary job over the past 12 months (plus 1); work intensity is measured as weekly working hours and treated as a reverse indicator (longer working hours receive a lower employment quality score); job protection is measured by whether insurance is provided (yes = 1, no = 0); and job stability is measured by whether a labor contract is

signed (yes = 1, no = 0). To construct the index, each dimension is first standardized using min-max normalization to eliminate dimensional differences, with work intensity reverse-normalized. The index is then calculated as the equally weighted average (25% each) of the four standardized dimensions, yielding a composite employment quality index ranging from 0 to 100, with higher values indicating higher employment quality. Regarding social trust, following the approaches of Zhou et al. [60] and Lyu et al. [61], this paper measures it using a single item from the CFPS questionnaire: “trust in strangers,” with values ranging from 1 to 5, where higher scores indicate higher levels of social trust.

The moderating variable of this paper is education level, which is assigned values following the conventional treatment of CFPS data: illiterate/semi-illiterate is coded as 1, primary school as 2, junior high school as 3, senior high school/vocational high school/technical secondary school as 4, junior college as 5, and bachelor’s degree or above as 6. The specific definitions are presented in Table 3.

Table 3. Mediating and Moderating Variables.

Variables	Indicator	Description and Measure
Mediating variables	Social trust	Trust in strangers. Values range from 1 to 5, with higher scores indicating higher levels of trust (1 = very distrustful, 5 = very trustful)
	Employment quality	Work income
		Work intensity
		Job protection
		Job stability
Moderating variable	Education	Illiterate/semi-illiterate = 1; primary school = 2; junior high school = 3; senior high school/vocational high school/technical secondary school = 4; junior college = 5; bachelor’s degree or above = 6

3.2.4. Control Variables

Referring to the existing literature, the control variables of this paper are selected at the levels of individual characteristics and household characteristics. The names and definitions of these variables are presented in Table 4.

Table 4. Control variables.

Variable Type	Variable Name	Description and Measure
Individual characteristics	Health	Values range from 1 to 5, with higher scores indicating better health (1 = unhealthy, 5 = healthy)
	Marriage	Marital status at the most recent interview (married with spouse = 1; unmarried = 0)
	Intelligence level	The respondent’s intelligence level (rated 1–7 by the interviewer based on observation during the interview, with higher scores indicating higher intelligence levels)
Household characteristics	Household size	Number of family members
	Child dependency ratio	The proportion of children under age 14 to the number of labor force participants
	Elderly dependency ratio	The proportion of persons over 60 years of age to the number of labor force participants

Table 4. *Cont.*

Variable Type	Variable Name	Description and Measure
Household characteristics	Household savings	Total cash and deposits (in Yuan) (added 1 and taken natural logarithm)
	Gift and courtesy expenditure	Annual expenditure on gifts and courtesies (in Yuan/year) (added 1 and taken natural logarithm)
	Government subsidies	Whether the household has received various subsidies from the government in cash or in kind (yes = 1, no = 0)
	Bank loans	Whether there are any outstanding bank loans (yes = 1, no = 0)
	Financial products	Whether the household currently holds financial products such as stocks, funds, government bonds, trust products, foreign exchange products, or internet wealth management products like Yu'e Bao (yes = 1, no = 0)
	Housing conditions	Current market value of the residence (in Yuan) (added 1 and taken natural logarithm)

3.3. Descriptive Statistics

Table 5 presents descriptive statistics for the main variables. The mean values of economic vulnerability under the two welfare thresholds are 0.2723 and 0.3018, respectively, suggesting that approximately 27.23% and 30.18% of rural households in the sample are in a state of economic vulnerability. The standard deviations are 0.4452 and 0.4591, respectively, indicating notable individual differences in economic vulnerability across households. Furthermore, the proportion of vulnerable households is higher under the higher welfare threshold, confirming that the setting of the welfare threshold significantly influences the measurement results of vulnerability.

Table 5. Summary statistics of main variables (N = 3121).

Variable Name	Mean	SD	Min	Max
Vul1	0.2723	0.4452	0	1
Vul2	0.3018	0.4591	0	1
Digital literacy	0.1972	0.1684	0.0001	0.8893
Employment quality	41.9327	18.6657	23.2729	90.9385
Social trust	2.5418	1.3084	1	5
Education	2.6488	1.1755	1	6
Health	3.0769	1.2263	1	5
Marriage	0.8411	0.3657	0	1
Intelligence level	5.1439	1.5282	1	7
Household size	3.9045	2.0115	1	13
Child dependency ratio	0.0983	0.2439	0	2
Elderly dependency ratio	0.2196	0.4336	0	3
Household savings	7.4106	4.6633	0	13.1224
Gift and courtesy expenditure	6.8046	2.7863	0	10.1267
Government subsidies	0.4636	0.4988	0	1
Bank loans	0.1256	0.3315	0	1
Financial products	0.0372	0.1892	0	1
Housing conditions	9.5309	4.7666	0	14.4033

Looking at the explanatory variable, digital literacy has a mean value of 0.1972 with a standard deviation of 0.1684, indicating that the overall level of digital literacy among rural households in the sample is relatively low, with substantial variation across households. The minimum value is 0.0001 and the maximum is 0.8893, further reflecting the uneven

distribution of digital literacy, where most households have weak digital capabilities and only a few possess relatively high levels of digital literacy.

Regarding the mediating variables, it is observed that employment quality has a mean of 41.9327 and a standard deviation of 18.6657, suggesting that the overall employment quality of sample households is at a moderate level, with significant disparities across households. Social trust has a mean of 2.5418, which falls in the middle range of the 1–5 scale, indicating that rural residents' trust in strangers is generally neutral.

Looking at the moderating variable, education level has a mean of 2.6488 and a standard deviation of 1.1755, indicating that the average education level of household heads in the sample is concentrated at the junior high school stage, suggesting that the overall level of human capital needs to be improved.

Regarding the control variables, it is observed that health status has a mean of 3.0769, indicating that the overall health level of household heads is above average. The mean value of marital status is 0.8411, indicating that more than 80% of household heads are married, which is consistent with the structural characteristics of rural households. The mean values of the child dependency ratio and elderly dependency ratio are 0.0983 and 0.2196, respectively, reflecting that sample households generally bear certain burdens of child-rearing and elderly care. Government subsidies have a mean of 0.4636, indicating that nearly half of the households receive policy assistance. Furthermore, the low holding rates of bank loans and financial products suggest that the financial participation of rural households needs to be improved.

