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Article

Can the Use of Digital Finance Promote the Enhancement and Quality Improvement of Household Consumption Among Farmers?

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Abstract: The key strategic point for facilitating domestic circulation is to enhance and expand household consumption. Based on a survey of 1080 farming households in Hunan, Hubei, and Jilin Provinces, this study examines the impact of digital finance use on the scale and structural upgrading of household consumption among farmers. The findings indicate that digital finance use effectively expands the scale of household consumption and promotes structural upgrades. The results remain robust through various endogenous and robust methods. Heterogeneity analysis reveals that the benefits of digital finance use are greater for middle- to high-income groups and those with lower education levels, indicating the presence of a digital divide effect. Furthermore, the construction of village communities, skill training, improvements in village logistics services, and the availability of medical clinic facilities can enhance the consumption-promoting effects of digital finance use. Mechanism analysis shows that digital finance primarily operates through alleviating credit constraints, enhancing risk prevention, and improving financial returns to influence the scale and structural upgrading of household consumption. This study provides policy insights for rural revitalization and unlocking the consumption potential of rural residents.

Keywords: use of digital finance; consumption upgrading; credit constraints; risk prevention; financial returns



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1. Introduction

In the context of accelerating the construction of a new development pattern that prioritizes domestic circulation and promotes mutual reinforcement between domestic and international circulations, household consumption is increasingly playing a stabilizing role as a “ballast stone” for China’s economic stability. In 2021, the Central Document No. 1 proposed the imperative of “comprehensively promoting rural consumption”, identifying the rural consumption market as a core focus for driving high-quality economic development under new circumstances (Zhang and Xu 2019). In recent years, the consumption level of rural households has continued to rise, accompanied by a shift in consumption concepts that has led to increasing diversification and personalization of household consumption structures.

However, challenges, such as the persistent decline in the overall household consumption rate and the slowing pace of consumption structure upgrading, have gradually emerged. A key reason for this is the neglect of the micro-level consumer decision-making process. According to data released by the National Bureau of Statistics of China, in 2020, the per capita consumption expenditure of rural residents was 13,713 yuan, with a nominal growth of 2.9%. However, after adjusting for price factors, there was an actual decline of 0.1%¹. This indicates that the real consumption expenditure of rural residents decreased in 2020². Traditionally, household consumption behavior, as the basic unit of socioeconomic activity, is viewed as rational in economic theory, based on the assumption that households

possess sufficient information to smooth consumption and maximize utility over their lifecycles (Fang and Yu 2014). However, many rural households exhibit significant irrational behaviors. For instance, rural families generally lack systematic financial knowledge, creating a knowledge gap that hinders their ability to effectively assess risks and returns, leaving them susceptible to misinformation or impulsive investment decisions. Due to the absence of stable income sources and social security, rural residents tend to favor low-risk or even risk-free assets, such as savings or gold, rather than allocating funds to higher-return but riskier investment products. This excessive risk aversion often results in suboptimal financial returns, thereby limiting wealth accumulation potential and contributing to significant welfare losses (Peng and Zhu 2018). What, then, leads to decision-making errors in economic behavior among rural households? Existing research suggests that the use of digital financial tools and services may influence household financial decisions and is closely related to various financial behaviors (Anderson et al. 2017). A low level of digital finance usage could be a significant factor contributing to erroneous or irrational economic decision-making among these households (Chamon and Prasad 2010).

Whether the improvement in the level of digital finance usage can effectively promote the expansion and quality enhancement of household consumption among farmers remains to be further explored. On one hand, as digital finance increasingly penetrates rural financial markets and retail finance, micro-level consumers are exposed to more digital financial products, asset protection services, and broader financial planning options. At the same time, market risks are gradually shifting toward individuals, leading rural households to increasingly rely on digital financial tools and financial knowledge for asset management and financial decision-making (Jiang et al. 2019).

Additionally, farmers must navigate complex and irreversible financial decisions, such as retirement planning and mortgages (Song et al. 2017). These decisions require them to make different forecasts about current income, future expenditures, and potential economic shocks based on household budget constraints and financial conditions, as well as to allocate reserve assets reasonably to mitigate risks.

