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The Impact of Digital Literacy on Agricultural Income in Rural Households: Insights from China

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Abstract: Digital literacy is an essential skill for accessing the advantages of the digital economy. This study constructs a framework for evaluating digital literacy and analyzes the impact of digital literacy on agricultural income at the household level, using survey data from the China Family Panel Studies (CFPS) in 2020. To address the endogeneity of digital literacy, we employ the Instrumental variable two-stage least squares (IV-2SLS) method. The results show that digital literacy has a positive effect on the agricultural income of rural households. Among the seven sub-indexes of digital literacy, utilizing mobile devices for information acquisition, watching short videos on the Internet, and engaging in WeChat communication have significant effects on household agricultural income. The disaggregated analysis shows that rural households with higher agricultural incomes and lower levels of education benefit the most. The mechanism analysis suggests that loan amount and agricultural technical efficiency positively mediate the nexus between digital literacy and agricultural income of rural households. This study offers valuable insights for governments to enhance rural household agricultural income and welfare.

Keywords: Digital literacy; Agricultural income; CFPS; Rural China

1. Introduction

In the era of the digital economy, the proficient and comprehensive utilization of digital technologies in agriculture has produced numerous favorable outcomes (Zhong et al., 2022). For instance, the application of big data analysis in agriculture helps agricultural producers predict market demand and optimize farming decisions (Bounkham et al., 2022; Li et al., 2021; Liu et al., 2021); the application of Internet of Things technology empowers agricultural producers to accurately monitor crop growth and promptly detect pests, thereby ensuring agricultural output and quality (Fabregas et al., 2019; Maredia et al, 2018; Min et al., 2020). Based on the positive relationship between digital technologies and agricultural production, numerous countries are actively promoting the adoption of digital technologies to facilitate high-quality advancements in agriculture.

In China, accelerating the application of digital technology in agriculture is one of the key economic tasks. To achieve this task, the Chinese government has improved the digital infrastructure in rural areas with remarkable results. According to the National Statistics, by the end of 2023, the internet penetration rate in rural areas of China has reached 66.5%, and the proportion of administrative villages with fiber and 4G accesses has exceeded 98% nationwide (NBSC, 2024). However, improving the digital infrastructure alone is not sufficient; it is also necessary to enhance the digital literacy of agricultural producers, including agricultural organizations and farmers (Li et al., 2024; Liu & Wang, 2021; Zhou et al., 2024). For farmers in China, they exhibit a limited level of digital literacy. According to a survey report published by the Chinese Academy of Social Sciences (CASS) in 2021, the digital literacy score of the farmers group is only 18.6 out of 100, which is significantly lower than that of other occupational groups. Such a pronounced disparity can hinder farmers ability to adopt modern agricultural technologies, access market information, improve agricultural productivity, and increase agricultural income. Therefore, it is critical to investigate the impact of farmers' digital literacy. The findings can offer valuable insights for policymakers seeking to enhance human capital in the agricultural sector, boost farm incomes, and facilitate a successful digital transition in agriculture.

Digital literacy, initially introduced by Gilster (1997), refers to an individual's ability to critically evaluate the content encountered on the Internet. Building upon this foundation, many scholars have subsequently advanced the concept of digital literacy (Eshet, 2004; Ha & Kim, 2024; Li et al., 2023; Magesa et al., 2023; Neumann et al., 2017; Wang & Wu, 2022). For instance, Eshet (2004) revealed that digital literacy encompasses more than just the capacity to retrieve information from the Internet; it includes a range of other skills, such as understanding instructions presented in user interfaces, assessing the credibility of information, and utilizing digital devices to create new and significant contents based on existing ones. In addition, the United Nations Educational Scientific and Cultural Organization (UNESCO) has defined digital literacy as the ability to manage, understand, integrate, communicate, and create information using digital technologies for employment, work, and entrepreneurship (UNESCO Institute for Statistics, 2018).

After understanding the concept of digital literacy, scholars have initiated discussions on the digital divide in relation to digital literacy. Zhou et al. (2024) demonstrated that the lack of digital literacy among rural residents hinders their access to the benefits derived from digital advancement. Other scholars highlighted the comparatively lower level of digital literacy among farmers (Lee et al., 2022; Liu & Zhou, 2023; Manlove & Whitacre, 2019; Zhang, 2023). Then, scholars have discovered that enhancing the digital literacy of farmers has positive effects (Luan et al., 2023; Wang et al., 2021;). The findings demonstrate that the digital literacy of farmers has a positive impact on non-agricultural activities such as non-farm employment and entrepreneurship (Buchan et al., 2024; Leng et al., 2020; Li et al., 2023; Ma et al., 2023). For instance, by promoting online payment and participation in online loans, digital literacy has a significant positive impact on farmers' entrepreneurial behavior (Wang et al., 2022).

In fact, the higher the level of digital literacy among farmers, the greater their capacity to access abundant information and material resources, thereby influencing not only non-agricultural activities but also agricultural practices and income generation. However, the research on the effect of farmers' digital literacy on their household agricultural income is limited. In addition, how to improve the digital literacy of farmers is insufficient. To fill the gaps, this study examines the impacts of farmers' digital literacy on their household agricultural income and explores its underlying mechanisms, while also examining the factors that affect farmers' digital literacy.

