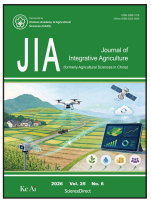
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RESEARCH ARTICLE

The impact of digital technology use on relocated households' income stability in China

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Highlights

- Digital technology use improves both income and income stability, with stronger effects at higher levels of use.
- Information acquisition and human capital are important influence mechanisms.
- Digital literacy amplifies the positive impact of digital technology on income stability.

Abstract

Ensuring the income stability of relocated households is essential for advancing rural revitalization and achieving common prosperity. While existing research has explored the impact of digital technology on income, few studies have addressed how digital technology use affects income stability. To fill this gap, based on survey data from relocated households in 16 counties across 8 provincial-level regions in China, this study examines the impact of digital technology use on the income stability of relocated households using Ordinary Least Squares (OLS) and Propensity Score Matching (PSM). The results show that digital technology use improves both income and income stability, with stronger effects at higher levels of use. This impact is driven by better access to information acquisition and enhanced human capital. Additionally, digital technology helps stabilize the income of households facing downward volatility. The income stabilizing effect is particularly significant among relocated households in central regions, rural resettlement areas, and those with higher education levels. Furthermore, digital literacy amplifies the positive impact of digital technology on income stability. These findings offer valuable insights for policymakers aiming to promote digital technology use to ensure the income stability of relocated households and foster common prosperity.

Keywords: digital technology use, income stability, relocated households, digital literacy

1. Introduction

"End poverty in all its forms everywhere" is the first of the 17 Sustainable Development Goals set by the United Nations for the period leading up to 2030 (Liu *et al.* 2020; Zhou *et al.* 2024). China's poverty alleviation through relocation (PAR) is a key project in this global effort, aiming to relocate impoverished populations from inhospitable areas (Rogers *et al.* 2020), improve the living standards of rural poor populations, and enhance their access to infrastructure and services (Lo *et al.* 2016). The PAR has significantly reduced the livelihood vulnerability of relocated households by reducing exposure and enhancing adaptability (Hong *et al.* 2024), and reducing income poverty and multidimensional poverty (Liu *et al.* 2023). The relocated households discussed in this study refer to the poor households that participated in the PAR during the "13th Five-Year Plan" period. However, the relocation process has led to challenges for many households due to changes in livelihoods, shifts in living environments, disruption of social networks, and a lack of follow-up support. These issues, combined with shocks such as COVID-19, have left many relocated households

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struggling (Lo *et al.* 2016; Yang *et al.* 2020; Guo *et al.* 2024). As a result, their income remains highly unstable (Chen *et al.* 2023), increasing their risk of falling back into poverty. To address this, the No. 1 Central Document of 2025 points out the need to "stabilize the scale and income of the labor force from the poverty-alleviated population, and firmly prevent large-scale re-impoverishment," and introduces a series of specific measures to advance the work of preventing re-impoverishment. These measures include conducting intensive employment initiatives to prevent re-impoverishment and enhancing the employment absorption capacity of assistance workshops, among others. Considering these realities, ensuring a steady and sustainable increase in the income of relocated households is a critical follow-up task for the PAR and remains a central issue of great social concern.

Income stability refers to the degree to which a household's income fluctuates minimally over time, maintaining a relatively stable level (Dynan *et al.* 2012). Existing research on income stability has primarily focused on two aspects: influencing factors and the various impacts of instability. Many studies have explored the factors affecting income stability, particularly in agricultural contexts. These factors include government subsidies or direct payment programs (El Benni *et al.* 2012; Severini *et al.* 2017; Nitta *et al.* 2022) and risk management tools such as insurance and mutual funds (Enjolras *et al.* 2014; Severini *et al.* 2019; Barratt *et al.* 2025). For example, Barratt *et al.* (2025) found that strategically combining frost index insurance with optimal seeding dates, especially in regions prone to frost, could be an important strategy to reduce financial impacts and enhance income stability. Additionally, farm management characteristics such as agricultural diversity (Harkness *et al.* 2021), the efficient use of agricultural chemicals (Harkness *et al.* 2023), cooperative membership (Ji *et al.* 2023), and ecological farming practices (Verkuil *et al.* 2024) affect income stability. Focusing on Netherlands farms as a case study, Verkuil *et al.* (2024) demonstrated that practices aligned with ecological farming principles can provide farmers with greater income stability, especially during periods of price volatility and climate shocks. Other studies have focused on the impact of income instability. Poon and Weersink (2011) argued that economic well-being is affected not only by income levels but also by income fluctuations. For instance, income volatility significantly affects saving decisions (Chamon *et al.* 2013; Wang-Ly and Newell 2024), consumption (Song *et al.* 2024), and health (Prause *et al.* 2009; Park *et al.* 2024). Additionally, uncertainty of income can inhibit the use of clean fuels among farm households (Chen *et al.* 2023), hindering sustainable economic and social development.

In recent years, the rapid development of the digital economy, driven by modern information networks and the integrated application of information and communication technology, has been notable. By December 2023, statistical data indicated that the number of rural Internet users in China had reached 326 million, accounting for 29.8% of the total Internet user population, with rural Internet penetration reaching 66.5% (China Internet Network Information Center 2024). Digital technology can effectively reduce the costs of information searches and transactions, increase opportunities for accessing information, and improve situations of information asymmetry (Khanal and Mishra 2016; Zheng *et al.* 2021; Zhu *et al.* 2022), playing a significant role in promoting rural economic transformation and enhancing the economic well-being of rural households (Ma *et al.* 2020; Min *et al.* 2020). For example, in agricultural production, digital technology use has positively impacted farmers' adoption of sustainable agricultural practices and integrated pest management (Ma and Wang 2020; Li *et al.* 2023), thereby improving food and nutrition security for farmers (Twumasi *et al.* 2021; Ardianti *et al.* 2023). Regarding farmers' well-being, digital technology has facilitated entrepreneurship and non-agricultural employment among rural laborers (Zhou *et al.* 2020; Fang *et al.* 2024), increasing farmers' incomes (Leng 2022; Khan *et al.* 2022; Phan 2023) and contributing to poverty reduction (Lechman and Popowska 2022; Gu *et al.* 2023). Additionally, the use of digital technology has improved the variety of household consumption while reducing consumption inequality (Wang *et al.* 2025), enhanced farmers' subjective well-being (Castellacci and Tveito 2018; Xiang and Zhang 2025), increased decision-making power for women (Zheng *et al.* 2023), and more.

Existing literature generally acknowledges that digital technology is a key driver of rural development and the improvement of farmers' welfare in the new development stage. However, as farmers increasingly face uncertainties in economic, environmental, and political conditions, income risks have become a growing concern (Trestini *et al.* 2018; Fabri *et al.* 2024). The income stability of relocated households is particularly important, as these households encounter additional challenges (Lo *et al.* 2016; Yang *et al.* 2020; Guo *et al.* 2024). Despite this, rigorous research on the relationship between digital technology and the income stability of relocated households is lacking. Therefore, this study seeks to answer two key questions: 1) Does the use of digital technology enhance the income stability of relocated households? 2) What are the underlying mechanisms? Addressing these questions is not only crucial for ensuring the sustained poverty alleviation of relocated households but will also provide valuable empirical evidence to support the advancement of China's digital rural strategy in the new development stage.

This study uses three periods of balanced panel data from relocated households across 16 counties in eight provinces in China to assess the impact of digital technology use on income stability. Compared to existing research, this study makes three main contributions. First, it offers a new research perspective. While much research has focused on income stability, studies from the digital technology perspective are relatively scarce. This study introduces a fresh angle to support steady and orderly income growth for relocated households. Second, it contributes to the content of existing research. This study not only evaluates whether and how digital technology use impacts income stability, but also explores its heterogeneous effects. Additionally, it investigates the moderating role of digital literacy in the relationship between digital technology use and income stability, thereby enriching the body of research on digital technology. Third, it utilizes nationally representative

longitudinal survey data from three periods of relocated households, which enhances the accuracy and realism of the estimates. Relocated households, with both common farmers' characteristics and specific vulnerabilities, are considered at greater risk of falling back into poverty. Thus, focusing on this group adds significant practical value.

