agriculture

MDPI

Article

Digital Literacy Level and Formal Credit Constraints: Probit Analysis of Farm Households' Borrowing Behavior in China

Ziyang Zhou, Ziwei Li, Guangyan Chen, Jinpeng Zou, Mingling Du and Fang Wang *

College of Management, Sichuan Agricultural University, Chengdu 611130, China; zhouziyang@stu.sicau.edu.cn (Z.Z.); 202003550@stu.sicau.edu.cn (Z.L.); 14639@sicau.edu.cn (G.C.); zoujinpeng@stu.sicau.edu.cn (J.Z.); dumingling@stu.sicau.edu.cn (M.D.)
* Correspondence: wangfangscnd@sicau.edu.cn

Abstract: With the rapid evolution of the rural digital economy, analyzing the impact of digital literacy level on farm households' formal borrowing is crucial for easing credit constraints and fostering rural economic growth. Leveraging the data from the 2020 China Family Panel Studies (CFPSs) and applying binary probit models and the Karlson–Holm–Breen (KHB) method, this study delineates the positive correlation between the digital literacy level and increased formal borrowing among farm households. The findings, which were robust against endogeneity and robustness tests, underscore the role of digital literacy level in augmenting farmers' earnings and social networks, with a notably stronger mediation by earnings. The effects are particularly significant for middle-aged and older, less educated males in the central and western regions, in contrast with younger, highly educated females in the east. This research advocates for enhancing rural digital infrastructure and education, alongside financial system reforms, to advance rural financial development and support sustainable rural revitalization.

Keywords: digital literacy; formal credit constraints; formal borrowing behavior; earnings; social network; probit model; KHB model

check for updates

Citation: Zhou, Z.; Li, Z.; Chen, G.; Zou, J.; Du, M.; Wang, F. Digital Literacy Level and Formal Credit Constraints: Probit Analysis of Farm Households' Borrowing Behavior in China. *Agriculture* **2024**, *14*, 832. https://doi.org/10.3390/agriculture14060832

Academic Editor: Sanzidur Rahman

Received: 17 April 2024
Revised: 18 May 2024
Accepted: 22 May 2024
Published: 26 May 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Credit constraints reveal significant implications for sustainable agricultural development in less developed regions [1,2]. The increasing marketization of rural areas escalates the demand for financial resources among smallholder farmers, exacerbating existing credit constraints [3]. These constraints are primarily fueled by information asymmetries, limited credit offerings, and inadequate collateral within the rural credit market [4]. Consequently, farm households face considerable challenges in securing affordable financing, which underscores the pressing need for enhanced financial support mechanisms to mitigate these constraints and foster optimal borrowing and lending behaviors [5]. Such interventions are pivotal not only for boosting farmers' income but also for improving overall welfare [6–9].

In these developing settings, credit constraints for agricultural households predominantly manifest through formal credit constraints. In China, 45.2% of rural households still face serious formal credit constraints, and the credit needs of rural households are still not effectively met [10]. Due to unstable earnings and lack of collateral [2], farmers also face practical challenges such as information asymmetry, incomplete credit markets, and high transaction costs [1], making it difficult for them to obtain credit support from formal financial institutions and thus causing them to face serious credit constraints. Compared with informal credit, formal credit has a more significant impact on agricultural income and farmer welfare [11,12]. Empirical evidence suggests that factors such as individual characteristics, household financial status [4], financial literacy [13], and social capital [14] significantly influence formal borrowing behaviors among these households. These constraints can be alleviated by optimizing agricultural credit policies [15], developing formal

rural credit markets [11], and promoting education [4], thereby promoting agricultural production and the sustainable development of rural households [1].

The swift advancement of digital technology has catalyzed a digital revolution, significantly permeating every facet of China's economic and societal structures [16,17], providing new ideas and solutions for further alleviating formal credit constraints and promoting formal borrowing behavior among rural households. With robust support from the national government, the enhancement of the rural Internet infrastructure has been remarkable. Over the past decade, Internet penetration in China's rural regions surged from 29% to 67%, with the number of Internet users in agricultural areas escalating from 178 million to 326 million (Figure 1) (Data source: The 35th to 53rd Statistical Reports on Internet Development in China, published by the China Internet Network Information Centre; available at https://www.cnnic.net.cn/). Data sourced from the China Internet Network Information Centre confirms this expansion. Concurrently, the academic discourse has evolved to consider how Internet usage influences farmers' formal borrowing behaviors. This evolution suggests that enhanced Internet access can mitigate credit constraints by improving information transparency [18], reducing transaction costs [19], and diminishing credit risks, thereby positively impacting farmers' formal borrowing activities [4]. However, the influence of digital technology extends beyond mere Internet usage; it necessitates a comprehensive examination through the lens of digital literacy.

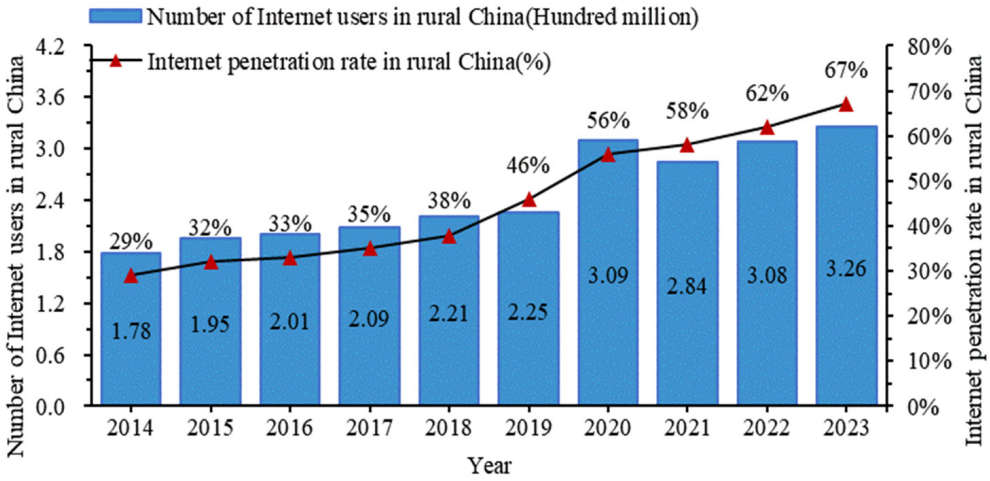


Figure 1. Trends in the number of Internet users and Internet penetration rate in rural China from 2014 to 2023.

Since 2013, research on digital literacy levels has gained traction [20]. The prevailing academic consensus, influenced by Eshet-Alkalai, posits that digital literacy encompasses many skills—intellectual, motor, social, and affective [21]. This multifaceted literacy includes competencies such as image literacy, re-creative literacy, pathway literacy, informational literacy, and social–emotional literacy [22]. It can be segmented into accessibility and extent of technology use, along with competencies in usage and transformation [23], measured across various domains, including learning, work, recreation, socializing, and digital financial management [24–26]. Although numerous studies have explored digital literacy's effects on sectors like education [27], sustainable production and consumption [28,29], healthcare [30], and political participation [31,32], the correlation between digital literacy and formal borrowing behaviors among farmers remains underexplored. This gap in research underscores a critical area for further inquiry: it examines how digital literacy influences the formal borrowing behaviors of farm households. The exploration of this relationship could provide vital insights into harnessing digital tools for enhancing financial access and economic empowerment in rural communities.

On this basis, this study employs the binary probit model and KHB method to empirically assess how digital literacy level affects the formal borrowing and lending behaviors

of farm households, as well as the pathways through which this influence manifests. This study makes several distinct contributions to the existing body of research. First, it provides a more comprehensive examination of how the digital literacy level influences farmers' formal borrowing behavior. This not only enriches the antecedents of formal borrowing behavior but also fills gaps in existing research. Second, it explicitly examines the mechanisms through which the digital literacy level influences the formal borrowing behaviors of farm households within a specific regional context, thereby deepening our understanding of the interplay between digital literacy and borrowing behaviors along various trajectories. This insight is particularly significant as it highlights the critical need for tailored digital literacy programs that can effectively enhance the financial capabilities and access of these households, potentially transforming their economic activities and sustainability [1]. Additionally, these research findings also provide insights and references for other developing countries facing similar credit constraints, contributing to the sustainable development and construction of developing countries [33].

The remaining sections of this study are structured as follows: Section 2 provides a theoretical analysis of the impact of digital literacy on the formal borrowing behavior of farm households and presents the research hypotheses. Section 3 describes in detail the data sources, variable selection, and model construction of the study. Section 4 presents the relevant results of the baseline regression, endogeneity test, robustness test, mediation effect test, and heterogeneity analysis of this study. Section 5 concludes the paper, proposes relevant strategies, and summarizes the limitations of the study and prospects for future research.