This study makes three contributions to the literature. First, according to the digital literacy definition provided by UNESCO and the data from China Family Panel Data Studies (CFPS) in 2020 China, we select seven sub-indexes and the equal weight method to assess the digital literacy of decision-makers in household agricultural activities. Then, we discuss the impact of decision-makers' digital literacy on their household agricultural income. Second, to overcome the potential endogeneity of digital literacy, we employ the Instrumental variable two-stage least squares (IV-2SLS) to conduct empirical analysis. Based on the IV-2SLS method, we can also gain insights into the factors influencing decision-makers' digital literacy. Third, we discuss the mechanism between decision-makers' digital literacy and their household agricultural income. The results show that by easing credit constraints and improving agricultural technical efficiency, the enhancement of decision-makers' digital literacy can increase their household agricultural income.

The remainder of this study is organized as follows: Section 2 presents the theoretical analysis and research hypothesis. Section 3 provides the data, variables, and descriptive statistics. Sections 4 and 5 present the empirical strategy and empirical results, respectively. Finally, Section 6 summarizes the conclusions and discusses the policy implications.

2. Theoretical Analysis and Research Hypotheses

This study explains the impact of decision-makers' digital literacy on their household agricultural income by facilitating access to credit and improving agricultural technical efficiency.

First, decision-makers in household agricultural activities with a high level of digital literacy can access credit more easily, thereby facilitating the increase of agricultural income. In the traditional agricultural loan market, a large number of decision-makers face credit constraints (Li et al., 2024; Yu et al., 2019). In the presence of credit constraints, decision-makers encounter challenges in adjusting their planting structure, expanding the scale of farmland, and adopting advanced agricultural technology. These challenges are not conducive to the increase of agricultural income (Kehinde & Ogundeji, 2022; Lakhan et al., 2020; Li et al., 2020). For instance, Li et al. (2020) found that difficult access to credit inhibits decision-makers from renting farmland and realizing large-scale management of farmland, which is an important strategy for them to increase household agricultural income.

Fortunately, the rapid development of digital finance (e.g. online credit) provides favorable conditions for easing the credit constraints faced by decision-makers (Benami & Carter, 2021; Ma et al., 2023; Weng et al., 2023; Xu et al., 2022). Online credit, with its simple application procedures and fast lending speeds, can meet the loan requirements of decision-makers (Li et al., 2020; Xu et al., 2022). It is noted that the adoption of online credit by decision-makers is contingent upon their level of digital literacy. The higher the digital literacy of decision-makers, the more likely they are to understand and adopt online credit. Thus, by easing credit constraints, the improvement of decision-makers' digital literacy can improve their household agricultural income.

Second, decision-makers in household agricultural activities with a high level of digital literacy can acquire adequate information and achieve higher technical efficiency in agricultural production, thereby facilitating an increase in agricultural income. Technical efficiency in agricultural production refers to the ratio between the minimum input required for an ideal agricultural production and the actual input used in producing the same agricultural output. The higher the level of technical efficiency in agricultural production, the higher the agricultural outcome. To improve agricultural technical efficiency, decision-makers need to obtain accurate and timely information regarding farmland management and meteorological data (Chandio et al., 2023; Huang et al., 2015; Mishra & Singh, 2023). In specific, correct information on farmland management helps decision-makers adopt organic fertilizer, which can enhance soil quality and increase crop yield (Chen et al., 2023; Mwalupaso et al., 2019); accurate and timely meteorological information assists decision-makers in harvesting before the arrival of adverse weather conditions, ensuring high agricultural output (Huang et al., 2015).

For decision-makers with a high level of digital literacy, they can access information in a timely and adequate manner. For instance, by using communication software, decision-makers can obtain information from others timely; by using the agricultural technology promotion platform, decision-makers can ask for accurate information from government departments to solve technical problems; by the short video platform, decision-makers can share their agricultural production experience and get feedback. Thus, by getting adequate information and improving technical efficiency, the improvement of decision-makers' digital literacy can improve their household agricultural income.

To sum up, we put forward the following hypothesis.

Hypothesis 1: Enhancing the digital literacy of decision-makers can improve their household agricultural income.

Hypothesis 2: By easing credit constraints, the digital literacy of decision-makers can positively affect their household agricultural income.

Hypothesis 3: By improving agricultural technical efficiency, the digital literacy of decision-makers can positively affect their household agricultural income.

3. Data, Variables, and Descriptive Statistics

3.1 Data

This study utilizes CFPS data collected in the 2020 wave. The CFPS database aims to capture and document the evolving landscape of China's society, economy, population dynamics, education system, and healthcare sector. It serves as a comprehensive repository for scholarly investigations and public policy evaluations. Based on implicit stratification and a multi-stage equal probability sample, the CFPS database encompasses household data from 25 provinces (municipalities, autonomous regions) in China, as well as the individual-level data within each household. So far, the CFPS has launched five waves of investigations, including the years of 2010, 2014, 2016, 2018, 2020. In each new wave, the survey questions are updated to some degree. This study employs the 2020 wave because this wave can provide more data closely related to the assessment of digital literacy, such as whether respondents watch short videos (e.g. Tik Tok), whether they watch or listen to courses on platforms, and whether they publish posts about their lives and work on WeChat Moments.