On the other hand, faced with traditional investment options, such as stocks, funds, bonds, and derivatives, alongside diverse, personalized, and refined digital financial products and services, farmers need to filter and analyze a wealth of complex information, weigh the pros and cons, and make rational decisions. This not only demands a high level of financial knowledge but also necessitates sufficient proficiency in digital financial tools (Wang et al. 2021).

Existing research on the relationship between digital finance usage and household consumption primarily focuses on the impacts of financial knowledge or smartphone usage on farmers' consumption behavior. However, these factors are merely important components or subsets of digital finance usage (Meng et al. 2019). First, farmers' access to digital financial tools, products, and services relies on terminal devices, such as smartphones and computers. Moreover, their use of digital finance may produce a "learning by doing" effect, improving their financial literacy, including the allocation of household financial assets and financial knowledge deficiencies, as they learn to use these tools. From a micro-perspective, current studies often analyze data from individual provinces without adequately considering inter-regional differences (Chen et al. 2021), or they may focus solely on the impact of a single tool, such as mobile payments, on rural residents' consumption (Allais 1952), neglecting the complexity of digital financial tools and services and their high demands for financial knowledge (Yin et al. 2015a; Chamon and Prasad 2010). Second, from the perspective of technological means and consumption scenarios, the improvement of household consumption through digital finance is reflected in new consumption and payment scenarios. Changes in consumption expenditure levels and structures are also influenced by the "learning by doing" effect, bridging the gap to the consumption decision-making levels of households with higher financial literacy. Third, from the perspective of transmission mechanisms, digital finance usage not only expands consumption methods and scenarios but also addresses how to reposition household consumption decision-making amidst

traditional financial credit constraints through methods such as “learning by doing” and the precise identification of digital finance technology targets, thereby boosting consumer confidence. Focusing solely on mobile payments and proficiency in smartphone usage overlooks farmers’ new understandings of household asset portfolios, credit constraints, and risk prevention within the framework of bounded rationality in consumption decisions. Overall, while current domestic and international research on digital finance usage and household consumption provides insightful ideas for this paper, further expansion in this field is still necessary.

Compared to existing research, the marginal contributions of this paper are as follows: (1) While previous studies on household consumption upgrading primarily focus on macro- and industry-level perspectives, this paper examines the changes in farmers’ consumption concepts and the optimization of consumption decision-making from a micro-level perspective. (2) This paper expands the mechanisms through which digital finance usage influences farmers’ consumption decisions by analyzing three aspects: alleviating credit constraints, enhancing risk prevention, and increasing financial returns. (3) Innovatively, this paper explores the differences in the impact of digital finance usage on household consumption based on variations in village-level infrastructure and basic services, offering strong practical implications.

2. Theoretical Analysis and Research Hypothesis

2.1. *The Impact of Digital Finance Usage on Household Consumption Behavior Among Farmers*

Digital finance refers to the use of digital technologies (such as mobile payments, internet banking, and big data analytics) to deliver convenient, efficient, and low-cost financial services, particularly targeting groups that have traditionally faced difficulties accessing financial services, such as rural residents and low-income populations. Currently, farming households face an increasingly complex economic and financial decision-making environment. They not only need to make choices about the allocation of existing resources but also must make predictions about future income expectations and macroeconomic changes, especially in the decision-making process regarding expenditures on developmental- and survival-oriented consumer products or services. Digital financial services and tools, primarily including digital payments, digital credit, digital wealth management, and digital insurance, provide crucial support for farming households’ production investments and consumption decisions (Yin et al. 2015b; Wen and Meng 2012; Huang and Hao 2021; Meng and Yan 2020; Luo 2020). However, farming households with low levels of digital finance usage often need to expend significant time and effort, and even incur economic costs, to acquire, filter, and analyze relevant information to mitigate issues of information asymmetry (Lan and Yang 2021; Zou and Wang 2020; Xiang 2018). In actual economic and consumption decision-making, farmers not only need to correctly understand relevant economic concepts but also possess basic computational skills. Farmers need to reasonably plan their household income, expenditures, and savings to optimize resource allocation. Without basic computational skills, they may fail to accurately estimate the proportion of expenses to income, leading to resource wastage or overconsumption. Additionally, farmers may overly rely on intuition in their consumption decisions due to a lack of computational ability, resulting in irrational choices. For instance, they may misjudge the actual value of discounted goods or be misled into participating in high-risk financial products. In the face of uncertainty shocks, those farmers with higher levels of digital finance usage are more likely to access formal credit (Du 2017; Li and Xu 2022), which also helps achieve diversified allocation and decentralized combinations of household assets, thereby unlocking household consumption potential (Yi and Zhou 2018; Zhou and Fan 2018; Ma and Ning 2017). On the other hand, the structure of household consumption is becoming increasingly diversified, gradually shifting from basic consumption to developmental- and enjoyment-oriented consumption (Shi and Wang 2017; Zhang et al. 2020; Mao et al. 2019; Zhang et al. 2021). This developmental- and enjoyment-oriented consumption exhibits characteristics of diversification, personalization, quality enhancement, refinement, and