The remainder of this paper is structured as follows: Section 2 presents the theoretical framework of the study. Section 3 outlines the data and methods used. Section 4 are results and discussion. The final section concludes with the main findings and policy implications.

2. Theoretical analysis

Income volatility refers to significant fluctuations in family income over time (Dynan *et al.* 2012), while income stability is the extent to which family income remains relatively constant. The stability of relocated household income largely stems from the consistency of both agricultural and non-agricultural income. The rapid growth of the digital economy has played a key role in stabilizing the incomes of relocated households. Digital technology, for example, helps households access employment information and market demand, which facilitates job finding and the sale of agricultural products at favorable prices (Leng 2022). Additionally, it provides access to educational resources and health services, improving labor skills and physical health (Haleem *et al.* 2022; Zhong *et al.* 2024), thereby strengthening the stability of both agricultural and non-agricultural income. In particular, digital technology primarily influences income stability by enhancing information acquisition and human capital accumulation.

2.1. Information acquisition

The theory of information asymmetry suggests that individuals with less information are often at a disadvantage in market economic activities. In remote rural areas, digital technology is gradually becoming an important source of information for farmers' production and livelihood decisions.

First, the use of digital technology can help relocated households access employment information, thereby enhancing income stability. Engaging in non-agricultural economic activities, which allow for diversification of livelihoods and incomes, is viewed as an important means to ensure income stability and escape from poverty (Haggblade *et al.* 2010; Phan *et al.* 2025). However, in the dual context of increased macroeconomic fluctuations and a lack of job-finding avenues in new resettlement locations, relocated households face significant employment vulnerabilities. The use of digital technology can overcome the spatial and temporal limitations of traditional job searching, helping the relocated households to obtain dynamic, multidimensional labor demand information in real-time and at low cost, and improving employment market information asymmetry (Leng 2022). Such instant access to information has advantages, such as reducing the difficulty and cost of job searching and enhancing the efficiency of job supply and demand matching. This can help relocated households reduce the probability of unemployment and shorten the transition periods between different positions. Moreover, the development of digitization has promoted the emergence of new industries, improved the employment environment, and provided more opportunities for non-farm employment (Sun and Li 2025), such as creating various jobs (e.g., food delivery, short video bloggers, and live-streaming sales). The use of digital technology has enabled relocated households to break free from the constraints of a single employment model and develop a diversified employment model. Through a diversified combination of employment channels, this model provides supplementary income sources and effectively disperses the income fluctuations associated with risks of a single profession. When an industry experiences fluctuations, income from other employment positions can provide a replacement buffer.

Second, the use of digital technology can help relocated households access agricultural information, thereby improving income stability. Asymmetry in information about weather changes, pest and disease impacts, prices, potential buyers, and sellers can affect farmers and traders' decisions (Ogutu *et al.* 2014; Haile *et al.* 2019), posing significant risks to agricultural income. However, the use of digital technology can provide information support for relocated households, and help to ensure agricultural income stability in two ways: (1) On the level of market risk control, by promptly obtaining and utilizing information about agricultural product price trends and market demand through digital technology (Shimamoto *et al.* 2015), relocated households can avoid the risks of severe price fluctuations caused by delayed information. This improvement in information asymmetry enhances the bargaining power of farmers (Jensen 2010; Van Campenhout *et al.* 2021) and, more importantly, establishes a price fluctuation buffer mechanism. When the market shows a downward trend, relocated households can adjust their sales strategies in a timely manner to reduce unsold losses; when demand rises, they can quickly respond to market opportunities. Furthermore, the expansion of digital sales channels helps to broaden market scope, disperse regional market risks, and maintain relatively stable sales volumes (Khanal and Mishra 2016; Fan and Salas Garcia 2018), thereby stabilizing income. (2) In terms of production risk control, the use of digital technology can significantly enhance the production decision-making capacity of relocated households, thereby effectively reducing the risks of production fluctuations caused by natural disasters, and the application of traditional technology. Through meteorological early warning platforms, farmers can obtain weather information in a timely manner (Zhu *et al.* 2021), allowing them to proactively implement flexible planting plans to avoid extreme weather impacts (e.g., heavy rain and frost), such as adjusting planting periods and taking protective measures. Moreover, the digital agricultural technology promotion system, which pushes new planting techniques and pest and disease prevention schemes (Li *et al.* 2023), helps relocated populations overcome the limitations of traditional field management, enhancing production efficiency and output stability. This synergy with the market-side information advantage, stable output matching flexible market response, ultimately constructs a systemic mechanism for stable agricultural income.

2.2. Human capital accumulation

Endogenous economic growth theory posits that human capital is a critical factor in promoting economic growth. The use of digital technology plays a non-negligible role in accumulating human capital for relocated households, particularly in education and health.

Digital technology use can enhance the labor skills of relocated households, thereby improving income stability. Relocated households generally face barriers such as low levels of education and insufficient occupational skills, resulting in low participation rates in the formal market economy (i.e., employment markets and entrepreneurial activities) (Lechman and Popowska 2022). Digital technology provides access to remote education and online skills training, offering more avenues for accessing educational resources and knowledge, and increasing opportunities for re-education (Haleem *et al.* 2022). With its flexibility, timeliness, and low cost, online skills training offers a convenient participation method for relocated populations. Specifically, the rise of short video platforms has made practical technical teaching more vivid and easy to understand. Relocated households do not need to gather for onsite training and can use fragmented time to master new skills. For example, they can learn modern agricultural techniques, e-commerce operations, and other practical skills whenever they want using digital technology. The accumulation of vocational skills broadens their employment options and enables them to flexibly adjust their career directions according to market demands, reducing unemployment risks caused by reliance on a single skill. Moreover, skills enhancement can increase the competitiveness of relocated households in the labor market, helping them enter the formal job market and engage in high-skilled work (Zhou *et al.* 2024). Compared to temporary or seasonal work, regular positions usually offer more stable salary systems and social security. Additionally, enhancing agricultural production skills, such as smart agricultural machinery operation and pest control, can strengthen the risk-response capabilities of relocated households, helping them achieve more stable agricultural incomes.

Digital technology can also help relocated households improve their health and meet the physical demands of both agricultural and non-agricultural work, thereby enhancing income stability. Health is not only a form of human capital but also a crucial input for generating other types of capital (Bleakley 2010). A healthy body is a fundamental prerequisite for participating in various jobs and earning income. Digital platforms have increasingly become a primary means for individuals to access medical resources and tools for daily health management, significantly improving their self-assessed health status (Luo *et al.* 2024; Zhong *et al.* 2024). This impact is manifested in several ways. First, the “Internet+Healthcare” model improves access to medical resources for relocated households, enabling them to conveniently and quickly access medical and health services, which encourages better healthcare consumption decisions (Zhong *et al.* 2024) and promotes improved health outcomes. Second, digital technology increases health awareness, motivating relocated households to adopt healthier behaviors, such as increased exercise, reduced alcohol consumption, and smoking cessation (Chen and Liu 2022). Third, the rapid growth of digital technology offers a variety of enjoyable and convenient leisure options that align with the preferences of relocated households for recreation and learning (Xiang and Zhang 2025). By engaging with digital technology, relocated households can enrich their entertainment, relax their mood, and alleviate mental stress, ultimately improving their health. Through these pathways, digital technology helps relocated households enhance their physical fitness, meet the demands of their jobs, and ensure income stability.

Based on this analysis, this study proposes the following hypotheses:

H1: Digital technology use can enhance the income stability of relocated households.