2. Theoretical Analyses

2.1. Digital Literacy Level and Formal Borrowing Behavior of Farm Households

Digital literacy is the systematic skill and strategy of using technology, cognition, emotion, and other elements in a digital environment, characterized by integration and interdisciplinarity [21]. It refers to the capacity of an individual to combine resources with their subjective initiative using digital technology [34,35]. In 2017, the International Federation of Library Associations and Institutions (IFLA) issued a statement on digital literacy, which argued that it involves an individual's capacity to creatively utilize the potential of digital tools, including two core components of media and information literacy (more insights can be found at the following link: https://repository.ifla.org/handle/123456789/1283, accessed on 18 August 2017). As a new form of human capital [36], this study defines the digital literacy level as the ability to analyze, evaluate, and communicate information using digital technology to solve practical problems, such as improving learning, optimizing collaboration, enhancing productivity, and performance [33]. The formal lending behavior of farm households refers to the lending behavior of farm households through formal financial institutions. Since the supply side of the rural lending market includes both formal and informal financial institutions [6], the lending behavior of farm households can be categorized into formal and private lending behavior. While formal financial institutions refer to those that are subject to general laws and are regulated by specialized banking regulators [6,37–39], informal finance, also known as private finance and informal finance, refers to institutions that are subject to general and commercial laws but are not regulated by specialized banking regulators [6].

An increased digital literacy level acts as a crucial driver for inducing positive financial behavior [40]. The swift development and universal application of digital technology have become an important medium for information exchange [41]. On the one hand, digital technology guarantees the continuous sharing of information, improves the accessibility of financial information to farmers [18], saves the time and costs associated with information searches [19], and helps to alleviate credit constraints due to information asymmetry. Conversely, digital technology saves financial service costs, lowers borrowing and lending risks, and simplifies the corresponding loan procedures, service procedures, etc. [42], which helps to alleviate the problem of credit constraints of farmers caused by higher transaction

costs. It is evident that an increase in digital literacy level can not only alleviate the problem of information asymmetry between farmers' borrowers and formal financial institutions but also reduce the service and transaction costs of both parties when borrowing and lending behaviors occur, thus positively affecting the formal borrowing and lending behaviors of farmers. In summary, the following hypothesis is proposed:

H1. *Digital literacy level positively and significantly affects farmers' formal borrowing behavior.*

2.2. Digital Literacy Level, Earnings, Social Networks, and Farmers' Formal Borrowing Behavior

An increased digital literacy level can increase operating, wage, and other types of earnings for farm households; improve their repayment ability; increase their confidence in borrowing; and thus alleviate formal credit constraints and promote the formal borrowing behavior of farm households. According to the theory of credit constraints, income level is crucial for alleviating credit constraints [43]. Employing digital technology can not only improve farmers' production efficiency and boost agricultural operating income [44], but also help farmers identify the new opportunities brought by the digital era, provide farmers with more job opportunities and more flexible working methods, and drive an increase in farmers' wage earnings [45]. Additionally, digital technology applications can also increase the level of other income types for farm households, thus raising their overall income [8]. Income reflects the debt-repayment capacity of farm households. As income rises, farmers' ability to repay improves, reducing the likelihood of credit constraints [46]. Increased income also heightens farmers' borrowing confidence, from the subjective confidence to overcoming the phenomenon of "self-exclusion" of financial behavior, thus increasing the possibility of formal borrowing behavior of farmers. Therefore, income may significantly mediate the relationship between digital literacy level and farmers' formal borrowing behavior. In summary, the following hypothesis is proposed:

H2. *An increased level of digital literacy can promote the formal borrowing behavior of farm households by increasing their earnings.*

An increased digital literacy level among farmers can expand their social scope, consolidate and strengthen social connections with kin and peers, enrich social networks, and promote information exchange, thereby alleviating formal credit constraints and facilitating farmers' formal lending behavior. According to social capital theory, the resources and support that farmers obtain through social networks can promote their behavior and decisions [47,48], thereby influencing their formal borrowing behavior. As digital technology proliferates and evolves, the social networks of people living in rural areas have transcended geographical limitations [49]. More and more farm households are more proactively participating in and creating social networks, so their social networks continue to expand [50]. On the one hand, rich social networks are conducive to facilitating information exchange, improving information asymmetry between farm household borrowers and formal financial institutions [51], easing credit constraints, and positively influencing the formal borrowing behavior of farm households. Conversely, as a form of social capital, social networks streamline processes, reduce transaction costs, and lower the cost of regulation through "acquaintanceship" [14], thus facilitating the realization of transactions [52]. For example, farmers with good banking relationships are more responsive to formal lending behavior [53]. Thus, social networks may act as mediators between the digital literacy level and formal lending behavior among farm households. In summary, the following hypothesis is proposed:

H3. *An increased level of digital literacy can promote the formal borrowing behavior of farm households by enriching social networks.*

Based on the above assumptions, an analytical framework is constructed to analyze how digital literacy levels affect the formal borrowing behavior of rural households (Figure 2).

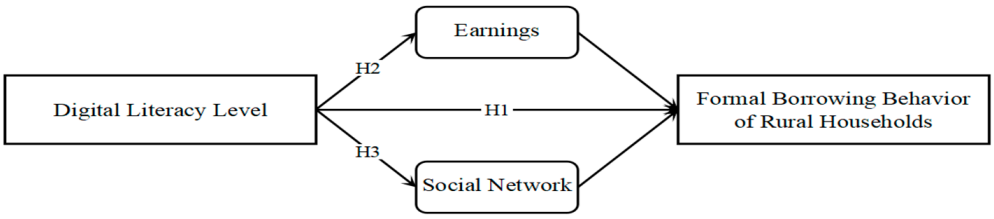


Figure 2. Analytical framework for the impact of digital literacy level on formal borrowing behavior of farm households.

3. Materials and Methods

3.1. Data Sources

Data for this study were sourced from the 2020 China Family Panel Studies (CFPS), conducted by Peking University's China Social Science Survey Centre. (Covering a wide range of mainland China's territory, the CFPS extends across 25 provinces, municipalities, and autonomous regions in China. Consisting of 16,000 household samples, it has the ability to reflect the socioeconomic conditions and household situations prevailing in most areas of China, thereby possessing a representative character in its survey findings.) The national survey data of CFPS has information about digital literacy and the formal borrowing behavior of farmers, which facilitates this paper's study of how digital literacy level influences their formal borrowing behaviors. Given the focus of the study on rural households, samples were chosen based on rural household registrations. Following the exclusion of samples with either missing observations or extreme values, a total of 6253 valid samples were acquired.

3.2. Variable Selection

3.2.1. Dependent Variable

The formal borrowing behavior of farmers is the dependent variable in this study, whether farmers borrow loans through formal channels, which is represented by a binary dummy variable. Due to the constraints imposed by the CFPS questionnaire, the present study employs an indirect methodology to identify the formal borrowing behavior of farmers. Referring to related studies [54–60], the CFPS2020 questionnaire asks "Whether you took out a loan to buy or renovate a home for purchasing or constructing a home, do you have any outstanding bank loans" and "In addition to the loan for purchasing or constructing or renovating a home, does your household have any other outstanding bank loans" as the measurement indicators. The presence of an outstanding bank loan can be regarded as an indirect indication of the farmer's use of formal borrowing channels. If the farmer responds affirmatively to either of the two aforementioned questions, the dependent variable receives a value of 1; otherwise, it receives a value of 0.

3.2.2. Primary Explanatory Variables

In this study, the primary explanatory variable is the digital literacy level. Digital technology was employed to assess the level of digital literacy among farmers in this research, which was defined as the basis of digital technology use for determining whether farmers possess the capability to utilize digital devices [24]. Further, the level of digital literacy of farm households was measured in terms of the extent of utilization of digital technology, and the variability in the ability of farm households to use digital technology [25]. The basis of digital technology use includes the extent of utilization of digital technology, the latter being a secondary indicator of the former. The utilization of mobile devices for Internet access was assessed in the CFPS2020 questionnaire to gauge farmers' engagement with digital technology, which was expressed as "Inuse". At the same time, considering the

differences in the ability of farmers to use digital technology [40,45,61], "Instudy" and "Information" served as the secondary indicators of the basis of digital technology use and are defined as the extent of utilization of digital technology. This provides a comprehensive assessment of digital literacy level based on the extent of digital technology utilization. Instudy is used to measure whether farmers engage in e-learning, while Information is used to assess the importance of the Internet in farmers' access to information.

3.2.3. Mediator Variables

Based on the theoretical analysis conducted earlier, the level of digital literacy may influence farmers' formal borrowing behavior through farmers' earnings and social networks. Based on existing studies [62,63], this study uses earnings and social networks as mediating variables to explore this mechanism. In the CFPS questionnaire, we use "the net household income per capita of farmers in the previous year" and "expenditure on favors and courtesies of farmers in the past 12 months" to measure earnings and social networks, respectively.