3.4. Methods

3.4.1. Baseline Regression Model

Based on the theoretical analysis and the selection of relevant indicators outlined above, this paper employs the Ordinary Least Squares (OLS) method to construct a benchmark regression model to examine the association between digital literacy and rural household economic vulnerability. In the model, the dependent variable is rural household economic vulnerability, the independent variable is digital literacy, and individual characteristics and household characteristics are selected as control variables to account for other factors that may influence economic vulnerability. The model is specified as follows:

$$Vul_i = \alpha + \beta Digital_i + \gamma Control_i + \varepsilon_i \quad (5)$$

In Equation (5), Vul_i represents the rural household economic vulnerability; $Digital_i$ represents digital literacy; $Control_i$ denotes the control variables that reflect other factors that may be associated with economic vulnerability; α is the intercept, representing the expected value of the dependent variable when all independent variables are zero; β is the coefficient of the impact of digital literacy on economic vulnerability, reflecting the change in economic vulnerability for each one-unit increase in digital literacy; γ represents the coefficients of the control variables, reflecting the impact of each control variable on economic vulnerability; and ε_i is the random disturbance term.

3.4.2. Mediating Effect Model

To examine the possible indirect transmission mechanisms between digital literacy and rural household economic vulnerability, this paper constructs a mediation model with employment quality and social trust as mediating variables. Following an analytical framework that combines the stepwise regression approach with bootstrap tests, the model is specified as follows:

$$Vul_i = \alpha_0 + \beta_0 Digital_i + \gamma_0 Control_i + \varepsilon_i \quad (6)$$

$$EmpQ_i = \alpha_1 + \beta_1 Digital_i + \gamma_1 Control_i + \varepsilon_i \quad (7)$$

$$Trust_i = \alpha_2 + \beta_2 Digital_i + \gamma_2 Control_i + \varepsilon_i \quad (8)$$

$$Vul_i = \alpha_3 + \beta_3 Digital_i + \delta_3 EmpQ_i + \gamma_3 Control_i + \varepsilon_i \quad (9)$$

$$Vul_i = \alpha_4 + \beta_4 Digital_i + \delta_4 Trust_i + \gamma_4 Control_i + \varepsilon_i \quad (10)$$

where $EmpQ_i$ denotes employment quality and $Trust_i$ denotes social trust. Equation (6) is the total effect equation, with coefficient β_0 capturing the total association between digital literacy and economic vulnerability. Equations (7) and (8) capture the associations between digital literacy and employment quality and social trust, respectively, with coefficients β_1 and β_2 measuring the respective associations. Equations (9) and (10) are the direct effect equations, where β_3 and β_4 represent the direct associations between digital literacy and economic vulnerability after controlling for each mediator, and δ_3 and δ_4 capture the associations of employment quality and social trust with economic vulnerability, respectively. ε_i is the random error term.

Based on the above model specification, this paper employs the bootstrap method (5000 replications) to test the indirect effects ($\beta_1 \times \delta_3$) and ($\beta_2 \times \delta_4$) by computing 95% confidence intervals to determine the significance of the mediation effects. Compared with the traditional stepwise regression approach [62], the bootstrap method does not rely on the normality assumption and provides more accurate tests of indirect effects [63]. It should be noted that the validity of mediation analysis relies on the sequential ignorability assumption—that is, conditional on observed covariates, the mediator can be treated as exogenous. Given that this study uses cross-sectional data, this assumption is difficult to fully satisfy; therefore, the mediation results should be interpreted as statistical indirect associations rather than strict causal mechanisms.

3.4.3. Moderating Effect Model

To further investigate whether the association between digital literacy and rural household economic vulnerability is moderated by education level, this paper examines the interaction between digital literacy and education level, that is, the product term of the two variables, and constructs a moderating effect analysis model. The model is specified as follows:

$$Vul_i = \alpha + \beta_1 Digital_i + \beta_2 Edu_i + \beta_3 Digital_i \times Edu_i + \gamma Control_i + \varepsilon_i \quad (11)$$

In Equation (11), Edu_i represents education level; $Digital_i \times Edu_i$ is the interaction term between digital literacy and education level, reflecting the moderating role of education level on the relationship between digital literacy and economic vulnerability; β_2 is the coefficient of education level; β_3 is the coefficient of the interaction term, representing the moderating effect of education level on the relationship between digital literacy and economic vulnerability; and ε_i is the random disturbance term.

4. Results

4.1. Model Estimation

Table 6 presents the baseline regression results, which show a significant and stable negative association between digital literacy and rural household economic vulnerability, supporting H1. This conclusion remains robust after progressively incorporating individual- and household-level control variables and provincial fixed effects. At the result level, higher levels of digital literacy are associated with greater efficiency in information acquisition, better access to market resources, and more optimized household decision-making, as

well as with diversified income channels and strengthened risk-coping capacity. This suggests that, with the continuous empowerment of digital technologies, improvements in household economic efficiency and risk resilience tend to co-occur with higher levels of digital literacy, and rural households with higher digital literacy tend to exhibit lower levels of economic vulnerability.

Table 6. Baseline regression results.

Variable Name	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	−0.708 *** (−15.917)	−0.769 *** (−18.222)	−0.606 *** (−12.215)	−0.657 *** (−13.659)	−0.307 *** (−6.705)	−0.352 *** (−8.036)
Health			−0.067 *** (−10.398)	−0.066 *** (−9.308)	−0.056 *** (−11.949)	−0.055 *** (−10.441)
Marriage			0.061 *** (3.311)	0.074 *** (3.900)	−0.046 ** (−2.342)	−0.034 * (−1.820)
Intelligence level			−0.014 ** (−2.442)	−0.018 *** (−3.162)	−0.007 (−1.526)	−0.011 ** (−2.403)
Household size					0.058 *** (14.572)	0.059 *** (14.724)
Child dependency ratio					0.107 *** (4.261)	0.120 *** (4.425)
Elderly dependency ratio					0.160 *** (9.637)	0.169 *** (9.759)
Household savings					−0.050 *** (−18.552)	−0.052 *** (−20.000)
Gift and courtesy expenditure					−0.005 ** (−2.414)	−0.005 ** (−2.373)
Government subsidies					0.007 (0.636)	0.014 (1.265)
Bank loans					−0.146 *** (−8.478)	−0.154 *** (−8.832)
Financial products					0.061 * (1.898)	0.080 *** (2.624)
Housing conditions					0.005 *** (3.608)	0.004 *** (2.902)
Constant	0.317 *** (10.405)	0.338 *** (10.078)	0.533 *** (11.323)	0.561 *** (11.886)	0.640 *** (10.022)	0.664 *** (10.193)
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3121	3121	3121	3121	3121	3121
R-squared	0.112	0.123	0.148	0.159	0.497	0.510