H2: Digital technology use can enhance the income stability by promoting information acquisition.

H3: Digital technology use can enhance the income stability by facilitating the accumulation of human capital.

Fig. 1 illustrates the theoretical framework.

3. Data and methods

3.1. Data

The data for this study were collected through surveys of relocated households. The research team conducted a baseline survey in 2016, followed by additional surveys in 2017, 2019, and 2021. The surveys covered 16 counties in eight provincial-level regions: Hubei, Hunan, Gansu, Shaanxi, Sichuan, Guizhou, Yunnan, and Guangxi, which represent

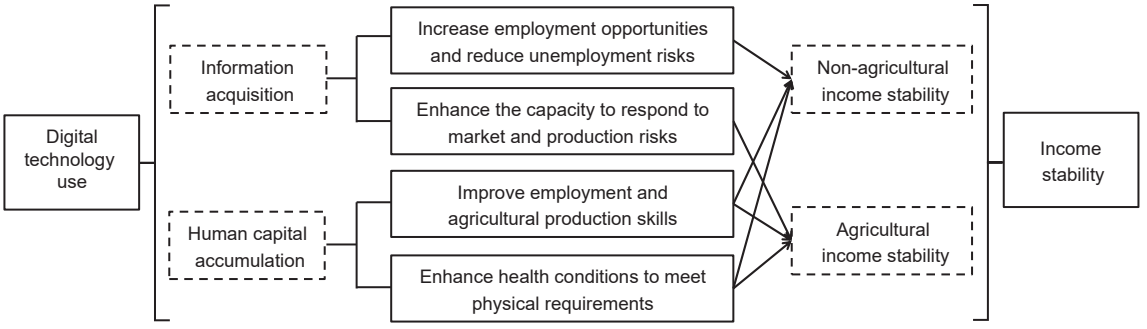


Fig. 1 Theoretical framework.

the primary areas of PAR implementation. This study used multistage sampling, which involved the following steps: (1) selecting 2–3 townships within each county based on the presence of relocated households and relocation plans; (2) choosing three administrative villages within each selected township; and (3) randomly selecting eight to 16 relocated households from each village for the sample. Face-to-face interviews were conducted with household heads based on a predetermined structured questionnaire.

Data from the 2019 and 2021 surveys were used for this study, as income stability requires continuous panel data. The 2019 survey included income data from 2018, while the 2021 survey covered income data from 2019 and 2020, satisfying the study's requirements. After excluding invalid questionnaires with missing key variables, 1,002 valid samples were retained.

3.2. Variable measurement and descriptive statistics

Dependent variable The dependent variable in this study is the income stability of relocated households, which is typically measured by income volatility. High income stability is associated with low volatility (Harkness *et al.* 2021). Following previous research (Poon and Weersink 2011; Harkness *et al.* 2021; Ji *et al.* 2023), income volatility is assessed using the natural logarithm of the absolute value of the coefficient of variation (ln*ACV*). The coefficient of variation (*CV*) is calculated by dividing the standard deviation of annual income over a period by the sample mean annual income for the same period. A higher *CV* indicates less stable income. The absolute value (*ACV*) accommodates the possibility of negative average income, while the logarithmic transformation (ln*ACV*) mitigates the influence of outliers.

Income is defined as total household income, which is the sum of operating income, wage income, property income, and transfer income. Income volatility is calculated by dividing the standard deviation of each household's income from 2018 to 2020 by the absolute value of the average income over the same period. Volatility values are generated for each relocated household using their income data from 2018 to 2020, making the income volatility data cross-sectional.

$$ACV_i=\left|\frac{SD_i}{\overline{y}_i}\right|=\left|\frac{\sqrt{\frac{1}{2}\sum_{t=2018}^{2020}(Y_{it}-\overline{y}_i)^2}}{\overline{y}_i}\right| \quad (1)$$

Independent variable The core independent variable in this study is digital technology use, which is examined from two perspectives: whether it is used and the intensity of its use. Following the approach of previous studies (Leng *et al.* 2024), digital technology use is measured by whether relocated households use mobile devices to access the Internet. The intensity of use is assessed by the average daily time spent using mobile phones to access the Internet (Nie *et al.* 2021), as reported in response to the question: "How many hours do you use your mobile phone to access the Internet on average each day?"

Building on existing research (El Benni *et al.* 2012; Ji *et al.* 2023; Liu *et al.* 2023), this study includes the following control variables: age and education level of the household head, political identity, household size, farm size, natural disasters, risk attitude, number of relatives and friends, adaptation situation, participation in industrial projects, public employment services and community factory. Additionally, we include the provincial-level regional dummy variables.

Mechanism variables The mechanism variables in this study include information acquisition and human capital accumulation. Information acquisition is defined as the types of information obtained by relocated households through the Internet (0=no information was obtained; 1=agricultural or employment information was obtained; 2=both agricultural and employment information were obtained). Human capital accumulation includes technical training and health. Technical training is defined as the number of times family members have participated in technical training related to agriculture and employment. The health level is defined as the self-evaluation of the household head's health status (Strongly unhealthy=1, Strongly healthy=5).

Moderating variable Digital literacy serves as a moderating variable in this study, which focuses on the digital literacy of relocated households in terms of information. In this field, digital literacy refers to an individual's ability to express information needs, retrieve and search for information through relevant skills, and manage and store digital information (Wang 2024). Drawing on existing studies (Wang 2024; Yang *et al.* 2025), the digital literacy of relocated households is measured through the following questions: (1) you are able to find the agricultural information you need on the Internet; (2) you can judge the truth of online information; (3) you often discuss agricultural information seen online with others. These three items are measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This study employs equal weighting and entropy methods to assess the digital literacy levels of relocated households.

Table 1 presents the definitions of the variables and descriptive statistics. The average income volatility for relocated households is –0.873. Regarding the key independent variables, 61.3% of households use digital technology, with an average daily usage of 1.244 hours. The average age of household heads is 56.855 years, and their education level is typically primary school. Household heads have a moderate level of risk attitude, and the average household size is 4.108 people, with a farm size of 5.007 mu (1 mu=1/15 ha), 36.305 close relatives and friends, and an adaptation situation level of 4.396. Among relocated households, 9.6% had a party member in the family, 19.1% had experienced natural disasters, and approximately half had participated in industrial development projects. A total of 86.9% of resettlement communities provide specialized public employment services for relocated households, while 44.9% have a factory. The average types of information acquisition and the number of technical training for the relocated households were 0.442 and 0.826, respectively. The average health level for relocated households is 3.610. The average digital literacy score is 2.355 (equal-weight method) and 0.330 (entropy method).

3.3. Model specification

The distributions of income and income volatility

Table 1 Variable definitions and descriptive statistics[1)]

Variables	Definition	Mean	SD
Dependent variable			
ACV of income	Coefficient of variation of income (ACV), calculated using eq. (1)	0.480	0.221
Income volatility	Obtained by taking the logarithm of ACV	–0.873	0.588
Key independent variables			
Digital technology use	Do you use a mobile device to access the Internet? Yes=1, No=0	0.613	0.487
Intensity of use	The average daily Internet use time (hours)	1.244	1.580
Control Variables			
Age	Actual age of the household head (years)	56.855	11.956
Education	The education level of the household head: No schooling=0, Preschool=1, Primary school=2, Junior high school=3, Senior high school or technical secondary school=4, Above senior high school=5	2.117	1.030
Political identity	Whether there is a party member in the household: Yes=1, No=0	0.096	0.295
Household size	The total number of people in the household (people)	4.108	1.592
Farm size	The total area of farmland owned by the household (mu)	5.007	8.464
Risk attitude	Are you a person who likes to take risks? Strongly dislike=0, Strongly like=10 (rated from low to high)	5.471	2.874
Natural disasters	Have you suffered from natural disasters in the past year? Yes=1, No=0	0.191	0.393
Number of relatives and friends	The number of relatives and friends you get along with (people)	36.305	43.092
Adaptation situation	How well have you adapted to the new community in the resettlement area: Very poorly adapted=1, Very well adapted=5	4.396	0.794
Industrial projects	Does your household participate in industrial development projects: Yes=1, No=0	0.503	0.500
Public employment services	Whether the resettlement community provides specialized public employment services: Yes=1, No=0	0.869	0.337
Community factory	Whether the resettlement community hosts a factory for the relocated population: Yes=1, No=0	0.449	0.498
Mechanism variables			
Information acquisition	The number of types of information obtained: no information was obtained=0, agricultural or employment information was obtained=1, both agricultural and employment information were obtained=2	0.442	0.601
Technical training	The number of times family members have participated in technical training (times)	0.826	1.699
Health	Self-evaluation of health status: Strongly unhealthy=1, Strongly healthy=5	3.610	1.100
Moderating variable			
Digital literacy (equal weight)	Calculated using the equal weight method	2.355	1.141
Digital literacy (entropy method)	Calculated using the entropy method	0.330	0.287