3.2.4. Control Variables

Integrating the characteristics of this study with insights from the related literature [14,56,60,64–68], the selection of control variables mainly contains three categories: personal, family, and regional characteristics. Control variables for personal characteristics encompass age, gender, educational attainment, marital status, and health status. Age reflects where farmers are in their life cycle, impacting their economic activities and risk tolerance. Gender influences how farmers access resources. Education level indicates farmers' knowledge and skills, affecting their understanding. Marital status may affect technology adoption, showing family responsibilities and financial pressures. Control variables related to household characteristics consist of household size and the aggregate value of consumer durables, whether the land is rented out, whether the household members own individually titled houses, and whether they work in agricultural production. The number of family members indicates the household's size and demographic makeup, impacting its financial dynamics. The worth of durable goods reflects the household's financial standing and lifestyle, affecting its borrowing capacity, while decisions regarding land leasing and agricultural involvement relate to the household's primary economic activities and income sources, crucially influencing its economic stability. Regional characteristics are the area where the farm household is located. The regional variable was chosen to consider the differing economic development levels across regions and how they might affect farm households' informal borrowing behavior.

3.2.5. Descriptive Statistical Analysis

Table 1 shows the definitions of the variables and the results of descriptive statistics. The variables Y, Inuse, Instudy, gender, marriage, house, land, agric, and region are encoded using 0 and 1, where 1 denotes the presence of a category and 0 indicates its absence. However, computing the average and deviation of binary variables is statistically erroneous. This arises because the values of these variables themselves indicate the existence or non-existence of categories, rendering their averages and deviations devoid of practical significance. Therefore, the study refrained from computing the mean and standard deviation of the nine aforementioned binary variables. The remaining data show that the age distribution of rural households is predominantly centered around the 30–50 age bracket, probably because farmers in this age group are more inclined to borrow through formal channels. The mean years of education for interviewees is only 9.24, reflecting the generally limited educational attainment in rural regions, which may be an important factor affecting the improvement of the digital literacy level of farm households.

Table 1. Variable definition and descriptive statistical analysis findings.

Variable Type	Variable Name	Variable Definition	Mean	Standard Deviation
Dependent Variable	Y	Whether to borrow through formal channels (Yes = 1, No = 0)	Not	Not
Primary Explanatory Variables	Inuse	The utilization of mobile devices for Internet access (Yes = 1, No = 0)		
	Instudy	Whether to use spare time to study online (Yes = 1, No = 0)		
	Information	The significance of the Internet as a channel for information (Very unimportant = 1, relatively unimportant = 2, moderately important = 3, relatively important = 4, very important = 5)	3.474	1.495
Mediator Variables	Earnings	The logarithm of per capita household net income over a 12 month period is recorded (RMB)	9.528	0.810
	Social Network	The logarithm of the 12 months favors the expenditure of the farmer household (RMB)	7.113	2.363
Individual Characteristics	Age	Age of respondents (Age under 30 = 1, 30–50 = 2, over 50 = 3)	2.141	0.759
	Gender	Gender of respondent (Male = 1, Female = 0)	Not	Not
	Education	Maximum years of education of the respondents (Year)	9.236	2.980
	Health	Physical health status of respondents (Unfit = 1, moderate = 2, well = 3, relatively well = 4, very healthy = 5)	2.800	1.202
	Marriage	The respondents' marital status (1 = married, 0 = unmarried)	Not	Not
Family Characteristics	Family	Family size (person)	4.662	2.024
	Assets	Logarithm of the total value of consumer durables (RMB)	8.956	2.724
	House	Whether family members own individual property rights in the home (Yes = 1, No = 0)	Not	Not
	Land	Whether to lease land (Yes = 1, No = 0)		
	Agric	Whether engaged in agricultural production or business activities (Yes = 1, No = 0)		
Regional Characteristics	Region	The eastern region = 1, the central and western regions = 0		

3.3. Model Construction

3.3.1. Benchmark Regression Model

To investigate how digital literacy level affects the formal borrowing behavior of farmers, this paper takes "whether farmers borrow through formal channels" as the dependent variable and the basis of digital technology use and its secondary indicator of the extent of utilization of digital technology as an explanatory variable and then introduces age, gender, education, health, marriage, family, assets, house, land, agricultural, and region as 11 control variables, to jointly construct the analytical framework and assess how digital literacy level affects the formal borrowing and lending behaviors of agricultural households.

Prior research has largely utilized binary logit or probit models to analyze farmers' borrowing behavior [67,69,70]. In this research, the dependent variable of farmers' formal borrowing behavior is a dichotomous variable, Y = 1 if farmers take loans through formal channels, and Y = 0 if farmers do not take loans or if farmers do not take loans through

formal channels. As a result, we use a binary probit model to explore how the digital literacy level impact farmers' formal borrowing behavior. The following equation is applied for this analysis:

$$\text{Prob}(Y_i = 1) = \varphi(\alpha_0 + \alpha_1 \text{Inuse} + \alpha_2 \text{Control}_i + \alpha_3 \text{Region}_i + \varepsilon_i) \quad (1)$$

$$\text{Prob}(Y_i = 1) = \varphi(\beta_0 + \beta_1 \text{Instudy} + \beta_2 \text{Control}_i + \beta_3 \text{Region}_i + \varepsilon_i) \quad (2)$$

$$\text{Prob}(Y_i = 1) = \varphi(\gamma_0 + \gamma_1 \text{Information} + \gamma_2 \text{Control}_i + \gamma_3 \text{Region}_i + \varepsilon_i) \quad (3)$$

$$\text{Prob}(Y_i = 1) = \varphi(\delta_0 + \delta_1 \text{Instudy} + \delta_2 \text{Information} + \delta_3 \text{Control}_i + \delta_4 \text{Region}_i + \varepsilon_i) \quad (4)$$

Y_i denotes whether the farm household obtains a loan through formal channels; Inuse represents the basis of digital technology use among agricultural households; Instudy and Information are secondary indicators of the basis of digital technology use, indicating the extent of utilization of digital technology among farm households; Control_i denotes the control variable (i = 1, 2, . . ., 11); Region_i denotes area fixed effects; and ε_i is a random disturbance component that measures factors influencing the formal borrowing behavior of farm households that are not easily observed directly.

3.3.2. Model for Assessing Mediation Effect

The model of the mediating effect is often employed in the three-step mediation method [71]. This method has become the most widely used mediation effect test method due to its relatively simple operation and since it is easy to understand and master. However, recent scholarly observations highlight that this approach applies solely under conditions where both explanatory and mediating variables remain continuous, and if either of the primary variables and the intermediary variables is a dichotomous variable, the regression coefficients of the model will be biased, which will lead to the regression results being affected. It is possible that the model has a more serious endogeneity problem when this method is used. Given that the dependent variable in this study exhibits dichotomous characteristics, the three-step method cannot be used for the mediation effect test. We refer to Preacher, Hayes' Bootstrapping mediation effect test method to construct the following model [72]:

$$Y_i = i_0 + a\text{Inuse}_i + \gamma_0 \text{Control}_i + \varepsilon_{0i} \quad (5)$$

$$M_i = i_1 + b\text{Inuse}_i + \gamma_1 \text{Control}_i + \varepsilon_{1i} \quad (6)$$

$$Y_i = i_2 + a'\text{Inuse}_i + cM_i + \gamma_2 \text{Control}_i + \varepsilon_{2i} \quad (7)$$

In Equations (5)–(7), Y_i, Inusei, and M_i denote the dependent variable, core explanatory variables, and mediating variables, respectively. i_0, i_1, and i_2 are intercept terms; a, b, and a′ are regression coefficients of Inuse; γ_0, γ_1, and γ_2 are regression coefficients of control variables; c denotes regression coefficients of the mediating variables; and ε_{0i}, ε_{1i}, and ε_{2i} denote the random perturbation terms. Equation (5) illustrates the collective impact of digital literacy levels on farmers' formal borrowing behavior; Equation (6) delineates how the digital literacy level affects earnings or the social network; and Equation (7) represents the indirect influence of digital literacy level on farmers' formal borrowing behavior via earnings or social network. The following are the specific steps of the mediation effect test: Initially, assess the significance of b and a′. Significance indicates the exclusion of 0 from the 95% confidence interval, suggesting the existence of a mediation path; nonsignificance implies the absence of such a path. Subsequently, evaluate the significance of c. Significance implies a partial mediation effect, while nonsignificance suggests a complete mediation effect.