digitization, closely integrated with digital financial tools and services, deeply embedding into digital technology and new consumption scenarios. Farmers need to possess strong digital finance knowledge and skills to effectively distinguish and utilize these tools (He et al. 2020; Zhang and Li 2021; Klapper et al. 2013). In summary, an increase in the level of digital finance usage not only impacts the overall consumption of farming households but also makes developmental- and enjoyment-oriented consumption more reliant on digital finance, thereby contributing to the expansion and quality enhancement of household consumption. Based on the above, we propose Research Hypothesis 1:

H1: *The use of digital finance will increase the consumption level of farming households and promote the expansion and quality enhancement of their consumption.*

2.2. The Credit Constraint Mechanism Through Which Digital Finance Usage Affects Household Consumption Behavior Among Farmers

The development of digital finance not only breaks the limitations of traditional credit models but also possesses advantages in credit efficiency while expanding its derivative functions based on basic functionalities (Mouna and Jarboui 2015; Nan et al. 2020; Li 2020). With advancements in cutting-edge technologies, such as big data and cloud computing, digital finance has been rapidly promoted in rural areas, significantly improving the accessibility and convenience of financial services, and greatly enhancing farmers' subjective willingness to consume, thereby driving the prosperity of the consumption market. According to liquidity constraint theory, insufficient development in financial markets prevents some consumers from achieving optimal cross-lifecycle consumption. On one hand, from the perspective of borrowing willingness and channels, the level of digital finance usage reflects farmers' ability to utilize financial knowledge, digital payments, and skills for resource allocation to ensure sustained income. Farmers with lower levels of digital finance usage often struggle to access sufficient information about formal financial channels and typically rely on informal lending to meet their credit needs (Dinkova et al. 2021; Agarwal et al. 2017). On the other hand, an increase in digital finance usage helps improve farmers' preferences for borrowing channels, enhancing their willingness to use formal financial lending and increasing the availability of loans (Yin et al. 2024; Zhan and Wang 2023; Lusardi and Tufano 2015). From the perspective of consumption potential, digital finance, through credit services such as "Huabei" and "Baitiao", assists farmers in identifying digital financial products and services that match their economic capabilities and consumption preferences, thus avoiding excessive borrowing that could negatively impact future income expectations (Wang et al. 2016). In terms of repayment ability, farmers with lower digital finance usage often have weaker credit management skills, making them prone to excessive debt, overdue loans, and debt accumulation to meet minimum repayment requirements (Qin et al. 2016). In contrast, farmers with higher levels of digital finance usage tend to have stronger financial literacy, enabling them to manage household cash flow and balance expenditures more effectively, resulting in a lower probability of overdue loans. Moreover, these farmers have greater income growth potential and a stronger repayment capacity (Dohmen et al. 2018). In summary, deepening the level of digital finance usage enhances farmers' willingness to consume, broadens borrowing channels, and improves borrowing capacity, allowing groups previously excluded from financial services more opportunities to access low-cost, tailored digital financial products and services. This not only facilitates intertemporal smoothing of consumption but also helps realize the potential for developmental- and enjoyment-oriented consumption. Based on the above, we propose Research Hypothesis 2:

H2: *The use of digital finance promotes the expansion and quality enhancement of household consumption among farmers by alleviating credit constraints.*

2.3. The Risk Prevention Mechanism Through Which Digital Finance Usage Affects Household Consumption Behavior Among Farmers