[1)] Risks encompass all types of risks, including business-related risks and risks in general life.

approximately follow a normal distribution. Therefore, this study employs the Ordinary Least Squares method for empirical analysis and establishes the following econometric model:

$$Volatility_i=\alpha_1+\beta_1 DT_i+\gamma_1 Controls_i+\varepsilon_i \quad (2)$$

where $Volatility_i$ represents the income volatility of relocated household i; DT_i represents the characteristics of digital technology use, including both whether it is used and the intensity of use; $Controls_i$ represents the control variables. The coefficients α_1, β_1, and γ_1 are to be estimated, and ε_i is the random error term. β_1 denotes the impact of digital technology use.

To further clarify the influencing mechanism of digital technology use on income stability, the following econometric models are established:

$$Information_i=\alpha_2+\beta_2 DT_i+\gamma_2 Controls_i+\varepsilon_i \quad (3)$$

$$Humancapital_i=\alpha_3+\beta_3 DT_i+\gamma_3 Controls_i+\varepsilon_i \quad (4)$$

where $Information_i$ and $Humancapital_i$ represent information acquisition and human capital accumulation, respectively. Human capital accumulation includes technical training and health. DT_i and $Controls_i$ are defined in eq. (2). The types of information acquisition and number of technical training are count variables, thus, we use the Poisson model for regression. Health condition is an ordered categorical variable, for which we use the Ordered Probit model for regression.

To further investigate the moderating effect of digital literacy, an interaction term between digital literacy and digital technology use is introduced based on eq. (2), leading to the following econometric model:

$$Volatility_i=\alpha_4+\beta_4 DT_i+a_4 DL_i+b_4 DT_i\times DL_i+\gamma_4 Controls_i+\varepsilon_i \quad (5)$$

where DL_i represents digital literacy and $DT_i\times DL_i$ represents the interaction term between digital technology use and digital literacy. Explanations for the remaining variables are the same as those described above.

4. Results and discussion

4.1. Baseline results

Table 2 presents the impact of digital technology use on income. Before the estimation, this study logarithmically transformed the income. The findings reveal that digital technology positively affects the income of relocated households. Additionally, the greater the intensity of digital

technology use, the more significant the impact. This aligns with previous studies highlighting the positive role of digital technology in increasing rural household incomes (Leng 2022; Phan 2023; Liu *et al.* 2025).

Next, we examine the impact of digital technology use on income volatility. The results are listed in Table 3. Column (1) presents the estimated effects of digital technology use, while Column (2) conveys the estimated effects of the intensity of digital technology use. The findings indicate that digital technology use significantly reduces income volatility. Specifically, both the use of digital technology and the intensity of its use have a significant negative impact on the income volatility of relocated households. This not only confirms the robustness of the results but also suggests that digital technology use helps stabilize income, with the effect increasing as usage intensifies. Thus, H1 is confirmed.

Regarding the control variables, the estimated coefficient of the household head's age on income volatility is positive and significant. Increasing age leads to skill depreciation, rigid employment channels, and reduced ability to diversify income sources, thereby exacerbating income volatility. The education level of the household head has a significant positive effect on income volatility. This may be because relocated households with higher education levels tend to engage in occupations with greater income volatility, such as entrepreneurship. While these activities often offer high returns, they are also associated with greater risks and instability. The household size has a positive and significant impact on income volatility, indicating that smaller households tend to experience more stable income, supporting findings from Ji *et al.* (2023). A possible explanation is that larger households include more dependents, whose caregiving needs limit younger members' income-generating opportunities and reduce overall income stability (Liu *et al.* 2022). Additionally, farm size has a positive and significant impact on income volatility, indicating that smaller farm sizes contribute to greater income stability. This is because large-scale farms, with heavy fixed investments and specialized operations, are more exposed to weather and market shocks and less able to diversify risks. This result is consistent with Poon and Weersink (2011) and El Benni *et al.* (2012), who also found higher volatility in larger farms due to amplified income risks. The positive and significant coefficient for natural disasters highlights that such events negatively affect

Table 2 Estimation results of the impact of digital technology use on income

Variables	(1)	(2)
Digital technology use	0.115***	
	(0.037)	
Intensity of use		0.036***
		(0.011)
Age	–0.001	–0.002
	(0.002)	(0.002)
Education	0.059***	0.060***
	(0.020)	(0.019)
Political identity	0.031	0.029
	(0.057)	(0.057)
Household size	0.169***	0.172***
	(0.013)	(0.013)
Farm size	0.006**	0.006***
	(0.002)	(0.002)
Risk attitude	0.011*	0.011*
	(0.006)	(0.006)
Natural disasters	–0.127**	–0.119**
	(0.051)	(0.051)
Number of relatives and friends	0.025	0.026
	(0.017)	(0.017)
Adaptation situation	0.007	0.010
	(0.021)	(0.021)
Industrial projects	0.111***	0.114***
	(0.037)	(0.037)
Public employment services	–0.058	–0.070
	(0.064)	(0.065)
Community factory	0.111**	0.118**
	(0.050)	(0.049)
Constant	9.837***	9.864***
	(0.177)	(0.176)
Regional dummy variable	Yes	Yes
Observations	1,002	1,002
R^2	0.295	0.296

***, P<0.01; **, P< 0.05; and *, P< 0.1. Robust standard errors are shown in parentheses.

Table 3 Estimation results of the impact of digital technology use on income volatility

Variables	(1)	(2)
Digital technology use	–0.152***	
	(0.038)	
Intensity of use		–0.034***
		(0.013)
Age	0.005***	0.005***
	(0.002)	(0.002)
Education	0.040**	0.037*
	(0.019)	(0.019)
Political identity	–0.057	–0.054
	(0.059)	(0.058)
Household size	0.021*	0.017
	(0.012)	(0.012)
Farm size	0.004*	0.003*
	(0.002)	(0.002)
Risk attitude	0.009	0.008
	(0.006)	(0.007)
Natural disasters	0.126***	0.116**
	(0.045)	(0.046)
Number of relatives and friends	–0.017	–0.018
	(0.018)	(0.018)
Adaptation situation	–0.033*	–0.036*
	(0.020)	(0.020)
Industrial projects	0.041	0.036
	(0.039)	(0.039)
Public employment services	0.031	0.050
	(0.065)	(0.065)
Community factory	–0.038	–0.049
	(0.050)	(0.050)
Constant	–1.166***	–1.223***
	(0.182)	(0.183)
Regional dummy variable	Yes	Yes
Observations	1,002	1,002
R^2	0.086	0.080

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

the income stability of relocated households by disrupting agricultural production and yields. The adaptation situation has a negative impact on income volatility. The better relocated households adapt to their new settlement (i.e., they have greater familiarity with ways to find jobs), the less their income tends to fluctuate.