3.3.3. The KHB Model

Although the Bootstrapping method can verify the existence of mediating effects, it cannot calculate the indirect effect of each mediating variable. The KHB model allows for the dissection of a variable's overall effect into direct and indirect components, enabling

the computation of the precise contribution of each mediating variable [73]. Compared to alternative mediation effect tests, the KHB method offers several advantages [74]. Firstly, it computes the disparity between outcomes derived from the coefficient difference and coefficient product methods in mediation effect analyses involving nonlinear probabilistic models. Secondly, it presents effects measured in Probit or Logit models. Thirdly, it effectively mitigates the sample self-selection issue inherent in the model while also addressing endogeneity problems arising from reverse causation, variable omission, and similar factors. Furthermore, the method's calculation process is simpler but yields comparable or superior results. It has undergone rigorous scrutiny by scholars such as Morgan, who has affirmed its merits [75]. Therefore, to further investigate the total, direct, and indirect impacts of intermediary factors on digital literacy level and the formal borrowing conduct of rural households, this study utilizes the KHB model for mediating effect estimation, with the model expression presented as follows:

$$Y^* = a_E + b_E X + c_E Z + d_E C + \mu_E \tag{8}$$

$$Y^* = a_F + b_F X + d_F C + \mu_F \tag{9}$$

In Equations (8) and (9), Y* is the unobservable dichotomous latent variable Y, X represents the core explanatory variable Inuse, Z stands as the intermediary variable, while C functions as the control variable. Within this paper, using binary Probit for regression, the final direct and total effects are

$$\beta_E = \frac{b_E}{g_E}, \beta_F = \frac{b_F}{g_F} \tag{10}$$

β_E and β_F in Equation (10) are the residual standard errors of Equations (8) and (9), and $\beta_E < \beta_F$. So the indirect effect is

$$\beta_F - \beta_E = \frac{b_F}{g_F} - \frac{b_E}{g_E} \tag{11}$$

4. Results

4.1. Analysis of Model Regression Results

Table 2 reflects the results of the baseline regression of the level of digital literacy on the formal borrowing and lending behavior of farm households, with robust standard errors in parentheses to correct for heteroskedasticity to ensure the reliability of the regression results.

Models (1) to (4) display the regression outcomes incorporating control variables. The regression coefficients of both Inuse and Information are significantly positive at a 1% level of significance and the regression coefficients regarding Instudy demonstrate statistically meaningful positive patterns at the 5% significance threshold. This suggests that heightened digital literacy levels substantially impact farmers' credit behavior regarding formal credit institutions, thereby confirming hypothesis H1.

Further analysis of the regression outcomes from models (1) and (4) reveals that the impact of Inuse is measured at 0.171, the effect of Instudy is 0.108, and the effect of Information is 0.057, which can be attributed to the fact that most Chinese farmers primarily engage with digital technology through basic financial transactions, such as borrowing and lending via online banking. Instudy, as a crucial method for enhancing farmers' digital literacy level, demands that they allocate additional time to self-directed online education, but fewer farmers are currently engaged in online learning, resulting in a smaller effect on the formal borrowing and lending behavior of farmers. The reason why Information has the lowest impact may be that it requires more from farmers. Before advancing, farmers must enhance their digital skills via online educational resources and then transform the knowledge that they have learned into a "means of production". For example, if a farmer wants to know the interest rates of loans from major banks, they need to collect relevant information on the Internet to make a loan decision. However, this certainly makes it more

difficult for farmers to apply the information, thus minimizing the impact on their formal lending behavior. The regression findings above indicate that Chinese farmers' present digital literacy level primarily manifests in their foundational use of digital tools, with less conspicuous proficiency demonstrated in the advanced utilization of such technologies [76].

Table 2. Results of the baseline regression model.

Variable	(1)	(2)	(3)	(4)
Inuse	0.171 ***			
	(0.045)			
Instudy		0.126 **		0.108 **
		(0.053)		(0.053)
Information			0.060 ***	0.057 ***
			(0.014)	(0.014)
Age	−0.095 ***	−0.135 ***	−0.104 ***	−0.101 ***
	(0.034)	(0.032)	(0.033)	(0.033)
Gender	0.008	0.008	0.009	0.009
	(0.037)	(0.036)	(0.037)	(0.037)
Education	0.017 **	0.018 **	0.017 **	0.014 *
	(0.007)	(0.007)	(0.007)	(0.007)
Health	0.047 ***	0.046 ***	0.049 ***	0.050 ***
	(0.016)	(0.016)	(0.016)	(0.016)
Marriage	0.160 ***	0.187 ***	0.151 ***	0.164 ***
	(0.054)	(0.055)	(0.054)	(0.055)
Family	0.066 ***	0.065 ***	0.066 ***	0.066 ***
	(0.009)	(0.009)	(0.009)	(0.009)
Assets	0.075 ***	0.077 ***	0.075 ***	0.074 ***
	(0.009)	(0.009)	(0.009)	(0.009)
House	−0.448 ***	−0.449 ***	−0.457 ***	−0.457 ***
	(0.070)	(0.069)	(0.070)	(0.069)
Land	−0.225 ***	−0.222 ***	−0.224 ***	−0.223 ***
	(0.050)	(0.049)	(0.050)	(0.050)
Agric	−0.071	−0.070	−0.071	−0.071
	(0.044)	(0.044)	(0.044)	(0.044)
_cons	−1.483 ***	−1.345 ***	−1.547 ***	−1.541 ***
	(0.158)	(0.154)	(0.161)	(0.160)
Region Effect	Yes	Yes	Yes	Yes
Pseudo R^2	0.055	0.054	0.056	0.057
N	6253	6253	6253	6253

Note: Standard errors robust to heteroskedasticity are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression results from models (1) to (4) reveal several significant findings: Firstly, at the personal characteristics level, age demonstrates a marked adverse relationship at the 1% significance level, indicating that senior farmers are less disposed towards utilizing formal channels for borrowing, possibly due to their reduced risk tolerance and preference for economic stability [77]. Conversely, health and marital status display significant positive correlations, indicating that healthier and married farmers are more likely to opt for formal loans. Secondly, regarding household characteristics, both household size and the total value of consumer durables exert a positive and significant influence on farmers' borrowing behavior. Household size indirectly reflects labor availability, with larger households having higher repayment capacity and thus a greater likelihood of formal borrowing [78]. Similarly, higher values of consumer durables signify better repayment capacity as perceived by formal credit institutions, leading to increased formal lending opportunities for farmers [4]. Lastly, the ownership of individual title housing and involvement in land transfer significantly deter formal borrowing behavior among farm households at the 1% significance level, contrary to previous studies [13]. This may be attributed to the fundamental economic and livelihood role of housing and land for most farm households. Formal borrowing entails higher interest rates and risks, potentially resulting in an asset mortgage or auction in the case of default, thereby harming their livelihoods.

4.2. Model Endogeneity Test

Despite employing a fixed-effects model in the previous benchmark regression to mitigate endogeneity issues arising from variable omissions, there remains the challenge of unobservable individual characteristics. Furthermore, the formal borrowing behavior might reciprocally enhance farmers' digital literacy level through financial education and the accrual of experience in formal lending, thus introducing potential bias from reverse causality into the results of this study. Instrumental variables are used to address potential endogeneity issues to ensure the reliability of the empirical results.

The research employs a dual-phase regression approach to formulate an Instrumental Variable Probit (IV-Probit) framework and Conditional Mixed-Process (CMP) model to examine potential endogeneity issues within the model. This paper refers to existing studies by scholars [79] and adopts the logarithmic form of the communication expenditures of farm households in 2018 (referred to as "Inphone") as the instrumental variable of digital literacy level. At the theoretical level, Inphone satisfies the two conditions of relevance and homogeneity. First, the communication expenditure of farm households reflects, to a certain extent, their investment status in digital devices and other aspects, which correlates closely with the foundation of Internet usage and satisfies the condition of correlation. Second, farmers' communication expenditures in 2018 did not directly affect their formal borrowing behavior in 2020, thus satisfying the homogeneity condition.

The outcomes from both testing approaches are detailed in Table 3. The findings from the initial and subsequent estimation stages of the IV-Probit model are displayed in Model (5) and Model (6). Firstly, based on the regression outcomes of the IV-Probit model's initial stage, the coefficient of Inphone is notably positive at the 1% significance threshold, demonstrating that the instrumental variables fulfill the correlation prerequisite. Secondly, according to the regression findings from the subsequent stage, the model's Wald chi2 statistic is 39.34, signifying significance at the 1% level, suggesting the presence of an endogeneity issue in the model. Consequently, employing instrumental variables becomes imperative. In addition, the outcomes of the weak instrumental variable examination reveal that both the AR and Wald test metrics stand at 41.78 and 10.55, respectively. Both metrics surpass 10 and hold significance at the 1% level, suggesting that Inphone does not qualify as a weak instrumental variable. Finally, following the rectification of the endogeneity issue within the model, the impact of digital literacy level on farmers' formal borrowing behavior demonstrates a notably positive association. The results of the one-stage and two-stage regressions of the CMP methodology are presented in model (7) and model (8), respectively. With a significance level of 1%, the parameter atanhrho_12 in the endogeneity test stands at −0.307, suggesting that the CMP methodology is suitable for this investigation. After tackling the endogeneity problem, the positive and substantial influence of farmers' digital literacy level on their formal borrowing behavior persists without faltering. The findings' robustness was confirmed by the estimation outcomes of both approaches.