Note: (1) t-values are reported in parentheses; (2) All models use cluster-robust standard errors at the village/community level (cid22); (3) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Endogeneity Test

To mitigate potential reverse causality in the baseline regression, this paper employs an instrumental variable (IV) approach for endogeneity testing. Following Li et al. [35] and Ma et al. [64], this paper uses the average digital literacy level of other households in the same village as the instrument for digital literacy. We recognize that this village-mean instrument may reflect unobserved community-level characteristics, such as local infrastructure quality, market access, and information diffusion networks, which are closely correlated with households' digital literacy levels. The exclusion restriction requires that the instrument affect the outcome only through digital literacy, which is a strong assumption that we cannot fully verify with the available data. Given this limitation, we do not interpret the IV results as establishing causality, but rather as an additional check on the direction and robustness of the association observed in the baseline OLS estimates. Under this premise,

the instrument is expected to satisfy the relevance condition: the average digital literacy of other households in the same village directly affects the focal household's digital literacy.

The estimation results are presented in Table 7. The IV estimation is based on a sample of 2874 households. The reduction from 3121 is due to the requirement that the construction of the village-mean instrument requires at least two valid observations per village, which excludes observations from villages with only one respondent. To ensure robustness, this paper reports two sets of 2SLS estimates: one using village-level cluster-robust standard errors (columns 1–3) and the other using heteroskedasticity-robust standard errors (columns 4–6). The first-stage regression results show that the instrument has a significant positive effect on digital literacy, with the instrument coefficient significant at the 1% level. Under the cluster-robust specification at the village level, the first-stage F-statistic is 9.89, close to the conventional threshold of 10, suggesting that weak instrument bias is not a serious concern. When using heteroskedasticity-robust standard errors, the F-statistic rises to 37.46, further supporting the relevance of the instrument. Given the consistency with the baseline model, we place greater emphasis on the clustered estimates. The second-stage 2SLS estimates show that, after controlling for endogeneity, the direction of the negative association between digital literacy and rural household economic vulnerability remains consistent with the baseline OLS results, with the clustered specification yielding significance at the 10% level for Vul1 and at the 5% level for Vul2. Consistent with the associational framing of this study, we interpret these results as providing supplementary support for the robustness of the main findings, rather than as evidence of a causal effect.

Table 7. Endogeneity test results (IV: Average digital literacy of other villagers).

Variable Name	2SLS—(Cluster SE)			2SLS—(Robust SE)		
	(1) First Stage: Digital Literacy	(2) Second Stage: Vul1	(3) Second Stage: Vul2	(4) First Stage: Digital Literacy	(5) Second Stage: Vul1	(6) Second Stage: Vul2
Average digital literacy of other villagers	0.261 *** (3.145)			0.261 *** (6.120)		
Digital literacy		−0.659 * (−1.758)	−0.725 ** (−1.984)		−0.659 ** (−1.973)	−0.725 ** (−2.111)
Constant	0.086 ** (2.144)	0.778 *** (7.125)	0.813 *** (7.346)	0.086 * (1.660)	0.778 *** (7.103)	0.813 *** (7.130)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2874	2874	2874	2874	2874	2874
R-squared	0.175	0.490	0.500	0.175	0.490	0.500

Note: (1) Columns 1–3 use village-level (cid22) cluster-robust standard errors; (2) Columns 4–6 use heteroskedasticity-robust standard errors (unclustered, with a first-stage F-statistic greater than 10, provided to further support the relevance of the instrument); (3) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Robustness Test

To verify the reliability of the benchmark regression results, this paper conducts robustness tests from multiple dimensions, with the results presented in Table 8, Table 9, and Table 10, respectively.

First, this paper replaces the vulnerability line standard. Following the approach of Bello et al. [53], the vulnerability line is adjusted from 29% in the benchmark regression to 50%, and the model is re-estimated. The results show that the negative association between digital literacy and rural household economic vulnerability holds under different vulnerability line standards, confirming the robustness of the research findings.

Table 8. Adjusted vulnerability threshold, Alternative variable measurement and sample exclusion.

Variable Name	Replacing the Vulnerability Line (50%)		Alternative Measurement of the Explanatory Variable		Excluding Municipality Samples	
	(1) Vul3	(2) Vul4	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	−0.071 *** (−2.972)	−0.087 *** (−3.321)			−0.303 *** (−6.850)	−0.353 *** (−8.091)
Digital_Literacy			−0.004 *** (−7.635)	−0.004 *** (−9.345)		
Constant	0.152 *** (5.522)	0.179 *** (5.744)	0.676 *** (10.935)	0.704 *** (11.214)	0.652 *** (15.749)	0.701 *** (16.762)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3121	3121	3121	3121	3029	3029
R-squared	0.211	0.237	0.499	0.512	0.498	0.511

Note: *** $p < 0.01$.**Table 9.** Logit and Probit regression results.

Variable Name	Logit_Vul1	Logit_Vul2	Probit_Vul1	Probit_Vul2
Digital literacy	−0.472 *** (−11.130)	−0.507 *** (−10.622)	−0.472 *** (−11.646)	−0.507 *** (−11.084)
Health	−0.050 *** (−13.356)	−0.049 *** (−12.020)	−0.050 *** (−13.704)	−0.049 *** (−12.077)
Marriage	0.009 (0.466)	0.018 (0.961)	0.012 (0.665)	0.018 (0.955)
Intelligence level	−0.008 ** (−2.089)	−0.011 *** (−3.155)	−0.007 ** (−2.074)	−0.010 *** (−2.866)
Household size	0.052 *** (17.923)	0.053 *** (17.598)	0.052 *** (18.595)	0.053 *** (18.184)
Child dependency ratio	0.114 *** (5.959)	0.128 *** (5.858)	0.113 *** (6.083)	0.131 *** (6.069)
Elderly dependency ratio	0.121 *** (11.403)	0.130 *** (10.794)	0.120 *** (11.603)	0.129 *** (10.999)
Household savings	−0.036 *** (−54.345)	−0.038 *** (−59.067)	−0.037 *** (−57.776)	−0.039 *** (−60.713)
Gift and courtesy expenditure	−0.003 (−1.346)	−0.003 (−1.309)	−0.003 (−1.513)	−0.003 (−1.401)
Government subsidies	0.020 * (1.902)	0.026 ** (2.465)	0.022 ** (2.095)	0.029 *** (2.740)
Bank loans	−0.117 *** (−7.997)	−0.126 *** (−7.948)	−0.120 *** (−8.126)	−0.128 *** (−8.070)
Financial products	−0.057 (−1.138)	0.000 (0.006)	−0.053 (−1.150)	0.002 (0.052)
Housing conditions	0.010 *** (6.907)	0.009 *** (5.838)	0.010 *** (7.077)	0.009 *** (5.731)
Provincial fixed effects	Yes	Yes	Yes	Yes
Observations	3116	3116	3116	3116