We utilize four steps to deal with the CFPS data collected in the 2020 wave. First, we selected the Household database and excluded a total of 5,127 urban household samples, resulting in a final dataset comprising 4,943 urban household samples. Second, we selected the Adult database and kept the corresponding variables of decision-makers in household agricultural activities. Third, we merged the Household and Adult databases. Fourth, we exclude 1,940 samples that exhibit missing and abnormal values for the dependent, independent, control, and mechanism variables. After undergoing the four steps mentioned above, the final dataset encompasses a total of 3,003 samples.

3.2 Variables

3.2.1 Dependent variable

The dependent variable is the household agricultural income, which refers to the total value of a single household obtained by selling agricultural and forestry products, poultry, livestock, fishery products, and sideline products (such as eggs and piglets). This variable is subjected to logarithmic processing in the empirical analysis.

3.2.2 Independent variable

The independent variable is the digital literacy of decision-makers in household agricultural activities. According to the definition of digital literacy, as stipulated by UNESCO, we construct a conceptual framework for evaluating their digital literacy (DL). This conceptual framework encompasses four aspects, including device and software operations (DL1), information and data literacy (DL2), communication and collaboration (DL3), and creating digital content (DL4) (see Table 1).

Table 1. The conceptual framework of digital literacy and its definitions

Framework of Digital Literacy (DL)	Definitions
Device and software operations (DL1)	1 if an individual utilizes mobile devices to access the Internet, 0 otherwise
	1 if an individual utilizes computers to access the Internet, 0 otherwise
Information and data literacy (DL2)	1 if an individual engages in online shopping, 0 otherwise
	1 if an individual watches short videos on the Internet, 0 otherwise
	1 if an individual learns online, 0 otherwise
Communication and collaboration (DL3)	1 if an individual utilizes WeChat [a], 0 otherwise
Creating digital content (DL4)	1 if an individual publishes posts about his life or work on Wechat Moments, 0 otherwise

Note: [a] WeChat is a popular social media platform in China.

Specifically speaking, DL1 includes the usage of mobile devices to access the Internet and the usage of computers to access the Internet; DL2 includes shopping online, watching short videos on the Internet, and learning on the Internet; DL3 includes the usage of WeChat, which is a popular social media platform in China; DL4 includes sharing personal or professional updates on WeChat Moments. Then, we employ a variety of methods to assign weights to each index within the conceptual framework of digital literacy, including the equal weight method, entropy method, and principal component analysis method. In the baseline regression, we employ the equal weight method to assign weights, while in the robustness analysis, we adopt the entropy method and principal component analysis method.

3.2.3 Control variables

To mitigate the impact of other factors on household agricultural income, this study incorporates a set of control variables. According to previous studies (Liu & Zhou, 2023; Wang et al., 2023; Wang et al., 2024), we select variables that capture the characteristics of decision-makers in household agricultural activities, household characteristics, and living conditions characteristics. Specifically, the characteristics of decision-makers encompass demographic factors such as age, gender, marital status, ethnicity, health status, and educational attainment. The household characteristics include the household size, whether any members of the household have migrated for work, and the number of books in the household. The living conditions encompass the cleanliness of rural roads and what kind of water does household normally uses for cooking.

3.2.4 Mechanism variables

Based on the conceptual framework in this study, we select two mediators: one refers to the amount of loan (M1), while the other relates to agricultural technical efficiency (M2). In the empirical analysis, the M1 is subjected to logarithmic processing. Regarding M2, we adopt the translog function based on the studies conducted by Bravo-Ureta et al. (2021) and Zheng et al. (2021) to derive M2. The translog function is constructed as follows:

$$\ln(y_i) = \alpha_0 + \sum_{k=1}^{2} \alpha_k \ln(x_{ik}) + \frac{1}{2}\sum_{k=1}^{2} \beta_k \ln(x_{ik})^2 + \gamma_1 ln(x_{i1}) ln(x_{i2}) + v_i - u_i \tag{1}$$

where, y_i refers to the agricultural output of household i, which is quantified as the total value obtained from selling agricultural and forestry products, poultry, livestock, fishery products, and sideline products. $\ln(y_i)$ refers to the logarithm of y_i. x_{ik} refers to the kth input of household i $(k = 1, 2)$. In specific, x_{i1} refers to the labor input of household i; x_{i2} refers to the capital input of household i. $\ln(x_{ik})$ refers to the logarithm of x_{ik}, and $\ln(x_{ik})^2$ is the squared term of $\ln(x_{ik})$. α_0, α_k, β_k, and γ_1 are parameters to be estimated. v_i refers to the idiosyncratic error, capturing random noises like climate change factors. $u_i \geq 0$ refers to the inefficiency term.