Table 3. The endogeneity assessment for the model.

Var	IV-Probit		CMP	
	(5)	(6)	(7)	(8)
Inuse		6.232 ***		0.256 ***
		(1.919)		(0.061)
Inphone	0.030 ***		0.122 ***	
	(0.008)		(0.028)	
Control Variable	Yes	Yes	Yes	Yes
Region Effect	Yes	Yes	Yes	Yes
Wald Chi2		39.34 ***		
Atanhrho_12				−0.307 ***
				(0.091)
Observations	4154	4154	4154	4154

Note: Standard errors, marked in parentheses, exhibit robustness. *** $p < 0.01$.

4.3. Model Robustness Tests

4.3.1. Replacement of the Model

Table 4 exhibits the findings from the tests assessing robustness. The results from the regression employing the binary Logit model are demonstrated in Model (9), and it is found that the regression results are the same as those obtained from the binary Probit model, with the key explanatory factor Inuse showing significant positivity at the 1% significance level, which suggests that alterations in model assumptions do not influence the findings of the analysis concerning digital literacy's impact on farmers' formal borrowing behavior.

Table 4. Results of robustness analysis.

Var	Change the Model Form (9)	Delayed Onephase Regression (10)
Inuse	0.287 ***	0.211 ***
	(0.078)	(0.040)
Control Variable	Yes	Yes
Region Effect	Yes	Yes
Obs	6253	8331
Pseudo R^2	0.056	0.047

Note: The robust standard errors are enclosed within parentheses. *** $p < 0.01$.

4.3.2. Lagging a Period

The empirical results for a single period in the database may be subject to change. Therefore, this paper lags by one period of data and uses the cross-section data of CFPS 2018 for regression, the regression still uses the Probit model, and model (10) is the result of the regression. The regression findings reveal that even with a lag of one period, the primary explanatory variable "Inuse" maintains a statistically significant positive effect at the 1% confidence level. This shows that the model is relatively robust and convincing.

4.4. Mechanism Tests

4.4.1. Mediated Effects Test

This section uses the Bootstrapping method to test whether there is a mediating effect of earnings and social network between Inuse and Y. Table 5 displays the precise examination outcomes. Path 1 and Path 2 denote the immediate and consequential impacts of the intermediary factors, earnings, and social network connections, controlling for other influences, and the upper and lower bound intervals of the mediating variables do not contain zero. The upper and lower limit intervals of the effects do not contain 0, which indicates that both earnings and social networks have significant mediating effects between Inuse and Y. Then, hypotheses H2 and H3 are proved.

Table 5. Test results of mediating effect between Inuse and farmers' formal lending behavior.

Effect	Inuse → Earnings → Y (Path 1)			Inuse → Social Network → Y (Path 2)		
	Coef	The Level of Confidence Interval Is Set at 95%		Coef	The Level of Confidence Interval Is Set at 95%	
		Lower	Upper		Lower	Upper
Indirect effect	0.014 *** (0.002)	0.010	0.018	0.004 *** (0.001)	0.002	0.006
Direct effect	0.032 *** (0.013)	0.007	0.057	0.043 *** (0.013)	0.016	0.069

Note: The robust standard errors are presented within parentheses. *** $p < 0.01$.

4.4.2. Analyzing the Direct and Indirect Effects Separately

From the examination of the mediation effect discussed earlier, it is evident that Inuse can influence Y through two intermediary factors: earnings and social network. Sub-

sequently, we employ the KHB approach to further break down the direct and indirect impacts of Inuse and quantify the extent of contribution from the two mediating variables in the indirect influence. The findings are displayed inTable 6. First, considering Path 3, the cumulative impact of Inuse on Y is 0.305, demonstrating significance at the 1% level; the direct impact is 0.219, which is also significant at the 1% level; and the indirect impact is 0.087, similarly significant at the 1% level. This indicates that the intermediate factor, earnings, partially mediates the effect of Inuse on Y. Second, examining Path 4, the total impact of Inuse on Y is 0.295, with direct and indirect impacts of 0.269 and 0.027, respectively, all of which pass the 1% significance test. This suggests that the intermediary variable social network similarly plays a partial mediating role in the effect of Inuse on Y. Thirdly, within the mediated impact of Inuse on Y, the indirect share of earnings and social network is 82.37% and 17.63%, respectively, which indicates that earnings play a greater mediating role than social networks in Y. The possible reason for this is that with the increase in the level of digital literacy of farmers, farmers are able to more conveniently access and understand Internet financial products, and the earnings of farmers may be improved after they purchase financial products, thus sending a signal to formal financial institutions that they have the ability to repay and increasing the availability of formal credit to farmers, which implies that farmers with substantial earnings have a higher probability of acquiring bank loans. Conversely, social capital predominantly embodies a social network relationship, which has a greater influence on the informal borrowing behavior of farmers and a relatively smaller influence on their formal borrowing behavior.

Table 6. Decomposition of the indirect effect of Inuse affecting the formal borrowing behavior of farm households.

Path	Decomposition	
Inuse → Earnings → Y (Path 3)	Total effect	0.305 *** (0.078)
	Direct effect	0.219 *** (0.078)
	Indirect effect	0.087 *** (0.014)
	Indirect effect proportion	82.37%
Inuse → Social Network → Y (Path 4)	Total effect	0.295 *** (0.077)
	Direct effect	0.269 *** (0.077)
	Indirect effect	0.027 *** (0.008)
	Indirect effect proportion	17.63%

Note: Robust standard errors are reported within brackets. *** $p < 0.01$.

4.5. Heterogeneity Analysis

Previous research has established that the level of digital literacy substantially influences farmers' formal borrowing patterns, although the influence of digital literacy might differ depending on farmers' diversity [80–82]. Therefore, this paper will analyze the heterogeneity according to gender, age, education, and region of the farmers.

Table 7 demonstrates the basic characteristics of the distribution of variables for heterogeneity analysis. Gender heterogeneity is divided into two categories: female and male, with more males in the observed sample; age heterogeneity is divided with reference to the definition of different age groups by the United Nations Health Organization (WHO), which classifies people younger than 45 years old as young people, and people older than or equal to 45 years old as middle-aged and old people, with a higher number of farmers below 45 years of age; and educational heterogeneity is divided into low educational attainment (with fewer than or equal to six years of schooling), intermediate educational attainment (with more than six years of schooling and fewer than or equal to 15 years), and

high education (more than 15 years of education), with more farmers having secondary education; and regional heterogeneity is divided into two categories, central and western China and eastern China, with farmers in the central and western regions accounting for the vast majority of the total.

Table 7. Basic description of heterogeneity analysis variables.

Category of Variables		Mode	Frequency	Relative Frequency
Gender	Female	1.00	2697	43.13%
	male		3556	56.87%
Age	Age under 45	0.00	3220	51.50%
	45 years old and above		3033	48.50%
Education	Inferior Education	2.00	1606	25.68%
	Secondary Education		3988	63.78%
	Higher Education		659	10.54%
Region	Central and western regions	0.00	4627	74.00%
	East Region		1626	26.00%

Table 8 reports the results of the gender and age heterogeneity analyses, whereas models (11) to (14) are the results of the regressions on gender heterogeneity. For males, Inuse, Instudy, and Information are all positively significant at 1% level of significance, and the level of digital literacy greatly impacts the formal loaning and borrowing practices among male agriculturalists, while for female farmers, both Inuse and Instudy have no significant effect on their formal borrowing behavior. Only Information positively affects the formal borrowing behavior of female farmers at a 5% level of significance. This difference may be because the main decision-makers in rural households tend to be men due to the influence of traditional Chinese culture and family economic status, so male farmers may be more inclined to actively use the Internet to improve their digital literacy to better enhance the reliability of household financial decisions. Models (15) to (18) show the regression results of age heterogeneity. The regression coefficients of Inuse and Instudy on the formal borrowing behavior of middle-aged and old farmers exhibit significance at the 1% level, whereas significance is absent for their youthful counterparts. The regression coefficients of Information on the formal borrowing behavior of both young and middle-aged and old farmers are significantly positively correlated, but the effect of Information is more significant for middle-aged and old-aged farmers. It can be seen that the main formal borrowing group in rural areas is middle-aged and old farmers. Middle-aged and old farmers have some savings after a long period of farming or working outside, and they have the willingness and repayment ability to borrow from the bank, while young farmers have a shorter working time and less savings, and they do not have enough repayment ability yet. However, youthful agriculturalists demonstrate a greater aptitude for acquiring knowledge and possess a heightened awareness of digital tools than middle-aged and old farmers due to their age, which leads to a larger regression coefficient of Information on the formal borrowing behavior of young farmers.