Note: (1) z-values are reported in parentheses; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (3) the table reports Average Marginal Effects (AMEs); (4) standard errors are clustered at the village level (cid22); (5) the reduction in sample size is due to automatic deletion of observations with perfect prediction.

Second, this paper replaces the measurement method of the explanatory variable. To avoid potential biases arising from a single measurement approach, the Principal Component Analysis (PCA) method is employed to recalculate the comprehensive digital literacy index. Based on 12 relevant items from the CFPS questionnaire, principal components are

extracted according to the criterion of eigenvalues greater than 1. The comprehensive score is then synthesized by weighting each factor by its variance contribution rate and subsequently standardized. The Kaiser–Meyer–Olkin (KMO) test yields a value of 0.8724, and Bartlett’s sphericity test yields a p -value of 0.000, indicating that the PCA results are valid. After substituting the recalculated digital literacy index into the regression, the coefficient of the core explanatory variable remains significantly negative, which is consistent with the benchmark regression results and verifies the robustness of the findings.

Table 10. Excluding attitudinal items and alternative definitions of rural.

Variable Name	Excluding Attitudinal Items		Alternative Rural Definition (Agricultural Hukou)	
	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2
Digital literacy_behavior	−0.274 *** (−6.198)	−0.316 *** (−7.159)		
Digital literacy			−0.313 *** (−6.792)	−0.361 *** (−7.958)
Constant	0.621 *** (9.594)	0.643 *** (9.720)	0.658 *** (7.690)	0.692 *** (7.952)
Individual level	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Observations	3121	3121	2866	2866
R-squared	0.495	0.507	0.503	0.515

Note: *** $p < 0.01$.

Third, this paper excludes municipality samples. Considering that the four municipalities directly under the central government—Beijing, Tianjin, Shanghai, and Chongqing—differ significantly from other provinces in terms of economic development levels and policy environments, the relevant samples are excluded and the model is re-estimated. The results show that the negative association between digital literacy and rural household economic vulnerability remains significant, further confirming the reliability of the research conclusions.

Fourth, this paper replaces the regression model. To rule out potential model specification bias, the benchmark OLS model is replaced with Logit and Probit models for re-estimation. Using the 29% vulnerability line as the threshold, the dependent variable is transformed into a binary dummy variable (coded as 1 if the vulnerability probability is $\geq 29\%$, and 0 otherwise). The regression results show that the Average Marginal Effects (AMEs) of digital literacy are significantly negative at the 1% level across both models, which is entirely consistent with the benchmark conclusions, fully demonstrating the high robustness of the research findings. The sample size decreases from 3121 to 3116 because the Logit and Probit models automatically drop observations for which the dependent variable is perfectly predicted by a province dummy, resulting in a loss of 5 observations. This slight reduction does not affect the robustness of the conclusions.

Fifth, we excluded attitudinal items from the digital literacy index. To test the robustness of the digital literacy index construction, this paper excluded attitudinal items—such as the perceived importance of the Internet for daily life, leisure, learning, work, and staying connected with family and friends—and recalculated the digital literacy index using only behavioral items (denoted as “Digital literacy_behavior”). The baseline model was then re-estimated. As shown in Table 10, columns (1) and (2), the coefficient of Digital literacy_behavior remains significantly negative at the 1% level, confirming that the findings are not driven by the inclusion of attitudinal items.

Sixth, we adopted an alternative definition of “rural.” To avoid the influence of rural classification criteria on the estimation results, this paper used the household head’s agricultural hukou as an alternative rural classification standard to re-select the sample and re-estimate the baseline model. It should be noted that the rural sample in the baseline regression was defined using the CFPS urban–rural classification variable, which is based on the National Bureau of Statistics’ urban–rural classification. As shown in Table 10, columns (3) and (4), the coefficient of digital literacy remains consistent in both direction and significance under the alternative rural definition, indicating that the findings are robust to the definition of rural classification.

4.4. Mediation Analysis

To clarify the underlying transmission mechanisms between digital literacy and rural household economic vulnerability, this paper employs both the stepwise regression approach and the bootstrap method (5000 replications) to test the mediating roles of employment quality and social trust. The results are presented in Tables 11 and 12.

Table 11. Results of mediating effect tests.

Variable Name	(1) Vul1	(2) Vul2	(3) Employment Quality (a)	(4) Vul1	(5) Vul2	(6) Social Trust (a)	(7) Vul1	(8) Vul2
Digital literacy	−0.307 *** (−6.705)	−0.352 *** (−8.036)	36.307 *** (10.326)	−0.284 *** (−6.867)	−0.326 *** (−7.872)	1.194 *** (7.813)	−0.284 *** (−6.167)	−0.327 *** (−7.487)
Employment quality				−0.001 * (−1.688)	−0.001 * (−1.890)			
Social trust							−0.020 *** (−4.827)	−0.021 *** (−4.952)
Constant	0.640 *** (10.022)	0.664 *** (10.193)	36.481 *** (7.433)	0.664 *** (10.013)	0.690 *** (10.218)	2.402 *** (11.592)	0.688 *** (10.584)	0.715 *** (10.721)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3121	3121	3121	3121	3121	3121	3121	3121
R-squared	0.497	0.510	0.254	0.497	0.510	0.056	0.500	0.513

Note: * $p < 0.1$, *** $p < 0.01$.

Table 12. Mediation analysis based on the bootstrap method.