Under conditions of uncertainty, participating in insurance is one of the important ways for residents to seek effective risk avoidance and enhance their preventive capabilities. The social insurance system has a broad coverage, benefiting a larger population and primarily aimed at meeting the basic living needs of farmers. In contrast, commercial insurance serves as a strong supplement to social insurance, filling the gaps not covered by social security and providing deeper protection for assets and personal safety, thereby significantly enhancing farmers' ability to cope with risks. As participants in the insurance market, farmers need a certain level of financial knowledge to understand complex insurance terms and calculate benefits, and the extent of digital finance usage plays a crucial role in filtering and analyzing insurance information (Cao et al. 2020). On one hand, farmers must comprehensively assess the likelihood of various potential risks and the welfare losses that may arise from them. Farmers with higher levels of digital finance usage typically possess stronger risk identification capabilities (Wu et al. 2018), enabling them to effectively avoid and diversify potential economic and financial risks through participation in insurance. On the other hand, farmers with greater digital finance usage face lower information asymmetry and information collection costs when selecting insurance, allowing them to accurately understand their risk profiles and seek better financial management solutions at lower costs (Huston 2012). For example, health insurance and accident insurance can ensure that a household's long-term income expectations do not significantly decline due to major illnesses or accidents. Meanwhile, pension insurance and life insurance cover the entire consumption cycle of a household, enhancing future income expectations and thereby unlocking consumption potential. Against the backdrop of low levels of rural social security and medical coverage, participation in commercial health insurance and pension insurance can substantially improve income security, increase current consumption levels, and enhance household welfare. In summary, increasing the level of digital finance usage helps enhance farmers' willingness and extent of participation in commercial insurance, strengthens their risk prevention capabilities in the face of uncertainty, reduces the motivation for precautionary savings, and thereby stimulates the release of consumption potential. Based on this, we propose Research Hypothesis 3:

H3: *The use of digital finance promotes the expansion and quality enhancement of household consumption among farmers by improving their risk prevention capabilities.*

2.4. The Wealth Management Benefit Mechanism Through Which Digital Finance Usage Affects Household Consumption Behavior Among Farmers

Currently, asset distribution in China is uneven, with a predominance of housing assets and a relatively low allocation of financial assets, such as stocks, funds, and bonds (Deuflhard et al. 2019). This situation, characterized by a high proportion of non-financial assets and poor liquidity, is detrimental to wealth appreciation and the enhancement of household welfare. Tools such as digital finance, digital insurance, and digital payment platforms have provided important channels for farmers to sell agricultural products, while digital wealth management products have broadened the ways in which farmers can diversify their asset portfolios. This diversification reduces the potential risks associated with a narrow asset allocation, avoiding an increased demand for precautionary savings due to poor future income expectations, thereby releasing the consumption potential of farmer households. An increase in the level of digital finance usage helps enhance farmers' understanding of the risks and returns associated with digital financial products, reducing investment errors and improving their ability to make rational financial decisions (Abreu and Mendes 2010). On one hand, effective asset management for farmer households requires a certain level of financial knowledge and information-seeking ability. Households with higher levels of digital finance usage typically have more resources and stronger capabilities in assessing digital financial risks, facing lower information and transaction costs. As a result,

they are more likely to participate in financial markets and risk investments, accelerating wealth accumulation through the acquisition of financial returns and risk rewards (He and Song 2020; Wu and Lü 2013). On the other hand, an increase in digital finance usage can change household risk preferences, promote entrepreneurship, and encourage families to allocate more assets to financial markets, thus achieving portfolio diversification (Gan et al. 2018; Liu 2021). In summary, an increase in the level of digital finance usage aids farmer households in making diversified investment decisions, stabilizing future income expectations, enhancing current income levels, and improving household welfare, which in turn promotes the expansion and quality enhancement of household consumption. Based on this, we propose Research Hypothesis 4:

H4: *The use of digital finance promotes the expansion and quality enhancement of household consumption among farmers by increasing financial management returns.*

Based on the literature and theoretical analysis above, the use of digital finance—through tools such as digital credit, digital insurance, digital wealth management, and digital payment—optimizes financing, investment, and wealth management behaviors. This alleviates financing constraints, enhances households' risk control capabilities, and achieves wealth appreciation, thereby increasing the consumption scale of rural households and promoting the optimization and upgrading of consumption structure. The mechanisms through which digital finance usage affects household consumption among farmers are illustrated in Figure 1.