Table 9 reports the results of the analyses of educational attainment and regional heterogeneity. Regression findings spanning from model (19) to model (24) elucidate how the digital literacy level influences the formal borrowing behavior of agricultural households across diverse educational durations. The findings indicate a significant and positive impact of Inuse on the formal borrowing practices among farmers with lower and secondary levels of education, and Inuse has the most significant and largest effect on farmers with lower education. Information significantly and positively affects the formal borrowing behavior of farmers with secondary education at a 1% level of significance. However, the test of the significance of digital literacy level on formal borrowing behavior of higher educated farmers was not passed. The reason for this is that farmers with secondary and lower education are deficient in digital literacy due to their knowledge, which makes it easier for them to fall into information asymmetry and allows formal

lending behavior to occur with a relative lag. However, as the level of Internet accessibility in rural areas of China increases year by year, digital financial tools become more common and easy to access and learn, resulting in a significant increase in their level of digital literacy, while farmers with higher education have already mastered the relevant digital skills and have higher financial literacy and digital literacy, so digital literacy does not have a significant impact on their lending behavior. Models (25) to (28) reflect the heterogeneous results for eastern and non-eastern China. Inuse significantly and positively impacts the formal borrowing tendencies of farmers across both the eastern and central-western regions, with a notably more pronounced effect observed among farmers residing in the latter areas. One potential explanation is that the degree of economic advancement in China's eastern area surpasses that of the central and western regions. This results in a more widespread adoption of the Internet among farmers in the east, thereby diminishing the significance of the increase in Internet usage. As the digital economy advances swiftly and Internet accessibility surges in the central and western regions, more and more farmers are learning financial knowledge independently on the Internet and improving their level of digital literacy as a way to meet their formal borrowing needs. Therefore, enhancing digital literacy has the potential to reduce the "digital gap" among farmers across various Chinese regions and improve the formal borrowing conduct of farmers residing in underdeveloped areas.

Table 8. Heterogeneity analysis of age and gender.

Var	Female		Male		Young People		Middleaged and Senior People	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Inuse	0.103		0.221 ***		0.079		0.196 ***	
	(0.069)		(0.060)		(0.076)		(0.057)	
Instudy		−0.011		0.189 ***		0.051		0.341 ***
		(0.084)		(0.069)		(0.060)		(0.112)
Information		0.053 **		0.060 ***		0.055 **		0.049 ***
		(0.022)		(0.018)		(0.023)		(0.017)
Control Variable	Yes		Yes		Yes		Yes	
Region Effect	Yes		Yes		Yes		Yes	
N	2697		3556		3220		3033	

Note: Robust standard errors are presented within brackets. ** $p < 0.05$, *** $p < 0.01$.

Table 9. Heterogeneity analysis of education and region.

Var	Inferior Education		Secondary Education		Higher Education		Central and Western Regions		Eastern Region	
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Inuse	0.239 ***		0.126 **		0.227		0.154 ***		0.228 **	
	(0.079)		(0.055)		(0.282)		(0.051)		(0.099)	
Instudy		0.450 *		0.113 *		0.025		0.146 **		−0.031
		(0.232)		(0.064)		(0.106)		(0.060)		(0.117)
Information		0.030		0.069 ***		0.040		0.048 ***		0.087 ***
		(0.023)		(0.017)		(0.065)		(0.016)		(0.028)
Control Variable	Yes		Yes		Yes		Yes		Yes	
Region Effect	Yes		Yes		Yes		Yes		Yes	
Obs	1606		3988		659		4627		1626	

Note: Standard errors are reported in robust parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and Policy Implications

5.1. Conclusions

As an important microeconomic subject in the rural financial market, the level of digital literacy of rural households has become an important factor affecting farmers' formal lending behavior, which is linked to the sustainable progression of the entire rural financial framework. The examination of conceivable avenues to foster the formal borrowing conduct of agricultural households through the perspective of digital literacy is of great theoretical and practical importance for easing formal credit constraints for farmers, accelerating the building of rural digital communities, and promoting rural revitalization. This study uses the 2020 CFPS data. Firstly, we use the Probit model to conduct regression

analysis; secondly, we use the IV-Probit and CMP methods to conduct endogeneity test; and finally, we use Bootstrapping and KHB method to conduct mechanism analysis, for a more comprehensive empirical investigation into the influence of digital literacy level on the formal borrowing behaviors of farmers and the mechanism of their role. The following research findings emerge:

1. The level of farmers' digital literacy level makes a notable positive impact on their formal borrowing conduct. Subsequent examinations reveal that the basis of digital technology use makes the greatest contribution, whereas the extent of utilization of digital technology makes a comparatively lesser contribution. The outcomes of the regression analysis still show good robustness after the introduction of the Logit model, by lagging one period for the robustness test and using an instrumental variable method for the endogeneity test.
2. Mechanistic analysis indicates that earnings and social network are the main pathways through which the digital literacy level affects the formal borrowing behavior of farmers, with both playing a partially mediating role, but the indirect effect of earnings is greater. Specifically, enhancing digital literacy level can notably boost farmers' earnings and enhance their social connections, whereas earnings and social networks positively influence farmers' adoption of formal borrowing practices. Meanwhile, among the indirect effects of digital literacy level affecting farmers' formal borrowing behavior, the indirect effects of earnings and social networks account for 82.37% and 17.63%, respectively. This indicates that earnings are much stronger than social networks in mediating the effect.
3. The analysis of diversity demonstrates that the positive effect of increasing digital literacy levels is more significant on the formal borrowing behavior of male, middle-aged, and old farmers, and the impact is more pronounced among less-educated farmers in central and western areas, whereas its significance is reduced for formal borrowing behaviors among female, youthful, and highly educated farmers, as well as farmers in the eastern regions.

5.2. Policy Implications

Based on the research outcomes above, we advocate the subsequent policy implications:

Firstly, the enhancement of digital literacy levels should be sped up among rural households, especially the extent of utilization of digital technology. First, the government should boost its funding for rural digital facilities and elevate the penetration rate of internet services in rural areas to guarantee that rural households have the basic ability to use digital technology. Second, the government should promote the popularization of and education about rural digital technology and financial literacy and establish a sound rural digital education system, to further improve the capacity of rural families in utilizing digital technology. Finally, the government should cooperate with formal rural financial service institutions to popularize rural households' digital financial knowledge, help rural residents understand financial products, and guide farmers to use formal credit services correctly.

Secondly, emphasis should be placed on strengthening digital technology training for middle-aged, elderly, low-educated, and male farmers, as well as including those residing in central and western areas. On the one hand, Chinese governments at all levels should prioritize the allocation of more Internet facilities to rural areas in central and western China to make up for the relative backwardness of their economic development, the lack of formal financial institutions, and the poor availability of formal borrowing and lending and thus leverage digital literacy to encourage farmers' engagement in official borrowing and lending activities within the locality. On the other hand, the government should provide targeted digital technology training for middle-aged, elderly, low-educated, and male farmers, such as hands-on teaching on platforms such as WeChat, Alipay, and online digital education, to enhance their intrinsic motivation to engage in formal lending. Concurrently, it is recommended that governments integrate digital inclusion efforts with

broader rural financial system reforms, such as the expansion of agricultural insurance, in order to enhance the sustainability and inclusiveness of rural financial systems.

Thirdly, the authorities ought to implement extensive strategies aimed at boosting the earnings of farmers while broadening their social networks. On the one hand, the government can formulate supportive policies to encourage farmers to use digital technology to participate in new economic activities, such as e-commerce and digital agriculture, to broaden their earnings-generating channels; on the other hand, the government should promote the role of new agricultural management bodies, facilitating the exchange of information and cooperation among farmers, and enriching the social network of farmers, thereby facilitating their formal borrowing and lending behaviors.

Although centered on Chinese farmers, this study's discoveries and policy insights hold universal significance, extending support to governments in underdeveloped regions sharing similar contexts to China. It facilitates the alleviation of formal credit limitations among rural households by advancing digital infrastructure and implementing reforms in rural financial frameworks.

5.3. Limitations and Perspectives

Naturally, this study exhibits certain limitations and deficiencies. Firstly, the data utilized herein are cross-sectional and thus unable to capture the dynamic changes in farmers' digital literacy levels. Secondly, the assessment of farmers' digital literacy primarily focuses on technology adoption, learning, and information access, yet digital literacy level is a multifaceted concept requiring a broader range of metrics for more accurate evaluation. Subsequent research endeavors could enhance refinement in these areas.