Effect Type	Pathway	Effect	Boot SE	Boot LLCI	Boot ULCI
Vul1					
Total effect	—	−0.307	0.037	−0.380	−0.234
Direct effect	—	−0.284	0.035	−0.353	−0.214
Indirect effect	Employment quality → Vul1	−0.024	0.011	−0.045	−0.003
Indirect effect	Social trust → Vul1	−0.024	0.006	−0.035	−0.013
Vul2					
Total effect	—	−0.352	0.038	−0.426	−0.278
Direct effect	—	−0.326	0.036	−0.397	−0.256
Indirect effect	Employment quality → Vul2	−0.026	0.011	−0.046	−0.005
Indirect effect	Social trust → Vul2	−0.025	0.006	−0.036	−0.014

Table 11 reports the path coefficient estimates from the stepwise regression approach. The results show that higher levels of digital literacy are associated with higher levels of employment quality and social trust among rural households. After incorporating the mediating variables, both employment quality and social trust are significantly negatively associated with vulnerability, and the coefficient of digital literacy remains significantly negative, indicating that both mediation paths are valid.

Table 12 reports the indirect effect estimates from the bootstrap method. The bootstrap mediation tests show that the 95% confidence intervals for all four mediation paths do not contain zero. For Vul1, the indirect effect through employment quality is -0.024 (95% CI: $-0.045, -0.003$), and through social trust is -0.024 (95% CI: $-0.035, -0.013$). For Vul2, the indirect effect through employment quality is -0.026 (95% CI: $-0.046, -0.005$), and through social trust is -0.025 (95% CI: $-0.036, -0.014$).

These results indicate that digital literacy is indirectly associated with rural household economic vulnerability through employment quality and social trust, supporting H2 and H3. Notably, while the mediating effect of employment quality is statistically significant, its magnitude is relatively small, suggesting it is only a partial channel.

4.5. Moderation Analysis

Table 13 presents the results of the moderation effect tests. Under both poverty line standards, the coefficient of the interaction term between digital literacy and education level is significantly positive at the 1% level, indicating that education level significantly moderates the relationship between digital literacy and rural household economic vulnerability. Specifically, the negative association between digital literacy and economic vulnerability is stronger among less-educated households. For less-educated rural households, digital literacy helps them access market information, formal financial services, and public policy resources, compensating to some extent for their human capital deficiencies. In contrast, more-educated households, with their accumulated human capital and social resources, already possess relatively stable risk-coping capacity, and the marginal contribution of digital literacy is correspondingly smaller. This result supports H4b, while H4a is not supported, thus confirming the second pathway proposed in the theoretical analysis.

Table 13. Results of moderating effect tests.

Variable Name	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	-0.080^{***} (-8.976)	-0.087^{***} (-8.358)	-0.071^{***} (-8.155)	-0.077^{***} (-7.538)	-0.036^{***} (-5.307)	-0.041^{***} (-5.058)
Education	-0.163^{***} (-16.845)	-0.172^{***} (-17.943)	-0.157^{***} (-15.934)	-0.165^{***} (-16.830)	-0.123^{***} (-12.680)	-0.131^{***} (-13.236)
Digital literacy $\times$ Education	0.064^{***} (13.441)	0.065^{***} (12.373)	0.065^{***} (14.064)	0.066^{***} (13.084)	0.060^{***} (15.126)	0.061^{***} (14.283)
Constant	0.202^{***} (9.361)	0.215^{***} (9.542)	0.350^{***} (7.471)	0.368^{***} (8.302)	0.505^{***} (7.827)	0.520^{***} (7.995)
Individual level	No	No	Yes	Yes	Yes	Yes
Household level	No	No	No	No	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3121	3121	3121	3121	3121	3121
R-squared	0.227	0.243	0.255	0.270	0.567	0.583

Note: (1) Digital literacy and education are standardized (z-scores); (2) The interaction term is the product of the two standardized variables; (3) *** $p < 0.01$.

To visually illustrate the moderating effect of education level, this paper divides the sample into three groups based on the household head's education level: low education (illiterate/semi-literate and primary school), medium education (junior high school), and high education (senior high school and above). This grouping reflects the hierarchical structure of rural education levels while ensuring sufficient statistical power in each group. Figure 1 presents the predicted marginal effects of digital literacy on rural household economic vulnerability across the three groups. The results show that the slope is steepest for the low-education group, followed by the medium-education group, and flattest for the high-education group, indicating that the negative association between digital literacy

and economic vulnerability weakens as education level increases. When digital literacy increases from low to high levels, the predicted reduction in vulnerability for the low-education group is approximately twice that of the high-education group. This graphical evidence is consistent with the positive and significant interaction term in Table 13, further confirming that the negative association between digital literacy and rural household economic vulnerability is more pronounced among less-educated households.

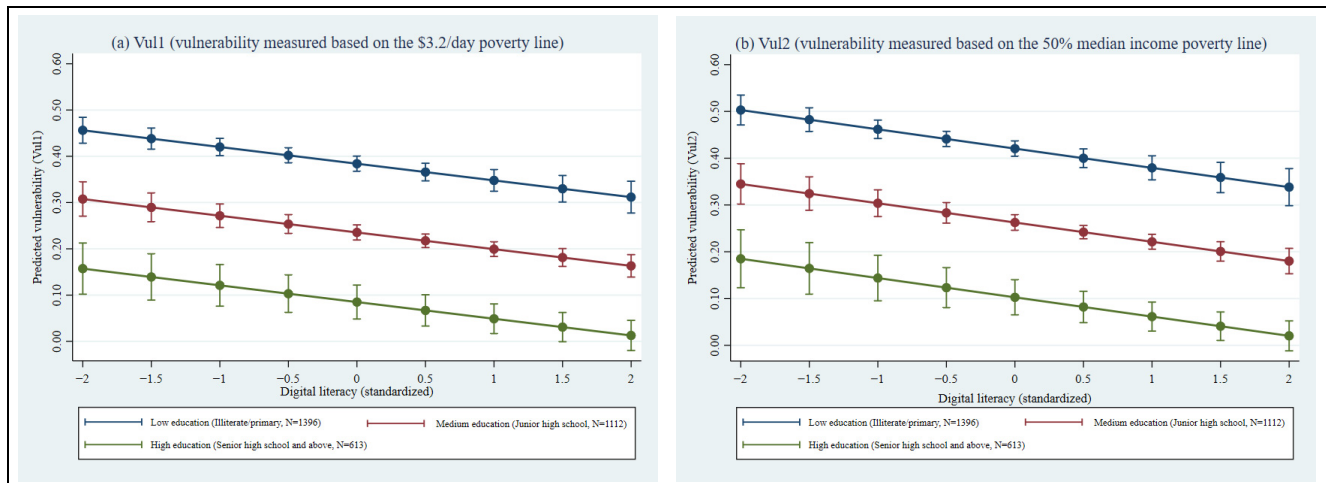


Figure 1. Marginal effects of digital literacy on rural household economic vulnerability across education groups. Note: The shaded bands represent 95% confidence intervals. The low education group includes illiterate/semi-literate and primary school (N = 1396); the medium education group includes junior high school (N = 1112); the high education group includes senior high school and above (N = 613). Vul1 and Vul2 are two alternative measures of household economic vulnerability based on different poverty lines.