4.2. Endogeneity discussion

In the previous analysis, the decision of relocated households to use digital technology was not randomly assigned, which may have introduced sample selection bias. To address this, we employ Propensity Score Matching (PSM). To obtain accurate estimates, we apply three commonly used matching methods: nearest-neighbor matching (n=4), radius matching (r=0.05), and kernel matching (bandwidth=0.06). The results in Table 4 indicate that the average treatment effect on the treated (ATT) for digital technology use is significant at the 1% level, with a mean of –0.140. Furthermore, the ATT estimates from the three matching methods are closely aligned, suggesting that the results are robust. This indicates that, after correcting for sample selection bias, digital technology use still significantly reduces the income volatility of relocated households.

Additionally, factors such as omitted variables and bidirectional causation may introduce endogeneity. For instance, income stability could influence a household's decision to purchase and use digital devices. Households with more stable incomes are more likely to invest in advanced technologies, while those with higher income volatility may be constrained by cost. To address this, we use instrumental variable (IV) methods to re-estimate the impact of digital technology use on income stability. Following the approaches of Zhou *et al.* (2020), Zhu *et al.* (2020), Ma *et al.* (2023), Wang (2024), and Yang and Zhu (2025), we use the digital technology use rate (%) in the resettlement community as an IV for digital technology use. This variable reflects the level of digital technology use among residents of the resettlement community, specifically measured as the ratio of digital technology users to other respondents in the same resettlement community (excluding the sampled respondents). The IV estimation results are presented in Table 5. Statistical tests, including Kleibergen-Paap rk LM statistic and Kleibergen-Paap rk Wald F statistic, confirm the validity of the instrument. As shown in Column (1), the average digital technology use rate significantly and positively affects the likelihood of digital technology use among relocated households. The results in Column (2) indicate that digital technology use significantly reduces income volatility. This suggests that, even after addressing the endogeneity issue, digital technology use has a stabilizing and negative effect on the income volatility of relocated households.

Table 4 PSM estimation results

Methods	Treatment group	Control group	ATT	S.E	T value
K-nearest neighbor matching	–0.929	–0.786	–0.143***	0.047	–3.08
Radius matching	–0.929	–0.791	–0.138***	0.044	–3.13
Kernel matching	–0.929	–0.790	–0.139***	0.044	–3.13
Mean	–0.929	–0.789	–0.140		

***, P<0.01; **, P<0.05; *, P<0.1.

4.3. Robustness check

To assess the robustness of our findings, we conduct robustness checks, including variable substitution, sample replacement, and the addition of control variables. The robustness test results are presented in Table 6.

First, we replace the original measure of digital technology use with household smartphone ownership, as smartphone ownership is a prerequisite for Internet access. Column (1) shows that the coefficient for smartphone ownership remains significantly negative at the 1% level, confirming the robustness of the previous estimates. However, the coefficient for smartphones slightly decreases, suggesting that some relocated households, despite owning smart devices, may not fully integrate the Internet into their daily activities due to unfamiliarity with its use. This highlights the need to support these households in utilizing the Internet effectively to bridge the "digital divide".

Second, relocated households with higher income levels often have more stable jobs and diverse income sources, resulting in minimal income fluctuations. Whether or not these households use digital technology, their income experiences minimal volatility, which could introduce bias in the estimation results. To address this, we exclude relocated households with incomes exceeding 100,000 CNY for the robustness checks. Column (2) shows that digital technology use continues to significantly reduce income volatility.

Finally, to account for community-level factors that may affect income volatility, we add two additional variables to the model: the distance from the household to the township government and the distance from the household to the county. Before estimating, this study applies a logarithmic transformation to these two variables. As shown in Column (3), the inclusion of these community-level variables still shows a significantly negative correlation between digital technology use and income volatility.

Table 5 Two-stage least squares estimation results

Variables	First stage: Digital technology use	Second stage: Income volatility
Digital technology use rate	0.293***	
	(0.072)	
Digital technology use		–0.559*
		(0.328)
Control variables	Yes	Yes
Regional dummy variable	Yes	Yes
Constant	0.531***	–0.851***
	(0.152)	(0.296)
Kleibergen-Paap rk LM	15.451	
Kleibergen-Paap rk Wald F	16.662	
Observations	987	987

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses. The reduction in observations is because some resettlement areas have only one relocated household, which makes calculating the digital technology use rate for these areas impossible. These samples were excluded from the two-stage least-squares estimation.

Table 6 Robustness test results

Variables	Replacing *X*	Replacing sample	Adding variables
	(1)	(2)	(3)
Digital devices	–0.140***		
	(0.040)		
Digital technology use		–0.171***	–0.148***
		(0.045)	(0.038)
Distance to the township government			0.027
			(0.019)
Distance to the county			0.029
			(0.021)
Control variables	Yes	Yes	Yes
Regional dummy variable	Yes	Yes	Yes
Constant	–1.164***	–1.182***	–1.327***
	(0.183)	(0.199)	(0.205)
Observations	1002	859	1002
R^2	0.082	0.085	0.089

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

4.4. Mechanism analysis

As mentioned earlier, this study investigates the impact of digital technology use on income stability through the channels of information acquisition and human capital accumulation. We now examine these two pathways.

Table 7 presents the results of the mechanism analysis. Columns (1) and (2) convey the effects of digital technology use on information acquisition, Columns (3) and (4) display the effects of digital technology use on technical training, and Columns (5) and (6) disclose the effects of digital technology use on health. The results indicate that digital technology use significantly increases the likelihood of information acquisition and human capital accumulation of relocated households. Specifically, Columns (1) and (2) indicate that digital technology use has a positive impact on information acquisition, with the effect becoming stronger as the level of digital technology use increases. This supports H2. One possible explanation is that digital technology enables relocated households to access timely non-agricultural employment information or agricultural market information. Acquiring non-agricultural employment information can help households secure non-agricultural jobs, diversify income sources, and improve income stability. Meanwhile, agricultural information allows them to better engage with the market, enhance access to buyers, and reduce income volatility caused by sales difficulties.

Columns (3)–(6) indicate that digital technology use also promotes human capital accumulation among relocated households. For health, the impact is greater with the increasing intensity of digital technology use, which confirms H3. The potential reasons for this include the technological advantages offered by digital tools. Through digital technology, relocated households can obtain more information from technical training (e.g., agricultural techniques and employment skills training) and about health, improving their work skills and overall health. Agricultural training (e.g., agricultural production techniques and product sales) can enhance the agricultural production capacity of relocated households, bolster their ability to cope with external risks, and stabilize their agricultural income. Employment training can enhance labor skills, help households secure better-paying jobs, and ensure a more stable non-agricultural income, thereby reducing their income instability risk. Additionally, the health benefits associated with digital technology use can enhance physical fitness, meet the demands of various occupations, and further contribute to income stability.

4.5. Heterogeneity analysis

This study also examines the heterogeneous impact of digital technology use on income volatility. The results of heterogeneity analysis are presented in Table 8.

First, recognizing the economic differences between China's eastern, central, and western regions, we estimate the impact of digital technology use on income volatility in the western and central regions, excluding the eastern region from the sample. Columns (1) and (2) show that in both regions, the estimated coefficients for digital technology use are negative and significant. However, the impact is stronger in the central region than in the western region. This may be due to the central region's more developed economy and more rapid growth of the digital economy, which creates more job opportunities and provides relocated households with better access to non-agricultural employment, thereby enhancing income stability.