After estimating Eq. (1), the technical efficiency (TE_i) for the household i can be calculated as follows:

$$TE_i = \frac{y_i}{y_i^*} = \frac{E(y_i|u_i, x_i)}{E(y_i|u_i = 0, x_i)} = \exp(-u_i) \tag{2}$$

where, y_i refers to the observed agricultural output. y_i^* refers to the maximum feasible agricultural output and is always higher than y_i. Because $y_i \leq y_i^*$, TE_i is range from zero to one.

3.3 Descriptive Statistics

Table 2 presents the definitions and descriptive statistics of variables, indicating that the mean value of household agricultural income in our sample is 14,200 CNY. The mean value of decision-makers' digital literacy is 0.35, showing that there is a large space for the improvement of digital literacy among decision-makers. As for control variables, the average age of decision-makers in household agricultural activities is 52 years, indicating that the demographic involved in agricultural decision-making is characterized by an advanced age. The gender and marital status averages are 0.64 and 0.88, respectively, indicating that the majority of the decision-makers in agriculture are male and married. 97% of decision-makers are Han Chinese, and they have good health status. The mean value of education is 2.25, meaning that most decision-makers are poorly educated. The average household size is 4 and 32% of rural households exhibit labor migration for employment. The average number of books per household is approximately 30. The mean cleanliness values for road conditions and access to clean water are 0.12 and 0.44, respectively, indicating the imperative for enhancing living conditions in rural China. The mean value of IV is 0.47, showing that decision-makers are not yet fully aware of the importance of the Internet in accessing information. The average of M1 and M2 are 8,200 CNY and 0.19, respectively.

Table 2. Variable definitions and descriptive statistics

Variables	Definitions	Mean	S.D.
	Dependent variable		
Household agricultural income	The revenue from the sale of agricultural and forestry products, including the crops you cultivated, forestry products, poultry, livestock, fishery products, and other sideline products (10,000 CNY) [a]	1.42	4.56
	Key variable		
Digital literacy	Digital literacy of decision-makers in household agricultural activities	0.35	0.24
	Control variables		
Age	Age of the decision-maker (years)	51.69	12.37
Age^2	The square of age (years)	2851	1271
Gender	1 if the decision-maker is male, 0 otherwise	0.64	0.48
Marriage	1 if the decision-maker is married, 0 otherwise	0.88	0.32
Minority	1 if the decision-maker is Han Chinese, 0 otherwise	0.97	0.15
Health status	The health status of the decision-maker (1 = excellent; 2 = very good; 3 = good; 4 = fair; 5 = poor)	3.01	1.25
Education	The education level of decision-maker (1 = illiteracy, 2 = primary school, 3 = junior high school, 4 = senior high school and above)	2.25	1.00
Household size	Number of people residing in the household	4.25	1.99
Migration for work	1 if any household members have migrated for employment purposes, 0 otherwise	0.32	0.46
Number of books	The number of books in the household	30.36	92.88
Cleanliness of roads	Road cleanliness level: 1 = very untidy to 7 = very tidy	0.12	0.13
Clean water	1 if the household uses potable water for cooking (such as tap water, mineral water, filtered water, and purified water), 0 otherwise	0.44	0.19
IV	The belief of decision-makers in obtaining information via the Internet: 1 = very unimportant to 5 = very important	0.47	0.49
	Mediating variables		
M1	Loan amount (10,000 CNY) [a]	0.82	3.81
M2	Agricultural technical efficiency	0.19	0.20

Note: S.D. refers to standard deviation. [a] CNY refers to the Chinese yuan. 1yuan = 0.137 USD.

4. Empirical Strategy

The Discussion section should interpret the results in perspective of previous studies and the working hypotheses, and report the research findings and implications in the broadest context possible.

4.1 OLS Model

According to the conceptual framework and CFPS data in the 2020 wave, we construct the following OLS model to quantify the effect of decision-makers' digital literacy on their household agricultural income.

$$y_i = \beta_0 + \beta_1 dliteracy_i + \beta_2 c_i + \varepsilon_i \tag{3}$$

where, y_i has been mentioned above, denoting the total value of agricultural and forestry products sold by household i. $dliteracy_i$ refers to the digital literacy of decision-makers in household agricultural activities. c_i refers to a set of control variables, including the characteristics of decision-makers, decision-makers' household characteristics, and living conditions characteristics. β_0, β_1, and β_2 are parameters to be estimated. ε_i refers to the error term.

4.2 IV-2SLS Method

The OLS model fails to address the endogeneity issues arising from digital literacy due to two reasons. Firstly, the digital literacy of decision-makers in household agricultural activities tends to be influenced by unobserved variables such as local customs and decision-makers' inherent capabilities (Chen et al., 2024a). Secondly, there is a potential reverse causation between decision-makers' digital literacy and household agricultural income (Liu & Zhou, 2023). That is, households with higher levels of agricultural income may demonstrate an increased inclination to the utilization of digital devices and information, consequently leading to an elevated level of digital literacy among household members. To solve the issue of endogeneity caused by unobserved variables and reverse causality, we employ the IV-2SLS method to conduct empirical analysis. Following Semykina & Wooldridge (2010), the IV-2SLS method contains two stages. The first stage is constructed as follows:

$$dliteracy_i = \gamma_0 + \gamma_1 IV_i + \gamma_2 c_i + \varepsilon_i \tag{4}$$