Author Contributions: Conceptualization, Z.Z. and Z.L.; methodology, Z.Z.; software, Z.L.; validation, Z.Z., Z.L. and F.W.; formal analysis, G.C.; investigation, M.D.; resources, Z.L.; data curation, Z.Z.; writing—original draft preparation, Z.Z.; writing—review and editing, F.W.; visualization, Z.L.; supervision, F.W.; project administration, J.Z.; funding acquisition, F.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the 2022 Sichuan Technology Planning Project (grant numbers 2022JDTD0022).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Issahaku, H.; Mahama, I.; Addy-Morton, R. Agricultural labour productivity and credit constraints: Implications for consumption in rural Ghana. *Afr. J. Econ. Manag. Stud.* **2020**, *11*, 331–351. [CrossRef]
2. Xu, J.; He, W.; Liu, Z.; Zhang, H. How do property rights affect credit restrictions? Evidence from China's forest right mortgages. *Small-Scale For.* **2021**, *20*, 235–262. [CrossRef]
3. Gong, M.; Wang, X.; Li, C. Research on the current situation of rural land transfer and its influencing factors under the background of the reform of "Three Rights Separation". *NingXia Soc. Sci.* **2019**, *1*, 92–101.
4. Zhang, W.; Wang, J. Analysis of rural households' borrowing behavior and its influencing factors in western China. *Procedia Comput. Sci.* **2022**, *199*, 1074–1081. [CrossRef]
5. Elias, H. Multiple credit constraints and borrowing behavior of farm households: Panel data evidence from rural Ethiopia. *Ethiop. J. Econ.* **2018**, *27*, 57–90.
6. Binswanger, H.P.; Khandker, S.R. The impact of formal finance on the rural economy of India. *J. Dev. Stud.* **1995**, *32*, 234–262. [CrossRef]
7. Pitt, M.M.; Khandker, S.R. The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? *J. Political Econ.* **1998**, *106*, 958–996. [CrossRef]
8. Choung, Y.; Chatterjee, S.; Pak, T.Y. Digital financial literacy and financial well-being. *Financ. Res. Lett.* **2023**, *58*, 104438. [CrossRef]
9. Prieger, J.E. The broadband digital divide and the economic benefits of mobile broadband for rural areas. *Telecommun. Policy* **2013**, *37*, 483–502. [CrossRef]
10. Wang, Y.; Luo, B.; Luo, J. Application of Internet information technology and farmer' formal credit constraint—Taking the survey data of 915 farmer households in Shaanxi as an example. *J. Nortuwest AF Univ. Soc. Sci. Ed.* **2023**, *23*, 113–126.

11. Li, X.; Huo, X. Impacts of land market policies on formal credit accessibility and agricultural net income: Evidence from China's apple growers. *Technol. Forecast. Soc. Chang.* **2021**, *173*, 121132. [CrossRef]
12. Chen, S.; Nie, F.; Luo, E.; Zeng, Y. The Impact of borrowing from formal, informal channel on farmers' family income—An empirical evidence from the underdevelopment areas in western China. *J. Agrotech. Econ.* **2021**, *5*, 35–47.
13. Guan, Z. Social capital, financial literacy and lending behaviour of farmers with different incomes: Evidence based on CHFS 2015 Data. *J. Commer. Econ.* **2020**, *5*, 5–8. [CrossRef]
14. Sun, H.; Hartarska, V.; Zhang, L.; Nadolnyak, D. The influence of social capital on farm household's borrowing behavior in Rural China. *Sustainability* **2018**, *10*, 4361. [CrossRef]
15. Amanullah, L.; GR, C.; SA, M. Credit constraints and rural farmers' welfare in an agrarian economy. *Heliyon* **2020**, *6*, e05252. [CrossRef]
16. Tapscott, D. *The Digital Economy: Promise and Peril in the Age of Networked Intelligence*; McGraw-Hill: New York, NY, USA, 1996. [CrossRef]
17. Tian, H.; Wang, Y.; Zhu, Z. Digital empowerment: The impact of Internet usage on farmers' credit and its heterogeneity. *J. Agrotech. Econ.* **2022**, *4*, 82–102.
18. Kiiza, B.; Pederson, G. ICT-based market information and adoption of agricultural seed technologies: Insights from Uganda. *Telecommun. Policy* **2012**, *36*, 253–259. [CrossRef]
19. Tadesse, G.; Bahiigwa, G. Mobile phones and farmers' marketing decisions in Ethiopia. *World Dev.* **2015**, *68*, 296–307. [CrossRef]
20. Tinmaz, H.; Lee, Y.T.; Fanea-Ivanovici, M.; Baber, H. A systematic review on digital literacy. *Smart Learn. Environ.* **2022**, *9*, 21. [CrossRef]
21. Eshet, Y. Digital literacy: A conceptual framework for survival skills in the digital era. *J. Educ. Multimed. Hypermedia* **2004**, *13*, 93–106.
22. Eshet, Y. Thinking in the digital era: A revised model for digital literacy. *Issues Informing Sci. Inf. Technol.* **2012**, *9*, 267–276.
23. Martin, A.; Grudziecki, J. DigEuLit: Concepts and tools for digital literacy development. *Innov. Teach. Learn. Inf. Comput. Sci.* **2006**, *5*, 249–267. [CrossRef]
24. Wang, J.; Cai, Z.; Ji, X. Digital literacy, farmer entrepreneurship, and relative poverty alleviation. *E-Government* **2022**, *8*, 15–31.
25. Sun, Z.; Gong, S.; Yu, Z. Influence of digital literacy on farmers' green production technology adoption behavior. *J. China Agric. Univ.* **2024**, *29*, 12–26.
26. Magesa, M.; Jonathan, J.; Urassa, J. Digital literacy of smallholder farmers in Tanzania. *Sustainability* **2023**, *15*, 13149. [CrossRef]
27. Park, H.; Kim, H.S.; Park, H.W. A scientometric study of digital literacy, ICT literacy, information literacy, and media literacy. *J. Data Inf. Sci.* **2021**, *6*, 116–138. [CrossRef]
28. Zhao, Q.; Pan, Y.; Xia, X. Internet can do help in the reduction of pesticide use by farmers: Evidence from rural China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 2063–2073. [CrossRef]
29. Hu, X.; Meng, H. Digital literacy and green consumption behavior: Exploring dual psychological mechanisms. *J. Consum. Behav.* **2023**, *22*, 272–287. [CrossRef]
30. König, L.; Kuhlmey, A.; Suhr, R. Digital health literacy of the population in Germany and its association with physical health, mental health, life satisfaction, and health behaviors: Nationally representative survey study. *JMIR Public Health Surveill.* **2024**, *10*, e48685. [CrossRef]
31. Polizzi, G. Internet users' utopian/dystopian imaginaries of society in the digital age: Theorizing critical digital literacy and civic engagement. *New Media Soc.* **2023**, *25*, 1205–1226. [CrossRef]
32. Guess, A.; Munger, K. Digital literacy and online political behavior. *Political Sci. Res. Methods* **2023**, *11*, 110–128. [CrossRef]
33. Reddy, P.; Sharma, B.; Chaudhary, K. Digital literacy: A review of literature. *Int. J. Technoethics (IJT)* **2020**, *11*, 65–94. [CrossRef]
34. Gigler, B.S. Informational Capabilities: The missing link for understanding the impact of ICT on development. *Closing Feedback Loop* **2014**, *17*, 17–42.
35. Bach, A.; Shaffer, G.; Wolfson, T. Digital human capital: Developing a framework for understanding the economic impact of digital exclusion in low-income communities. *J. Inf. Policy* **2013**, *3*, 247–266. [CrossRef]
36. Wang, H. Digital literacy and rural household income: The formation of digital inequality. *Chin. Rural Econ.* **2024**, *3*, 86–106.
37. Fang, C.; Shi, Q. Public pension and borrowing behavior: Evidence from rural China. *China Financ. Rev. Int.* **2023**, *13*, 63–78. [CrossRef]
38. Adams, D.W.; Hunter, R.E. (Eds.) *Informal Finance in Low-Income Countries*; Routledge: New York, NY, USA, 2019. [CrossRef]
39. Navajas, S.; Schreiner, M.; Meyer, R.L.; Gonzalez-Vega, C.; Rodriguez-Meza, J. Microcredit and the poorest of the poor: Theory and evidence from Bolivia. *World Dev.* **2000**, *28*, 333–346. [CrossRef]
40. Kass-Hanna, J.; Lyons, A.C.; Liu, F. Building financial resilience through financial and digital literacy in South Asia and Sub-Saharan Africa. *Emerg. Mark. Rev.* **2022**, *51*, 100846. [CrossRef]
41. Wyckhuys, K.A.; Bentley, J.W.; Lie, R.; Nghiem, L.T.P.; Fredrix, M. Maximizing farm-level uptake and diffusion of biological control innovations in today's digital era. *BioControl* **2018**, *63*, 133–148. [CrossRef]
42. Tchamyou, V.S.; Erreygers, G.; Cassimon, D. Inequality, ICT and financial access in Africa. *Technol. Forecast. Soc. Chang.* **2019**, *139*, 169–184. [CrossRef]
43. Stiglitz, J.E.; Weiss, A. Credit rationing in markets with imperfect information. *Am. Econ. Rev.* **1981**, *71*, 393–410.