Second, we explore the heterogeneity of digital technology

Table 7 Influencing mechanisms of digital technology use on income stability

Variables	Information acquisition		Technical training		Health	
	(1)	(2)	(3)	(4)	(5)	(6)
Digital technology use	18.750***		0.396***		0.230***	
	(0.010)		(0.145)		(0.075)	
Intensity of use		0.244***		0.030		0.092***
		(0.022)		(0.031)		(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummy variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–19.039***	–1.170***	–0.820*	–0.546	–	–
	(0.299)	(0.343)	(0.471)	(0.495)	–	–
Observations	1,002	1,002	1,002	1,002	1,002	1,002
pseudo R^2	0.274	0.123	0.120	0.113	0.034	0.036

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

Table 8 Heterogeneity results

Variables	Region		Resettlement location		Education level	
	Central	Western	Urban	Rural	Low level	High level
	(1)	(2)	(3)	(4)	(5)	(6)
Digital technology use	–0.229***	–0.125***	–0.131**	–0.153***	–0.151***	–0.185**
	(0.088)	(0.046)	(0.064)	(0.054)	(0.050)	(0.074)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummy variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.983**	–1.332***	–1.567***	–0.972***	–1.170***	–0.963**
	(0.386)	(0.206)	(0.276)	(0.261)	(0.222)	(0.403)
Observations	256	746	467	535	669	333
R^2	0.093	0.093	0.154	0.065	0.098	0.108

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

use between urban and rural resettlements. Urban resettlement involves relocation to cities and towns, while rural resettlement refers to relocation within or near existing villages. To examine this, we estimate subsamples for the two resettlement types. The results in Columns (3) and (4) reveal that digital technology use significantly reduces income volatility for both resettlement groups. This mitigating effect is marginally more pronounced in the rural resettlement group. Urban resettlement tends to weaken agricultural ties due to geographical isolation; consequently, households relocated far from their original villages might find it challenging to engage in farming activities (Lo *et al.* 2016), leading to a decrease or cessation in agricultural production. Therefore, digital technology significantly bolsters the stability of non-agricultural income for relocated households by broadening employment opportunities and enhancing skill compatibility. In the case of rural resettlements, digital technology stabilizes both agricultural and non-agricultural incomes. This is because rural resettlements preserve agricultural livelihoods and digital technology concurrently penetrates both the agricultural (e.g., smart farming tools and e-commerce platforms for agricultural products) and employment sectors (e.g., local part-time non-farm jobs). These findings highlight the dual role of digital technology in reducing agricultural income volatility and expanding non-agricultural employment opportunities (Muto and Yamano 2009; Aker *et al.* 2016; Fang *et al.* 2024).

Finally, as a key indicator of human capital, education level plays a significant role in digital inequality (Wang 2024). As noted in the descriptive statistics, the average education level of relocated households is primary school. Based on this, we classify relocated households into two groups: those with an education level of primary school or below are categorized as having low education, and those with an education level above primary school are considered to have high education. Columns (5) and (6) present the results for these two education groups. The coefficients for digital technology use in both groups are negative and significantly different from zero. However, the impact is stronger in the high education group than in the low education group. These findings suggest that relocated households with higher education levels gain more from digital technology use than those with lower education levels. This is consistent with expectations, as households with higher education tend to have better learning abilities, greater interest, and more enthusiasm, enabling them to effectively leverage digital technology in their economic activities and reduce income volatility (Wang 2024).

4.6. Further discussion

For households with consistently rising income, income stability may not necessarily be a concern. Income stability becomes crucial primarily when households face significant risks or events that cause their income to fluctuate or decline. This leads to the question: how does digital technology use affect households with different income trends? Drawing from Sosu and Schmidt (2022), this study classifies income volatility into two types: upward volatility and downward volatility. If the household income increased continuously from 2018 to 2020, or increased in only one period while remaining unchanged in others, it is classified as upward volatility; otherwise, it is classified as downward volatility. Based on this classification, the study calculated the proportion of different types of household income changes. A total of 466 relocated households (46.51%) exhibited upward income volatility, including 400 households (39.92%) that experienced continuous increases and 66 households (6.59%) that first increased and then remained stable. In contrast, 536 relocated households (53.49%) showed downward income volatility, of which 50 households (4.99%) experienced continuous declines, 360 households (35.93%) first increased and then declined, 120 households (11.98%) first declined and then increased, and 6 households (0.60%) first declined and then remained stable. It should be noted that unmentioned types of income change (e.g., those with entirely unchanged income) were not represented in the study sample.

The effects of digital technology use on income volatility for these two types of households are estimated separately, and the results are shown in Table 9. The coefficient in Column (1) is negative but not statistically significant, suggesting that digital technology use does not significantly affect income volatility for households experiencing upward volatility. In contrast, the coefficient in Column (2) is negative and statistically significant at the 1% level, indicating that digital technology use reduces income volatility for households experiencing downward volatility. This finding is significant, suggesting that digital technology use can effectively stabilize income for relocated households facing income decline or fluctuation.

Table 9 Digital technology use and income volatility: Analysis based on different forms of volatility

Variables	Upward volatility	Downward volatility
Digital technology use	–0.077	–0.212***
	(0.053)	(0.060)
Control variables	Yes	Yes
Regional dummy variable	Yes	Yes
Constant	–1.137***	–1.100***
	(0.243)	(0.266)
Observations	466	536
R^2	0.087	0.125

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

The digital divide has evolved beyond issues of accessibility and availability of digital technology to encompass disparities in the ability to fully benefit from digital advancements due to differences in personal skills and competencies (Zhou *et al.* 2024). While the application of digital technology provides equal opportunities for farmers, not all have the same capacity to leverage these opportunities. Specifically, the digital literacy of relocated households may influence how digital technology use affects income stability.

To explore this, this study examines the moderating effect of digital literacy on the relationship between digital technology use and income volatility. Using the digital literacy measure outlined earlier, an interaction term between digital technology use and digital literacy was created and estimated using Model (5). The results are presented in Table 10. Columns (1) and (2) show the estimates obtained with the equal-weight method, while Columns (3) and (4) use the entropy method. The coefficients for the interaction term between digital technology use and digital literacy are significantly negative, indicating that digital literacy has a moderating effect on the relationship between digital technology use and income volatility. This suggests that higher digital literacy enhances the positive impact of digital technology on income stability. Relocated households with greater digital literacy are better able to master digital technology, effectively utilize various applications, and access and evaluate information online, thereby reaping greater benefits from the "digital dividend" (Yang *et al.* 2025).

5. Conclusion and policy implications

This study examined how digital technology use affects income stability, the mechanisms behind this impact, and its heterogeneous effects across different groups, using survey data from relocated households in 16 counties across eight provinces in China. The findings indicate that digital technology positively influences the income and income stability of relocated households, with greater usage leading to a more significant effect. The mechanism analysis reveals that digital technology improves income stability by enhancing access to information acquisition and facilitating the accumulation of human capital. A further analysis shows that the impact is stronger in central regions, rural resettlement areas, and among relocated households with higher education levels. Additionally, this study suggests that digital technology does not significantly improve the income stability of households experiencing upward volatility, but it can enhance the stability of those facing downward volatility. Moreover, digital literacy plays a key role in strengthening the positive effects of digital technology on income stability.