where, $dliteracy_i$ and c_i are the same as those in Eq. (3). IV_i refers to the instrumental variable. ε_i refers to the error term. Following the study of Vatsa et al. (2023), we employ decision-makers' beliefs regarding the significance of information acquisition through the Internet as an IV. The logic is that if decision-makers in household agricultural activities recognize the indispensability of Internet usage in accessing a vast array of information, they are more likely to utilize mobile devices or computers for accessing online resources. Moreover, the ability to access online resources is a fundamental aspect of digital literacy. Then, we empirically test the validity of the instrumental variable. Furthermore, the first stage F-test is 50.96, which exceeds the critical threshold of 10, indicating a significant relationship between the IV and decision-makers' digital literacy. In the Weak Identification test, the Cragg-Donald Wald F statistic is 51.34, which exceeds the critical value at the 10% significance level, indicating no weak instrumental variable.

The second stage is constructed as follows:

$$y_i = \rho_0 + \rho^* dliteracy_i + \rho_1 c_i + \varepsilon_i \tag{5}$$

where, y_i and c_i are the same as those in Eq. (3). $dliteracy_i$ are the predicted values from Eq. (4). ρ_0, ρ^*, and ρ_1 are parameters to be estimated. ε_i is the error term. By estimating Eq. (4) and Eq. (5), we can solve the issue of endogeneity and obtain a consistent estimate of ρ^*.

5. Empirical Results

5.1 Baseline Analysis

5.1.1 The result of OLS model

Table 3. Impact of digital literacy on household agricultural income: OLS model estimates

Variables	Household Agricultural Income	Household Agricultural Income
Digital literacy	0.776 (0.336)**	0.677 (0.402)*
Age		0.074 (0.045)*
Age^2		-0.001 (0.000)
Gender		0.535 (0.169)***
Marriage		0.425 (0.275)
Minority		0.463 (0.537)
Health status		-0.192 (0.063)***
Education		0.160 (0.081)**
Household size		0.084 (0.043)**
Migration for work		-0.266 (0.175)
Number of books		-0.001 (0.001)
Cleanliness of roads		0.133 (0.130)
Clean water		0.511 (0.187)***
Constant	5.749 (0.142)***	1.640 (1.397)
R^2	0.112	0.119
Observations	3,003	3,003

Note: Robust standard errors are presented in parentheses. ***< 0.01, **< 0.05, and *< 0.10.

Table 3 presents the estimated results of the OLS model. Column 2 of Table 3 represents the estimated outcomes when control variables are not taken into account. In Column 2, the coefficient of digital literacy is positive and significant at the 5% level. After controlling for the variables and applying robust standard error, we present the estimated results in Column 3. As indicated in Column 3, the coefficient of digital literacy also demonstrates a significantly positive association, albeit with a lower value when compared to the results reported in Column 2. This result coincides with Chen et al. (2024b), who found that the size of the coefficient of digital literacy decreases as the control variables increase.

5.1.2 The first stage of IV-2SLS

Column 2 of Table 4 shows the estimated results of the first stage of IV-2SLS. In Column 2, the variable of age demonstrates a statistically significant negative impact at the 1% significance level, suggesting a substantial decline in digital literacy with increasing age. In general, older farmers encounter challenges in fostering digital literacy due to their limited enthusiasm and ability to embrace emerging digital technology. Once a certain threshold of age is reached, the impact of age on digital literacy becomes significantly attenuated. The findings of age-related assessments in this study are consistent with those reported by Liu & Zhou (2023). The coefficient of gender is significantly positive, indicating a pronounced male advantage in digital literacy proficiency compared to females. Education has a positive and significant effect on digital literacy, confirming the importance of formal education in enhancing digital literacy. The variable of migration for work shows a statistically significant positive effect at the 5% significance level, suggesting that engaging in migrant work helps to improve the digital literacy of individuals and their families. The cleanliness of roads has a statistically significant positive impact on digital literacy. Last but not least, the IV's impact on digital literacy is significantly positive, suggesting that individuals who recognize the importance of accessing information through the Internet possess a higher level of digital literacy.

Table 4. Impact of digital literacy on household agricultural income: IV-2SLS method estimates

Variables	Digital Literacy	Household Agricultural Income
Digital literacy		3.689 (1.043)***
Age	-0.018 (0.002)***	0.128 (0.050)**
Age^2	0.000 (0.000)***	-0.001 (0.000)**
Gender	0.184 (0.007)***	0.453 (0.172)***
Marriage	0.013 (0.012)	0.356 (0.278)
Minority	-0.005 (0.023)	0.479 (0.546)
Health status	0.004 (0.003)	-0.202 (0.064)***
Education	0.016 (0.004)***	0.087 (0.085)
Household size	-0.002 (0.002)	0.094 (0.043)**
Migration for work	0.020 (0.008)**	-0.318 (0.177)*
Number of books	0.000 (0.000)**	-0.001 (0.001)
Cleanliness of roads	0.011 (0.004)**	0.076 (0.132)
Clean water	0.002 (0.008)	0.507 (0.188)***
IV	0.053 (0.002)***	
Constant	0.702 (0.061)***	-1.000 (1.684)
R^2	0.412	0.100
Observations	3,003	3,003

Note: Robust standard errors are presented in parentheses. $^{***}< 0.01$, $^{**}< 0.05$, and $^{*}< 0.10$.