44. Ogutu, S.O.; Okello, J.J.; Otieno, D.J. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of Kenya. *World Dev.* **2014**, *64*, 311–321. [CrossRef]
45. Liu, B.; Zhou, J. Digital literacy, farmers' income increase and rural Internal income gap. *Sustainability* **2023**, *15*, 11422. [CrossRef]
46. Baiyegunhi, L.J.S.; Fraser, G.C.G.; Darroch, M.A.G. Credit constraints and household welfare in the Eastern Cape Province, South Africa. *Afr. J. Agric. Res.* **2010**, *5*, 2243–2252.
47. Portes, A. Social capital: Its origins and applications in modern sociology. *Annu. Rev. Sociol.* **1998**, *24*, 1–24. [CrossRef]
48. Burt, R. Structural holes versus network closure as social capital. In *Social Capital*; Routledge: New York, NY, USA, 2017; pp. 31–56.
49. Stern, M.J.; Adams, A.E. Do rural residents really use the internet to build social capital? An empirical investigation. *Am. Behav. Sci.* **2010**, *53*, 1389–1422. [CrossRef]
50. Zeng, H.; Chen, J.; Gao, Q. The impact of digital technology use on farmers' land transfer-in: Empirical evidence from Jiangsu, China. *Agriculture* **2024**, *14*, 89. [CrossRef]
51. Yaméogo, T.B.; Fonta, W.M.; Wünscher, T. Can social capital influence smallholder farmers' climate-change adaptation decisions? Evidence from three semi-arid communities in Burkina Faso, West Africa. *Soc. Sci.* **2018**, *7*, 33. [CrossRef]
52. Biggart, N.W.; Castanias, R.P. Collateralized social relations: The social in economic calculation. *Am. J. Econ. Sociol.* **2001**, *60*, 471–500. [CrossRef]
53. Zhang, H.; Luo, J.; Luo, T.; Wang, L. Social capital, income level and rural household's borrowing responses—Evidence from 784 rural households in apple production sites. *Res. Econ. Manag.* **2018**, *39*, 82–94.
54. Feng, D.; Gao, M.; Zhou, L. Religion and household borrowing: Evidence from China. *Int. Rev. Econ. Financ.* **2023**, *88*, 60–72. [CrossRef]
55. Liu, Y.; Li, H.; Fang, X. Who should the elderly borrow money from under formal financial exclusion? Evidence from China. *Econ. Anal. Policy* **2024**, *81*, 964–982. [CrossRef]
56. Yu, G.; Xiang, H. Rural E-commerce development and farmers' digital credit behavior: Evidence from China family panel studies. *PLoS ONE* **2021**, *16*, e0258162. [CrossRef]
57. Tang, H.; Xu, Y. Social capital, individual characteristics of farmers and lending behavior—Evidence from China Family Tracking Survey (CFPS) Data. *J. Henan Norm. Univ. Philos. Soc. Sci.* **2023**, *3*, 88–93.
58. Chen, Q.; Dong, X. Women's empowerment in family decision-making and farmers' lending behavior—Empirical research based on CFPS. *J. Agrotech. Econ.* **2020**, *12*, 94–108.
59. Yang, Q.; Xu, Q.; Lu, Y.; Liu, J. The impact of public health insurance on household credit availability in rural China: Evidence from NRCMS. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6595. [CrossRef]
60. Chen, C.; Liu, B.; Wang, Z. Can land transfer relax credit constraints? Evidence from China. *Econ. Model.* **2023**, *122*, 106248. [CrossRef]
61. Bai, Q.; Chen, H.; Zhou, J.; Li, G.; Zang, D.; Sow, Y.; Shen, Q. Digital literacy and farmers' entrepreneurial behavior—Empirical analysis based on CHFS2019 micro data. *PLoS ONE* **2023**, *18*, e0288245. [CrossRef]
62. Yi, X.; Zhang, B.; Yang, R.; Yang, B. Family social networks and saving behavior of farm households: An empirical study based on rural China. *J. Manag. World* **2012**, *5*, 43–51+187.
63. Zhu, S.; Xiong, F.; Zhu, J. The impact of Internet use on rural households' income: An analysis of the mediating effect based on social capital. *J. Agro-For. Econ. Manag.* **2022**, *21*, 518–526.
64. Ogouvide, T.; Adegbola, Y.; Zossou, R.; Zannou, A.; Biaou, G. Farmers' preferences and willingness to pay for microcredit in Benin: Results from in-the-field choice experiments in Benin. *Agric. Financ. Rev.* **2020**, *80*, 665–692. [CrossRef]
65. Ding, Z.; Abdulai, A. Smallholder preferences and willingness-to-pay measures for microcredit: Evidence from Sichuan province in China. *China Agric. Econ. Rev.* **2018**, *10*, 462–481. [CrossRef]
66. Mbam, B.; Nwibo, S.; Nwofoke, C.; Egwu, P.; Odoh, N. Analysis Of Smallholder Farmers Repayment Of Bank Of Agriculture Loan In Ezza South Local Government Area Of Ebonyi State, Nigeria. *Int. J.* **2021**, *8*, 198–208.
67. Ouattara, N.; Xiong, X.; Bakayoko, M.; Bi, T.; Sedebo, D.; Ballo, Z. What influences rice farmers' choices of credit sources in Côte d'Ivoire? An econometric analysis using the multinomial conditional logit model. *Prog. Dev. Stud.* **2022**, *22*, 149–173. [CrossRef]
68. Kong, R.; Peng, Y.; Meng, N.; Fu, H.; Zhou, L.; Zhang, Y.; Turvey, C. Heterogeneous choice in the demand for agriculture credit in China: Results from an in-the-field choice experiment. *China Agric. Econ. Rev.* **2021**, *13*, 456–474. [CrossRef]
69. Balana, B.; Mekonnen, D.; Haile, B.; Hagos, F.; Yimam, S.; Ringler, C. Demand and supply constraints of credit in smallholder farming: Evidence from Ethiopia and Tanzania. *World Dev.* **2022**, *159*, 106033. [CrossRef]
70. Visser, M.; Jumare, H.; Brick, K. Risk preferences and poverty traps in the uptake of credit and insurance amongst small-scale farmers in South Africa. *J. Econ. Behav. Organ.* **2020**, *180*, 826–836. [CrossRef]
71. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173. [CrossRef]
72. Preacher, K.J.; Hayes, A.F. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behav. Res. Methods* **2008**, *40*, 879–891. [CrossRef]
73. Karlson, K.B.; Holm, A.; Breen, R. Comparing regression coefficients between same-sample nested models using logit and probit: A new method. *Sociol. Methodol.* **2012**, *42*, 286–313. [CrossRef]
74. Breen, R.; Karlson, K.; Holm, A. Total, direct, and indirect effects in logit and probit models. *Sociol. Methods Res.* **2013**, *42*, 164–191. [CrossRef]

75. Morgan, S. Models of college entry in the United States and the challenges of estimating primary and secondary effects. *Sociol. Methods Res.* **2012**, *41*, 17–56. [CrossRef]
76. Baek, J.; Choi, J.; Kim, H.; Hong, S.; Kim, Y.; Choi, S.; Kim, E. Digital literacy and associated factors in community-dwelling older adults in South Korea: A qualitative study. *Innov. Aging* **2022**, *6*, 587. [CrossRef]
77. Li, P.; Song, X.; Li, J. Research on farmers' households credit behavior and social capital acquisition. *Front. Psychol.* **2022**, *13*, 961862.
78. Chandio, A.A.; Jiang, Y.; Wei, F.; Rehman, A.; Liu, D. Famers' access to credit: Does collateral matter or cash flow matter?—Evidence from Sindh, Pakistan. *Cogent Econ. Financ.* **2017**, *5*, 1369383. [CrossRef]
79. Zhang, J.; Zhang, X. The impact of Internet use on the decision-making of farmland transfer and its mechanism: Evidence from the CFPS data. *Chin. Rural Econ.* **2020**, *3*, 57–77.
80. Li, F.; Zang, D.; Chandio, A.A.; Yang, D.; Jiang, Y. Farmers' adoption of digital technology and agricultural entrepreneurial willingness: Evidence from China. *Technol. Soc.* **2023**, *73*, 102253. [CrossRef]
81. Gong, S.; Sun, Z.; Wang, B.; Yu, Z. Could digital literacy contribute to the improvement of green production efficiency in agriculture? *SAGE Open* **2024**, *14*, 21582440241232789. [CrossRef]
82. Hao, Y.; Zhang, B. The impact of digital financial usage on resident's income inequality in China: An empirical analysis based on CHFS data. *J. Asian Econ.* **2024**, *91*, 101706. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.