4.6. Heterogeneity Analysis

4.6.1. Gender Heterogeneity

To examine the gender heterogeneity in the relationship between digital literacy and rural household economic vulnerability, this paper divides the sample into male-headed and female-headed households based on the gender of the household head. The subsample regression results are presented in Table 14. The results show that, for both male-headed and female-headed households, higher levels of digital literacy are associated with lower levels of economic vulnerability, and the negative association is stronger in female-headed households than in male-headed households. Furthermore, this paper tests the between-group coefficient difference by introducing an interaction term between digital literacy and a female household head dummy variable. The results show that the interaction term is significantly negative at the 1% level, confirming the statistical significance of the gender difference.

On the one hand, constrained by traditional gender roles and the division of labor, rural women face more pronounced structural constraints in the labor market, with limited career development opportunities, resource acquisition capabilities, and risk-hedging channels, and a weaker foundation of household economic resilience. Consequently, the negative association between digital literacy and vulnerability is more pronounced in female-headed households. Digital technologies effectively break the spatiotemporal and identity constraints of traditional employment, offering women new pathways for flexible entrepreneurship and home-based income generation, while also lowering barriers to accessing productive and living resources through online finance and government services, which are associated with strengthened household risk-coping capacity. On the other

hand, digital literacy is associated with the transformation of women's roles and decision-making power within the household, facilitating their deeper participation in household economic decision-making and resource allocation, which is associated with improved structural efficiency of household consumption, savings, and investment. In contrast, male-headed households already possess better resource endowments and development conditions in the traditional labor market, and the marginal contribution of digital literacy is relatively limited.

Table 14. Results of gender heterogeneity.

Variable Name	Male		Female		Between-Group Difference	
	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	−0.280 *** (−6.071)	−0.309 *** (−7.050)	−0.416 *** (−4.850)	−0.541 *** (−6.006)	−0.272 *** (−5.509)	−0.305 *** (−6.605)
digital_female					−0.215 *** (−3.123)	−0.271 *** (−4.044)
Constant	0.520 *** (6.263)	0.533 *** (6.167)	0.839 *** (8.037)	0.875 *** (8.610)	0.554 *** (8.517)	0.568 *** (8.517)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2506	2506	615	615	3121	3121
R-squared	0.505	0.521	0.542	0.566	0.514	0.530

Note: *** $p < 0.01$.

4.6.2. Age Heterogeneity

To examine the age heterogeneity in the relationship between digital literacy and rural household economic vulnerability, this paper divides the sample into two groups based on the age of the household head: the young and middle-aged group (aged 18–59) and the elderly group (aged 60 and above). The subsample regression results are presented in Table 15. The results show that, for both the young and middle-aged group and the elderly group, higher levels of digital literacy are associated with lower levels of economic vulnerability. Furthermore, the interaction term between digital literacy and the elderly household head dummy variable is significantly negative at the 1% level, confirming that the coefficient difference between the two groups is statistically significant.

Table 15. Results of age heterogeneity.

Variable Name	Young and Middle-Aged Group		Elderly Group		Between-Group Difference	
	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	−0.211 *** (−5.391)	−0.270 *** (−6.559)	−0.467 *** (−3.224)	−0.443 *** (−3.210)	−0.210 *** (−4.833)	−0.268 *** (−6.121)
digital_elderly					−0.365 *** (−2.603)	−0.271 * (−1.930)
Constant	0.589 *** (8.943)	0.640 *** (9.441)	0.752 *** (11.473)	0.699 *** (10.843)	0.593 *** (9.351)	0.624 *** (9.609)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2433	2433	688	688	3121	3121
R-squared	0.480	0.494	0.515	0.518	0.504	0.515

Note: * $p < 0.1$, *** $p < 0.01$.

The elderly group is characterized by higher economic vulnerability and weaker risk-coping capacity, often facing challenges such as limited income sources, heavy burdens of elderly care and medical expenses, and restricted access to traditional employment channels. Digital literacy helps them conveniently access online social security, digital financial services, and telemedicine, thereby reducing the cost of risk response, improving social security coverage, and lowering barriers to public services and financial support, which are associated with enhanced capacity to cope with sudden risks such as illness and accidents.

In contrast, the young and middle-aged group possesses stronger labor capacity and employment competitiveness, with more diverse income sources and a lower baseline level of economic vulnerability, so the marginal contribution of digital literacy is relatively limited. At the same time, this group has more widespread exposure to and application of digital technologies, and the economic returns from marginal improvements in digital literacy tend to diminish, further explaining why this group benefits less than the elderly group.

4.6.3. Income Level Heterogeneity

To examine the income heterogeneity in the relationship between digital literacy and rural household economic vulnerability, this paper divides the sample into low-income and high-income households based on the median household per capita income. The subsample regression results are presented in Table 16. The results show that, for both low-income and high-income households, higher levels of digital literacy are associated with lower levels of economic vulnerability, and the negative association is stronger in low-income households than in high-income households. Furthermore, this paper tests the between-group coefficient difference by introducing an interaction term between digital literacy and a high-income dummy variable. The results show that the interaction term is significantly positive at the 1% level, confirming that the coefficient difference between low-income and high-income groups is statistically significant.

Table 16. Results of income level heterogeneity.