5.1.3 The second stage of IV-2SLS

Column 3 of Table 4 presents the estimated results of the second stage of IV-2SLS. In Column 3, the key variable of digital literacy significantly positively affects the household agricultural income. The coefficient of digital literacy is valued at 3.689, indicating that the increase in digital literacy by 0.1 leads to a corresponding increase of 0.3689 in the logarithm of household agricultural income. Based on this result, the Hypothesis 1 is tested.

As for control variables, the variable of age has a positive effect on household agricultural income. The reason is that compared to the young, the elderly possess extensive agricultural production experience, which holds significant implications for attaining optimal agricultural outcomes. However, beyond a certain threshold, an increase in age exhibits a negative effect on household agricultural income. This result can be explained by the coefficient of health status. The coefficient of health status is negative and significant, indicating a decline in agricultural income generation as decision-makers' health deteriorates. The coefficient of gender is positive and significant, showing that male decision-makers tend to generate higher agricultural income compared to their female counterparts. The coefficient of household size exhibits a positive correlation, whereas the coefficient of migration for work demonstrates a negative association. Meanwhile, the variable of clean water has a positive effect on household agricultural income, denoting that the construction of water conservancy infrastructure has a positive impact on agricultural productivity.

The Conclusions section should clarify the main conclusions of the research, highlighting its significance and relevance. The limitations of the work and the directions of future research may also be mentioned. Please contain nothing not substantiated in the main text. Do not make this section a mere repetition of the Abstract.

5.2. Robustness Check

To reinforce the validity of our main empirical results, we utilize the entropy method and principal component analysis method to determine the weights of decision-makers' digital literacy. Then, we utilize the IV-2SLS method to analyze the impacts of decision-makers' digital literacy on their household agricultural income. By utilizing the entropy method and IV-2SLS method, the estimates of the second stage of IV-2SLS are shown in Column 2 of Table 5. As it shows, the coefficient of digital literacy is statistically significant and positive. By utilizing the principal component analysis method and IV-2SLS method, he estimates of the second stage of IV-2SLS are shown in Column 3 of Table 5. As it shows, digital literacy positively affects household agricultural income. The results in Table 5 indicate that the positive relationship between digital literacy and household agricultural income remains robust.

Table 5. The robustness tests: IV-2SLS method estimates

Variables	Household Agricultural Income	Household Agricultural Income
Digital literacy	4.399 (1.246)***	1.793 (0.507)***
Age	0.150 (0.053)***	0.103 (0.047)**
Age^2	-0.001 (0.000)**	-0.001 (0.000)
Gender	0.427 (0.174)**	0.488 (0.170)***
Marriage	0.384 (0.277)	0.356 (0.278)
Minority	0.496 (0.546)	0.470 (0.551)
Health status	-0.206 (0.064)***	-0.209 (0.064)***
Education	0.086 (0.086)	0.089 (0.085)
Household size	0.093 (0.043)**	0.098 (0.043)**
Migration for work	-0.288 (0.178)	-0.327 (0.177)*
Number of books	-0.001 (0.001)	-0.001 (0.00)
Cleanliness of roads	0.074 (0.133)	0.073 (0.132)
Clean water	0.491 (0.188)***	0.513 (0.188)***
Constant	-1.199 (1.734)	-1.758 (1.808)
R^2	0.100	0.102
Observations	3,003	3,003

Note: Robust standard errors are presented in parentheses. ***< 0.01, **< 0.05, and *< 0.10.

5.3. Further Analysis: Impacts of Sub-Indexes of Digital Literacy

We further analyze the seven sub-indexes of digital literacy on household agricultural income. The related results are shown in Table 6. In Column 2 of Table 6, the estimates show that the utilization of mobile devices for Internet access has a statistically significant and positive impact on agricultural income, with a significance level of 10%. In Column 5, the results indicate that watching short videos through networking platforms has a positive impact on household agricultural income. In Column 7, the coefficient is positive and significant at the 5% level, meaning that the utilization of WeChat has a significantly positive effect on household agricultural income. However, in other Columns of Table 6, the coefficients of digital literacy are insignificant. Therefore, compared to other sub-indexes of digital literacy, utilizing mobile devices for information acquisition, watching short videos on the Internet, and engaging in WeChat communication are more effective.

Table 6. Heterogeneity analysis: different sub-indexes of digital literacy

Variables	Mobile Devices	Computers	Shopping Online	Video Snacking	Learning Online	Utilizing Wechat	Publishing Posts
Digital literacy	0.358*	-0.475	-0.019	0.387**	0.342	0.402**	-0.109
	(0.189)	(0.404)	(0.222)	(0.185)	(0.309)	(0.189)	(0.194)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.869	2.543*	2.256	1.830	2.088	1.799	2.311*
	(1.367)	(1.366)	(1.379)	(1.369)	(1.357)	(1.369)	(1.362)
R^2	0.119	0.118	0.118	0.119	0.118	0.120	0.118
Observations	3,003	3,003	3,003	3,003	3,003	3,003	3,003

Note: Robust standard errors are presented in parentheses. ***< 0.01, **< 0.05, and *< 0.10.