Our findings offer several policy recommendations. First, the government should invest in improving Internet infrastructure in resettlement areas by accelerating broadband expansion and reducing the costs associated with digital technology use. Concurrently, relevant training should be provided to relocated households to increase their awareness of digital technology's importance, thereby improving their Internet access and application. Second, it is essential to refine digital technology platforms by enhancing data collection and information dissemination capabilities. This includes delivering key information such as weather alerts and job postings, along with providing online training and medical resources. For example, severe weather alerts can be promptly delivered and a "Direct Employment" feature that consolidates job requirements and compensation details can be established. Third, there is a need to customize digital technology services to meet the specific needs of relocated households, particularly in western regions, urban resettlement areas, and among households with lower educational levels, to ensure a more equitable distribution of digital benefits. For instance, designing illustrated digital tool manuals for families with lower education levels would be beneficial. Finally, developing a digital literacy training program is crucial to enhancing the usage of digital technology. Implementing community classes and personalized guidance for practical skills training, such as smartphone use, online information searches, and scam recognition, would enable relocated households to access, evaluate, and utilize information more effectively. This

Table 10 Digital technology use and income volatility: Moderating effect of digital literacy

Variables	Equal weight		Entropy method	
	(1)	(2)	(3)	(4)
Digital technology use	–0.124***	–0.154***	–0.120***	–0.152***
	(0.042)	(0.044)	(0.042)	(0.044)
Digital literacy (equal weight)	–0.027	–0.018		
	(0.018)	(0.018)		
Digital technology use×Digital literacy		–0.076**		
		(0.037)		
Digital literacy (entropy method)			–0.123*	–0.083
			(0.070)	(0.070)
Digital technology use×Digital literacy				–0.317**
				(0.148)
Control variables	Yes	Yes	Yes	Yes
Regional dummy variable	Yes	Yes	Yes	Yes
Constant	–1.148***	–1.115***	–1.177***	–1.135***
	(0.182)	(0.183)	(0.182)	(0.183)
Observations	1,002	1,002	1,002	1,002
R^2	0.088	0.091	0.088	0.092

***, P<0.01; **, P<0.05; *, P<0.1. Robust standard errors are shown in parentheses.

would enable them to fully leverage the capabilities of digital technology and to seamlessly integrate it into their daily lives.

This study has several limitations. First, its assessment of digital technology use focuses primarily on access and duration by mobile devices, with a lack of investigation into the use of fixed terminals. Moreover, there is insufficient attention to dimensions such as the purpose of use (e.g., education and entertainment) and the quality of use (e.g., problem-solving with digital tools). Future research should depict the characteristics of digital technology use more comprehensively by taking these key dimensions into account. Second, the impact of digital technology on health may have potential lag effects, making it challenging to capture these effects in the data from the same year. Furthermore, as the duration of relocated households in the resettlement community increases, they may use digital technology more extensively, potentially leading to adverse health outcomes such as increased sedentary behavior. These issues require further investigation in future research.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing processs

During the preparation of this manuscript, the authors used ChatGPT 4.0 to assist in improving the clarity and readability of the language. All content generated was carefully reviewed and revised by the authors as necessary, and the authors take full responsibility for the final content of the article.

References

Aker J C, Ghosh I, Burrell J. 2016. The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, **47**, 35–48.

Ardianti D M, Hartono D, Widyastaman P A. 2023. Offline and hungry: The effect of internet use on the food insecurity of Indonesian agricultural households. *Agricultural and Food Economics*, **11**, 1–18.

Barratt J, Kath J, Mushtaq S, Collins B, Chenu K, Christopher J, An-Vo D A. 2025. Strategic use of index-based frost insurance to reduce financial risk and improve income stability for wheat producers in Australia. *Agricultural Systems*, **226**, 104306.

Bleakley H. 2010. Health, human capital, and development. *Annual Review of Economics*, **2**, 283–310.

Van Campenhout B, Spielman D J, Lecoutere E. 2021. Information and communication technologies to provide agricultural advice to smallholder farmers: Experimental evidence from Uganda. *American Journal of Agricultural Economics*, **103**, 317–337.

Castellacci F, Tveito V. 2018. Internet use and well-being: A survey and a theoretical framework. *Research Policy*, **47**, 308–325.

Chamon M, Liu K, Prasad E. 2013. Income uncertainty and household savings in China. *Journal of Development Economics*, **105**, 164–177.

Chen F, Filipski M, Luo Y, Qiu H. 2023. Why is firewood use so persistent? The role of income uncertainty. *Energy for Sustainable Development*, **76**, 101285.

Chen L, Liu W. 2022. The effect of Internet access on body weight: Evidence from China. *Journal of Health Economics*, **85**, 102670.

Dynan K, Elmendorf D, Sichel D. 2012. The evolution of household income volatility. *The B.E. Journal of Economic Analysis & Policy*, **12**, 1–42.

El Benni N, Finger R, Mann S. 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. *Agricultural Finance Review*, **72**, 301–324.

Enjolras G, Capitanio F, Aubert M, Adinolfi F. 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. *New Medit*, **13**, 31–40.

Fabri C, Vermeulen S, Van Passel S, Schaub S. 2024. Crop diversification and the effect of weather shocks on Italian farmers' income and income risk. *Journal of Agricultural Economics*, **75**, 955–980.

Fan Q, Salas Garcia V B. 2018. Information access and smallholder farmers' market participation in Peru. *Journal of Agricultural Economics*, **69**, 476–494.

Fang L, Quan Y, Mao H, Chen S. 2024. The impact of information communication technology adoption on rural labourers' off-farm employment: An analysis based on China family panel studies. *Applied Economics*, **56**, 7861–7875.

Gu R, Zhang W, Chen K, Nie F. 2023. Can information and communication technologies contribute to poverty reduction? Evidence from poor counties in China. *Information Technology for Development*, **29**, 128–150.

Guo H, Rogers S, Li J, Li C. 2024. Farmers to urban citizens? Understanding resettled households' adaptation to urban life in Shaanxi, China. *Cities*, **145**, 104667.

Haggblade S, Hazell P, Reardon T. 2010. The rural non-farm economy: Prospects for growth and poverty reduction. *World Development*, **38**, 1429–1441.

Haile M G, Wossen T, Kalkuhl M. 2019. Access to information, price expectations and welfare: The role of mobile phone adoption in Ethiopia. *Technological Forecasting and Social Change*, **145**, 82–92.

Haleem A, Javaid M, Qadri M A, Suman R. 2022. Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers*, **3**, 275–285.

Harkness C, Areal F J, Semenov M A, Senapati N, Shield I F, Bishop J. 2023. Towards stability of food production and farm income in a variable climate. *Ecological Economics*, **204**, 107676.

Harkness C, Areal F J, Semenov M A, Senapati N, Shield I F, Bishop J. 2021. Stability of farm income: The role of agricultural diversity and agri-environment scheme payments. *Agricultural Systems*, **187**, 103009.

Hong J, Liu M, Qiu H, Feng X. 2024. Can a poverty alleviation programme really help vulnerable rural households? Insights from China. *Applied Economics*, **56**, 6333–6346.

Jensen R T. 2010. Information, efficiency, and welfare in agricultural markets. *Agricultural Economics*, **41**, 203–216.

Ji C, Zhuo N, Jin S. 2023. Does cooperative membership stabilize farm income volatility? Evidence from the pig sector in China. *China Agricultural Economic Review*, **15**, 623–641.

Khan N, Ray R L, Zhang S, Osabuohien E, Ihtisham M. 2022. Influence of mobile phone and internet technology on income of rural farmers: Evidence from Khyber Pakhtunkhwa Province, Pakistan. *Technology in Society*, **68**, 101866.

Khanal A R, Mishra A K. 2016. Financial performance of small farm business households: The role of internet. *China Agricultural Economic Review*, **8**, 553–571.

Lechman E, Popowska M. 2022. Harnessing digital technologies for poverty reduction. Evidence for low-income and lower-middle income countries. *Telecommunications Policy*, **46**, 102313.

Leng X. 2022. Digital revolution and rural family income: Evidence from China. *Journal of Rural Studies*, **94**, 336–343.

Leng X, Zhang Y, Cheng R. 2024. Digital technology, labor allocation, and nutrition intake: Evidence from China. *Technological Forecasting and Social Change*, **201**, 123228.

Li K, Jin Y, Zhou J. 2023. Are vulnerable farmers more easily influenced? Heterogeneous effects of Internet use on the adoption of integrated pest management. *Journal of Integrative Agriculture*, **22**, 3220–3233.