Variable Name	Low-Income Households		High-Income Households		Between-Group Difference	
	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2
Digital literacy	−0.446 *** (−7.193)	−0.527 *** (−7.877)	−0.226 *** (−4.490)	−0.229 *** (−4.672)	−0.530 *** (−8.629)	−0.591 *** (−8.699)
digital_high					0.369 *** (4.223)	0.409 *** (4.348)
Constant	0.131 *** (2.939)	0.118 *** (2.674)	0.488 *** (7.640)	0.533 *** (7.810)	0.658 *** (10.015)	0.694 *** (10.272)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1576	1576	1545	1545	3121	3121
R-squared	0.538	0.527	0.394	0.424	0.501	0.515

Note: *** $p < 0.01$.

Low-income households face the core challenge of limited access to traditional development opportunities and weak information acquisition capabilities, constrained by information asymmetry and poor resource matching, which makes it difficult for them to seize market opportunities and policy dividends. Digital literacy helps them access market information, stabilize production-sales linkages, and obtain inclusive financial support, which is associated with improved household economic efficiency and risk-coping capacity.

Consequently, the negative association between digital literacy and vulnerability is more pronounced in low-income households. High-income households, on the other hand, have already built stronger economic resilience through diversified asset allocation and relatively well-established risk-hedging mechanisms. Digital literacy is more closely associated with the efficiency of existing wealth management, and its marginal contribution to reducing vulnerability is relatively limited.

4.6.4. Regional Heterogeneity

To systematically examine the regional heterogeneity in the relationship between digital literacy and rural household economic vulnerability, this paper divides the full sample into three regions—eastern, central, and western—and conducts subsample regression analyses. The results are presented in Table 17. The results show that, for all three regions, higher levels of digital literacy are associated with lower levels of economic vulnerability, with a clear regional gradient: the negative association is strongest in the central region, followed by the western region, and weakest in the eastern region. Furthermore, the interaction term tests show that, with the eastern region as the reference group, the interaction terms between digital literacy and the central and western region dummy variables are both significantly negative at the 1% level, confirming that the negative associations in both the central and western regions are significantly stronger than in the eastern region, thus validating the statistical significance of the regional heterogeneity. It should be noted that provincial fixed effects are not controlled for in the regional subsample regressions. This is because, on the one hand, the model specification needs to remain consistent across the subsample regressions and the full-sample interaction regressions for comparability of coefficient differences; on the other hand, regional classification is based on provincial-level categorization, and the eastern, central, and western region dummy variables are inherently collinear with provincial fixed effects, making it impossible to include both simultaneously. At the same time, the baseline regression has already included provincial fixed effects to confirm the robustness of the core findings, and the simplified specification in this table is intended to focus on regional differences in the association between digital literacy and rural household economic vulnerability.

Table 17. Results of regional heterogeneity.

Variable Name	Eastern Region		Central Region		Western Region		Between-Group Difference	
	(1) Vul1	(2) Vul2	(3) Vul1	(4) Vul2	(5) Vul1	(6) Vul2	(7) Vul1	(8) Vul2
Digital literacy	−0.183 *** (−3.581)	−0.198 *** (−3.723)	−0.409 *** (−5.648)	−0.465 *** (−6.673)	−0.388 *** (−5.980)	−0.449 *** (−6.339)	−0.154 *** (−3.340)	−0.179 *** (−3.825)
digital_central							−0.228 *** (−2.881)	−0.257 *** (−3.370)
digital_western							−0.282 *** (−3.973)	−0.309 *** (−4.298)
Constant	0.560 *** (9.580)	0.599 *** (9.487)	0.691 *** (10.290)	0.765 *** (11.285)	0.741 *** (12.659)	0.797 *** (14.739)	0.619 *** (15.731)	0.661 *** (15.422)
Individual level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	No	No	No	No	No	No	No	No
Observations	1101	1101	857	857	1163	1163	3121	3121
R-squared	0.467	0.481	0.506	0.503	0.483	0.502	0.492	0.505

Note: *** $p < 0.01$.

Specifically, the eastern region has a solid rural economic foundation, well-established digital infrastructure, and a mature digital industrial structure. Rural households' digital literacy levels are generally high, and the penetration of digital skills and the saturation of application scenarios are approaching their limits; therefore, the marginal contribution of digital literacy is relatively limited. The central region, as a hub for undertaking industrial

transfer from the east and radiating development to the west, has seen accelerated digital village construction in recent years, with rural households' digital literacy at a critical stage of rapid improvement. Leveraging its geographical advantage of connecting the east and the west, this region has a solid foundation in urban–rural integrated development, market-oriented factor allocation, and effective policy implementation, allowing the digital dividend to permeate more fully into rural households, and thus the marginal contribution of digital literacy is more pronounced. The western region is characterized by vast rural areas, where digital technologies help local households overcome geographical and spatial constraints, connect with emerging development models such as e-commerce for specialty agricultural products and rural tourism, and enhance risk-coping capacity through services such as digital finance and online social security. However, constrained by relatively insufficient digital infrastructure coverage and the limited penetration of digital skills, the marginal contribution of digital literacy is weaker than in the central region but significantly stronger than in the eastern region.

5. Discussion

5.1. Theoretical Significance

Based on data from the 2022 China Family Panel Studies (CFPS), this paper examines the direction and pathways of the association between digital literacy and rural household economic vulnerability, and further analyzes its transmission mechanisms and moderating effects. The findings provide a useful reference for household risk prevention in rural areas in the digital economy era.

The main findings are discussed in comparison with previous literature as follows.

First, this study confirms a significant negative association between digital literacy and rural household economic vulnerability, a conclusion that holds across various model specifications and measurement approaches. This is consistent with existing findings that digital capabilities contribute to enhanced farm household production resilience and reduced financial vulnerability [4,24,25]. As a core element of new human capital in the digital era, digital literacy is associated with improved household information acquisition capacity and economic decision-making efficiency [33,34]. This study extends this evidence to the domain of household economic vulnerability.

Second, this study identifies two mediating pathways through which digital literacy is negatively associated with economic vulnerability, revealing its transmission mechanisms from the dual dimensions of economic resources and social capital. On the one hand, digital literacy is associated with improved labor market performance and employment stability, which in turn is associated with reduced household vulnerability, consistent with existing evidence that digital literacy enhances rural labor employment quality [38,39,41]. On the other hand, digital literacy is associated with expanded social networks and reduced information constraints, which in turn is associated with enhanced social trust among rural residents [42], as well as with reduced transaction costs and facilitated risk-sharing [43,45,65].