5.4 Heterogeneity Analysis

To enhance our understanding, we conduct heterogeneity analysis based on household agricultural incomes and educational levels. The heterogeneity results based on household agricultural incomes are shown in Columns 2 and 3 of Table 7. As indicated in Column 2, the coefficient of digital literacy is not statistically significant. However, in Column 3, the coefficient demonstrates both statistical significance and a positive impact. The heterogeneity results based on educational levels are shown in Columns 4 and 5 of Table 7. The coefficient of digital literacy is found to be both statistically significant and positive in Column 4, whereas it appears to lack statistical significance in Column 5. This suggests that the improvement of digital literacy primarily benefits rural households with lower levels of education. The potential explanation for this finding is that despite farmers in China having a lower level of formal education, they can enhance their digital literacy through technical training, thereby reaping the benefits of improved digital literacy. On the contrary, for farmers with a higher level of education, they are likely to possess an enhanced digital literacy and have difficulty moving up further.

Table 7. Heterogeneity analysis: household agricultural income and education level

Variables	**Income (Below the 50th Quantile)**	**Income (Above the 50th Quantile)**	**Low Level of Education [A]**	**High Level of Education [B]**
Digital literacy	10.016 (9.335)	3.530 (1.049)***	4.137 (1.112)***	0.105 (3.620)
Controls	Yes	Yes	Yes	Yes
Constant	18.501 (9.712)*	-0.869 (1.701)	-2.382 (1.886)	6.489 (5.395)
R^2	0.241	0.100	0.103	0.117
Observations	64	2,939	2,686	317

Note: Robust standard errors are presented in parentheses. ***< 0.01.

[a] Low level of education includes illiteracy, primary school, and junior high school.

[b] High level of education includes senior high school and above.

5.5 Mechanism Analysis

To confirm Hypothesis 2 and 3, we conduct mechanism analysis based on the IV-2SLS and OLS model. The analysis results are presented in Table 8, with the amount of loan (M1) being employed as the mediating variable. In Table 8, the results of the first stage of IV-2SLS are presented in Column 2, while Column 3 displays the outcomes of the second stage. As indicated in Column 3, digital literacy has a positive and significant effect on M1. The results of the OLS model are presented in Column 4. Column 4 reveals a significant positive correlation between M1 and household agricultural income. From Columns 3 and 4, we conclude that M1 plays a positive mediating role in the association between digital literacy and household agricultural income. Thus, the Hypothesis 2 is tested.

Table 8. Mechanism analysis: the amount of loan (M1) channel

Variables	**Impact of Digital Literacy on M1 (IV-2SLS)**		**Impact of M1 on Income (OLS)**
	Digital literacy	M1	Agricultural income
Digital literacy		1.996 (0.748)***	
M1			0.040 (0.024)*
Age	-0.018 (0.002)***	0.058 (0.037)	0.062 (0.045)
Age^2	0.000 (0.000)***	-0.001 (0.000)**	-0.000 (0.000)
Gender	0.018 (0.007)***	0.393 (0.125)***	0.543 (0.167)***
Marriage	0.013 (0.012)	0.009 (0.188)	0.605 (0.260)**
Minority	-0.005 (0.024)	-0.275 (0.482)	0.369 (0.530)
Health status	0.004 (0.003)	0.105 (0.049)**	-0.200 (0.063)***
Education	0.016 (0.004)***	-0.144 (0.064)**	0.185 (0.080)**
Household size	-0.002 (0.002)	0.126 (0.034)***	0.077 (0.043)*
Migration for work	0.016 (0.007)**	-0.099 (0.139)	-0.170 (0.170)
Number of books	0.000 (0.000)**	-0.001 (0.000)*	-0.000 (0.001)
Cleanliness of roads	0.011 (0.004)**	-0.180 (0.118)	0.155 (0.129)
Clean water	0.002 (0.008)	0.242 (0.132)*	0.521 (0.188)***
IV	0.053 (0.002)***		
Constant	0.701 (0.061)***	-0.0537 (1.296)	3.831 (0.871)***
R^2	0.412	0.143	0.117
Observations	3,003	3,003	3,003

Note: Robust standard errors are presented in parentheses. ***< 0.01, **< 0.05, and *< 0.10.

Table 9 presents the results of the mediation effect of agricultural technical efficiency (M2). In Table 9, Columns

2 and 3 show the first and second stages of IV-2SLS estimation, respectively. As indicated in Column 3, the impact of digital literacy on M2 is significant and positive. Column 4 shows the OLS estimation results and reveals a significant positive relationship between M2 and household agricultural income. Combining the results in Columns 3 and 4, we conclude that M2 positively mediates the relationship between digital literacy and household agricultural income. Thus, the Hypothesis 3 is tested.