Liu M, Feng X, Wang S, Qiu H. 2020. China's poverty alleviation over the last 40 years: Successes and challenges. *Australian Journal of Agricultural and Resource Economics*, **64**, 209–228.
Liu M, Feng X, Zhang C, Qiu H. 2022. The implementation effects and mechanism of poverty alleviation through relocation. *China Rural Survey*, (5), 61–79. (in Chinese)
Liu M, Feng X, Zhao Y, Qiu H. 2023. Impact of poverty alleviation through relocation: From the perspectives of income and multidimensional poverty. *Journal of Rural Studies*, **99**, 35–44.
Liu W, Xiao W, Li Y, Westlund H. 2025. How internet access impacts rural households' income in China: Evidence from the China family panel survey. *Applied Economics*, **57**, 2793–2808.
Lo K, Xue L, Wang M. 2016. Spatial restructuring through poverty alleviation resettlement in rural China. *Journal of Rural Studies*, **47**, 496–505.
Luo X, Pu H, Wang S, Zhong D, Liu F, Li Z. 2024. Influence of Internet use on Chinese residents' health: The mediating role of health knowledge. *Technology in Society*, **76**, 102413.
Ma W, Nie P, Zhang P, Renwick A. 2020. Impact of Internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, **24**, 503–523.
Ma W, Vatsa P, Zheng H, Donkor E, Owusu V. 2023. Does adoption of information and communication technology reduce objective and subjective well-being inequality? Evidence from China. *Social Indicators Research*, **169**, 55–77.
Ma W, Wang X. 2020. Internet use, sustainable agricultural practices and rural incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics*, **64**, 1087–1112.
Min S, Liu M, Huang J. 2020. Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *Journal of Asian Economics*, **70**, 101219.
Muto M, Yamano T. 2009. The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda. *World Development*, **37**, 1887–1896.
Nie P, Ma W, Sousa-Poza A. 2021. The relationship between smartphone use and subjective well-being in rural China. *Electronic Commerce Research*, **21**, 983–1009.
Nitta A, Yamamoto Y, Severini S, Kondo K, Sawauchi D. 2022. Effects of direct payments on rice income variability in Japan. *Australian Journal of Agricultural and Resource Economics*, **66**, 118–135.
Ogutu S O, Okello J J, Otieno D J. 2014. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of Kenya. *World Development*, **64**, 311–321.
Park Y M M, Baek J H, Lee H S, Elfassy T, Brown C C, Schootman M, Narcisse M R, Ko S H, McElfish P A, Thomsen M R, Amick B C, Lee S S, Han K. 2024. Income variability and incident cardiovascular disease in diabetes: A population-based cohort study. *European Heart Journal*, **45**, 1920–1933.
Phan C T, Perera D, Ramsawak R, Pham T. 2025. The impacts of social network on non-farm self-employment: Evidence from Vietnam. *Journal of Rural Studies*, **114**, 103530.
Phan V P. 2023. Is the Internet penetration pro-poor? Evidence from a panel data analysis. *Telecommunications Policy*, **47**, 102612.
Poon K, Weersink A. 2011. Factors affecting variability in farm and off-farm income. *Agricultural Finance Review*, **71**, 379–397.
Prause J, Dooley D, Huh J. 2009. Income volatility and psychological depression. *American Journal of Community Psychology*, **43**, 57–70.
Rogers S, Li J, Lo K, Guo H, Li C. 2020. China's rapidly evolving practice of poverty resettlement: Moving millions to eliminate poverty. *Development Policy Review*, **38**, 541–554.
Severini S, Tantari A, Di Tommaso G. 2017. Effect of agricultural policy on income and revenue risks in Italian farms: Implications for the use of risk management policies. *Agricultural Finance Review*, **77**, 295–311.
Severini S, Di Tommaso G, Finger R. 2019. Effects of the income stabilization tool on farm income level, variability and concentration in Italian agriculture. *Agricultural and Food Economics*, **7**, 1–22.
Shimamoto D, Yamada H, Gummert M. 2015. Mobile phones and market information: Evidence from rural Cambodia. *Food Policy*, **57**, 135–141.
Song Y, Gong Y, Song Y, Chen X. 2024. Exploring the impact of digital inclusive finance on consumption volatility: Insights from household entrepreneurship and income volatility. *Technological Forecasting and Social Change*, **200**, 123179.
Sosu E M, Schmidt P. 2022. Changes in cognitive outcomes in early childhood: The role of family income and volatility. *Frontiers in Psychology*, **13**, 758082.
Sun Y, Li S. 2025. The impact of digital development on non-agricultural employment of rural women: Evidence from the broadband China strategy. *Applied Economics*, **57**, 2224–2240.
Trestini S, Szathvary S, Pomarici E, Boatto V. 2018. Assessing the risk profile of dairy farms: Application of the income stabilisation tool in Italy. *Agricultural Finance Review*, **78**, 195–208.
Twumasi M A, Jiang Y, Asante D, Addai B, Akuamoah-Boateng S, Fosu P. 2021. Internet use and farm households food and nutrition security nexus: The case of rural Ghana. *Technology in Society*, **65**, 101592.
Verkuil L A, Verburg P H, Levers C, Stratton A E, Schulp C J E. 2024. Bright spots of agroecology in the Netherlands: A spatial analysis of agroecological practices and income stability. *Agricultural Systems*, **220**, 104086.
Wang H. 2024. Digital literacy and rural household income: The formation of digital inequality. *Chinese Rural Economy*, (3), 86–106. (in Chinese)
Wang-Ly N, Newell B R. 2024. Income volatility and saving decisions: Experimental evidence. *Journal of Behavioral and Experimental Finance*, **43**, 100941.
Wang S, Sha Z, Sun X, Li C. 2025. The role of rural Internet adoption in shaping consumption breadth and inequality: Evidence from the Chinese Social Survey. *Applied Economics*, **57**, 2962–2978.
Xiang J, Zhang C. 2025. Decoding the "digital code" of happiness: Elaboration based on absolute income and relative income. *Social Indicators Research*, **178**, 1025–1052.
Yang N, Wang Y, Jin H, Qi Q, Yang Y. 2025. Impacts of Internet information literacy on farmers' relative poverty vulnerability: Evidence from CGSS survey data in China. *Social Indicators Research*, **178**, 1169–1200.
Yang Q, Zhu Y. 2025. The emerging short-form video platforms improve household dietary diversity of rural residents: Evidence from China. *Food Policy*, **131**, 102797.
Yang Y, de Sherbinin A, Liu Y. 2020. China's poverty alleviation resettlement: Progress, problems and solutions. *Habitat International*, **98**, 102135.
Zheng H, Ma W, Wang F, Li G. 2021. Does Internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy*, **102**, 102044.
Zheng H, Zhou Y, Rahut D B. 2023. Smartphone use, off-farm employment, and women's decision-making power: Evidence from rural China. *Review of Development Economics*, **27**, 1327–1353.
Zhong M, Qiang D, Wang J, Sun W. 2024. Improving health and reducing health inequality: An innovation of digitalization? *Social Science & Medicine*, **348**, 116847.
Zhou D, Zha F, Qiu W, Zhang X. 2024. Does digital literacy reduce the risk of returning to poverty? Evidence from China. *Telecommunications Policy*, **48**, 102768.
Zhou X, Cui Y, Zhang S. 2020. Internet use and rural residents' income growth. *China Agricultural Economic Review*, **12**, 315–327.
Zhu Q, Zhu C, Bai J, Peng C. 2022. Can informatization boost famers' income and narrow the income disparity in rural China? *China Economic Quarterly*, **22**, 237–256. (in Chinese)
Zhu X, Hu R, Zhang C, Shi G. 2021. Does Internet use improve technical efficiency? Evidence from apple production in China. *Technological Forecasting and Social Change*, **166**, 120662.
Zhu Z, Ma W, Sousa-Poza A, Leng C. 2020. The effect of Internet usage on perceptions of social fairness: Evidence from rural China. *China Economic Review*, **62**, 101508.

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