Third, this study finds that education level moderates the relationship between digital literacy and rural household economic vulnerability, with the negative association being stronger among less-educated households. A plausible explanation is that more-educated households, even without outstanding digital skills, can still access information and services through traditional channels [46,66], so the marginal contribution of digital literacy is smaller. In contrast, less-educated households lack these traditional channels, and digital literacy provides them with an effective pathway, making its marginal contribution more pronounced. This finding suggests that, in rural contexts, digital literacy may serve as a

compensatory mechanism for limited formal education, offering new empirical evidence on the relationship between digital technology and human capital.

Fourth, the heterogeneity analysis reveals significant group and regional differences in the negative association between digital literacy and rural household economic vulnerability. In terms of household head characteristics, the negative association is stronger in female-headed households, consistent with existing evidence that digital literacy has a stronger empowering effect on women and vulnerable groups [37], and also in line with the structural disadvantages faced by rural women in the labor market under traditional gender divisions of labor. In terms of age, the negative association is stronger in elderly-headed households, consistent with the reality that the elderly group faces more limited traditional employment channels and single income sources. In terms of income, the negative association is stronger in low-income households, suggesting that digital literacy may have a compensatory effect. In terms of region, the negative association is strongest in the central region, followed by the western region, and weakest in the eastern region. This gradient is closely related to regional differences in digital infrastructure development and the penetration of digital skills, and is consistent with the finding that the benefits of digital technology vary across different groups [30].

5.2. Implications for Sustainable Development

The contributions of this study to the sustainability literature are threefold. First, by empirically establishing the negative association between digital literacy and rural household economic vulnerability, this study provides micro-level evidence for the achievement of SDG 1 (No Poverty)—digital literacy is associated with buffering external risk shocks, reducing the risk of falling back into poverty, and strengthening the sustainable livelihood foundation of farm households, thereby contributing to enhanced household economic resilience from the ground up. Second, the identification of the mediating pathway through employment quality enriches the understanding of the mechanisms underlying SDG 8 (Decent Work and Economic Growth). Digital literacy is associated not only with increased farm household income, but also with diversified employment channels, improved labor market participation, and stabilized non-farm income, which in turn contribute to the formation of a long-term, risk-resilient sustainable livelihood model. Finally, the heterogeneity analysis reveals that the negative association between digital literacy and vulnerability is more pronounced among female-headed, elderly-headed, low-income, and central and western region households. This finding directly resonates with the core objective of SDG 10 (Reduced Inequalities), suggesting that digital inclusion policies hold potential value in narrowing group-based and regional disparities. Overall, digital literacy is associated with reduced household economic vulnerability and strengthened household risk resilience, jointly advancing the three sustainable development goals of poverty reduction, decent employment, and development equity, and serving as an important pathway toward inclusive and sustainable rural development.

5.3. Limitations

Although this study offers valuable insights into the relationship between digital literacy and rural household economic vulnerability, several limitations should be acknowledged.

First, the use of cross-sectional data from the 2022 CFPS limits our ability to draw strict causal inferences. The negative association between digital literacy and rural household economic vulnerability should therefore be interpreted as a statistical correlation rather than a causal effect. While we have employed instrumental variable estimation to mitigate potential endogeneity concerns, the cross-sectional nature of the data precludes strong

causal claims. Future research could benefit from panel data or more comprehensive identification strategies to further examine the direction of this association.

Second, the mediation analysis relies on the sequential ignorability assumption, which is difficult to justify with cross-sectional data. Consequently, the mediating roles of employment quality and social trust should be understood as statistical indirect associations rather than causal transmission mechanisms.

Third, social trust is measured using a single item from the CFPS questionnaire—"trust in strangers"—which may not fully capture the multidimensional nature of the concept. Future studies could consider employing multi-dimensional scales to improve measurement accuracy and validity.

6. Conclusions

6.1. Main Findings

This study empirically examines the association between digital literacy and rural household economic vulnerability, as well as its underlying mechanisms. The results reveal a significant negative association between digital literacy and rural household economic vulnerability, a finding that holds across a range of robustness checks and supports Hypothesis 1. The mediation analysis indicates that employment quality and social trust serve as two key transmission channels through which digital literacy is associated with lower economic vulnerability, lending support to Hypotheses 2 and 3. The moderation analysis further reveals that education level moderates this association, with the negative relationship being stronger among less-educated households, thereby supporting Hypothesis 4b, while Hypothesis 4a is not supported. Heterogeneity analysis shows that the negative association between digital literacy and rural household economic vulnerability is more pronounced among female-headed, elderly-headed, low-income, and central and western region households.

6.2. Policy Implications

The above findings suggest an association between improving rural households' digital literacy and reducing their economic vulnerability. Accordingly, the following policy recommendations are proposed.

First, accelerate the development of rural digital infrastructure and service systems to strengthen the hardware foundation for digital literacy improvement. Digital infrastructure serves as a prerequisite for enhancing rural households' digital literacy and mitigating economic vulnerability. Efforts should continue to promote the integrated construction of rural network coverage, smart agricultural equipment, and digital public service facilities, thereby enhancing rural households' digital access and usage convenience while lowering barriers to information acquisition and digital application. Digital platforms can be leveraged to establish service systems for agricultural technology extension, market information matching, and direct production-sales linkages, facilitating the deep integration of digital technologies with agricultural production and household management. This would enable digital infrastructure to provide a solid hardware foundation for empowering economic resilience through digital literacy.

Second, prioritize digital literacy training for less-educated rural households while simultaneously improving rural education quality, creating synergies between short-term capacity building and long-term human capital accumulation. In the short term, flexible and diversified teaching methods should be adopted to ensure the effectiveness and accessibility of training programs. In the long term, continued efforts are needed to consolidate the quality of compulsory education in rural areas, expand the coverage of upper secondary education, and optimize the supply of educational resources, thereby enhancing rural

residents' foundational cognitive and learning capacities to sustain the accumulation and effective application of digital literacy over time.

Third, adopt targeted and differentiated policies to enhance the relevance and effectiveness of digital literacy interventions in reducing rural household economic vulnerability. At the group level, digital resources and training services should be directed toward female-headed, elderly-headed, and low-income households, further unlocking the potential role of digital literacy for highly vulnerable groups. At the regional level, greater investment in rural digital development should be directed to the central and western regions to address infrastructure and public service gaps, fully unleashing the empowering potential of digital literacy in less-developed areas. In the eastern region, the focus should shift toward deepening the application of digital technologies and improving efficiency to further consolidate household economic resilience.

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