Table 9. Mechanism analysis: the agricultural technical efficiency (M2) channel

Variables	Impact of Digital Literacy on M2 (IV-2SLS)		Impact of M2 on Income (OLS)
	Digital literacy	M2	Agricultural income
Digital literacy		0.097 (0.048)**	
M2			16.420 (0.305)***
Age	-0.018 (0.002)***	0.002 (0.002)	0.046 (0.029)
Age^2	0.000 (0.000)***	0.000 (0.000)	-0.000 (0.000)
Gender	0.018 (0.007)***	0.023 (0.008)***	0.126 (0.111)
Marriage	0.013 (0.012)	0.005 (0.013)	0.317 (0.185)*
Minority	-0.005 (0.024)	0.036 (0.023)	-0.123 (0.382)
Health status	0.004 (0.003)	-0.012 (0.003)***	-0.006 (0.042)
Education	0.016 (0.004)***	0.005 (0.004)	0.048 (0.053)
Household size	-0.002 (0.002)	0.001 (0.002)	0.076 (0.029)***
Migration for work	0.016 (0.008)**	-0.016 (0.008)**	-0.007 (0.115)
Number of books	0.000 (0.000)**	-0.000 (0.000)**	0.001 (0.001)
Cleanliness of roads	0.011 (0.004)**	-0.001 (0.006)	0.131 (0.081)
Clean water	0.002 (0.007)	0.017 (0.008)**	0.225 (0.124)*
IV	0.053 (0.002)***		
Constant	0.701 (0.061)***	0.035 (0.080)	0.246 (0.896)
R^2	0.412	0.109	0.576
Observations	3,003	3,003	3,003

Note: Robust standard errors are presented in parentheses. ***< 0.01, **< 0.05, and *< 0.10.

6. Conclusions and Policy Implications

This study investigates the impact of decision-makers' digital literacy on their household agricultural income, based on the CFPS collected in the 2020 wave and the IV-2SLS model. To assess the digital literacy of decision-makers in household agricultural activities, we select seven sub-indexes and a variety of methods (including the equal weight method, entropy method, and principal component analysis method) to assign weights to each index. Furthermore, we discuss the impacts of different sub-indexes of digital literacy on household agricultural income, analyze the heterogeneity analysis based on household agricultural income and educational levels, and explore the mechanisms linking decision-makers' digital literacy and their household agricultural income.

The following conclusions are drawn. First, the core characteristic of digital literacy is the ability to manage, understand, integrate, communicate, and create information using digital technology. Based on this, the framework of digital literacy encompasses four dimensions and seven sub-indexes. Based on seven sub-indexes and the equal weight method, we assess the digital literacy of decision-makers in household agricultural activities. The result shows that the mean value of decision-makers' digital literacy is 0.35, indicating that there exists a substantial scope for enhancing digital literacy. Second, decision-makers' digital literacy can positively affect their agricultural income. In the seven sub-indexes of digital literacy, utilizing mobile devices for information acquisition, watching short videos on the Internet, and engaging in WeChat communication have significant effects. Third, the disaggregated analysis shows that rural households with higher agricultural incomes and lower levels of education benefit the most. The mechanism analysis suggests that loan amount and agricultural technical efficiency positively mediate the nexus between digital literacy and agricultural income of rural households. Fourth, the estimation results derived from the first stage of IV-2SLS show that the variables of gender, education, migration for work, and road cleanliness have positive and significant effects on household agricultural income.

This study has clear policy implications. First, governments should attach great importance to the important role of digital literacy in increasing household agricultural income in rural areas. In addition to raising awareness, effective measures should be taken. The fundamental and effective approach entails the provision of digital literacy training for farmers. For instance, enriching the education content and training form by utilizing both online and offline methods; enhancing the caliber of instructional programs by reinforcing the collaboration between institutions of higher education and professional training establishments; and providing tailored training resources by taking into account the growth characteristics of different crops.

Second, it is imperative to encourage young people with migrant work experience to participate in agricultural production. For this purpose, the government deserves to implement a comprehensive set of policy measures, including reallocating dedicated funds to provide targeted support for young people's migrant work experience, deploying technical experts to offer information services and technical support, and promoting brand building in agriculture.

Third, to effectively enhance digital literacy and household agricultural income, supporting policies need to be targeted to key groups. Farmers with limited educational attainment and rural households characterized by lower agricultural income are the groups that warrant attention. Meanwhile, developing and making full use of all sub-indexes of digital literacy to increase agricultural income of rural households is necessary, such as WeChat and TikTok.

Finally, we point out the limitations and the outlook of the study. This study concludes that digital literacy significantly enhances household agricultural income through its positive impacts on loan amount and agricultural technical efficiency. However, due to data limitations, we are unable to analyze the underlying mechanisms that drive the impacts of digital literacy on loan amounts and agricultural technical efficiency. Further research may bridge this limitation when data are available.

Author Contributions

Conceptualization, X.G.; methodology, X.G.; software, X.G.; data curation, X.G.; writing—original draft preparation, X.G.; writing—review and editing, X.G.; supervision, X.G. All authors have read and agreed to the published version of the manuscript.

Data Availability

The authors do not have permission to share data. The CFPS database was launched by the Institute of Social Science Survey (ISSS) of Peking University, China. The CFPS database includes the public and private database. This study utilizes the public database.

Conflicts of Interest

The authors declare no conflict of interest.

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