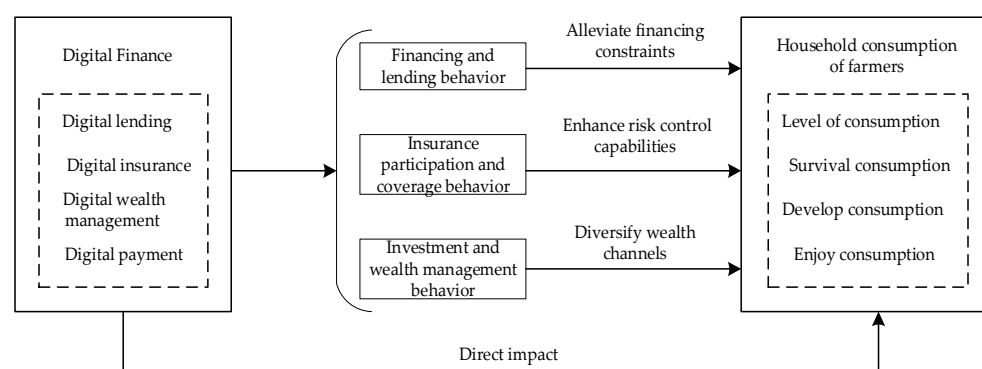


Figure 1. Mechanism diagram of the impact of digital finance usage on household consumption among farmers.

3. Data, Models, and Variables

3.1. Data

The data for this study come from field visits and surveys conducted by the research team in July and August 2022 in rural areas of Hunan and Hubei Provinces in Central China, as well as Jilin Province in Northeast China. Respondents included household heads, other family members involved in economic consumption decisions, and village leaders or committee members. The selection criteria for the surveyed regions involved randomly choosing four counties (or cities) from each of the three provinces, followed by randomly selecting three townships within each county. Subsequently, three villages were randomly chosen from each township, and questionnaires were distributed to ten households in each village. Additionally, the research team designed a village questionnaire, collecting data from a total of 36 village surveys across the 4 counties, 3 townships, and 3 villages. Through random sampling and one-on-one questionnaire interviews, a total of 1080 questionnaires were distributed. After screening based on key variables, 1080 valid questionnaires were obtained, with 360 from Hunan, 360 from Hubei, and 360 from Jilin Provinces. The farmer questionnaire primarily covered respondents' personal information, family circumstances, detailed consumption and expenditure data, and their usage of digital finance. The village

questionnaire focused on economic and demographic information, natural resources and environmental data, infrastructure conditions, and internet and community information.

3.2. Models

To examine the impact of residents' digital finance usage on the scale and structure of household consumption among farmers, an OLS (ordinary least squares) model was established. The specific form of the model was as follows:

$$Consum_total_i = \alpha + \beta Fin_factor_i + \lambda X_i + \varepsilon_i \quad (1)$$

$$Consum_{ij} = \alpha + \beta Fin_factor_i + \lambda X_i + \varepsilon_i \quad (2)$$

In the equation, $Consum_i$ represents the total consumption expenditure of household i , and $Consum_{ij}$ denotes the expenditure of household i in category j . Fin_factor_i is the core explanatory variable, indicating the index of digital financial use by farmers. X_i represents control variables at the household head level, family level, and village level, while ε_i is the unobservable error term.

3.3. Variables

3.3.1. Dependent Variable: Household Consumption of Farmers

Household consumption expenditures of rural households typically encompass multiple categories, including food, daily necessities, clothing, cultural and entertainment expenses, medical insurance, and transportation and communication costs. This study used the total scale of household consumption ($Consum_total$) to represent the magnitude of consumption. The overall trend in the structure of resident consumption indicates a shift from survival-oriented consumption to development-oriented and enjoyment-oriented consumption. Based on the existing research (Yin and Zhang 2019), this study categorized household expenditures on food, daily necessities, utilities, and other goods and services as survival-oriented consumption ($Consum1$), transportation and communication, education, medical services, and related services were classified as development-oriented consumption ($Consum2$), while public welfare, social interactions, entertainment, and related services were categorized as enjoyment-oriented consumption ($Consum3$). Additionally, considering the characteristics of durable goods—such as low purchase frequency, long consumption cycles, and high single expenditures, along with the challenges in accurately calculating the actual consumption of durable goods over different years—this study excluded housing maintenance and utility repairs from survival-oriented consumption to obtain a measure of survival-oriented consumption that does not include durable goods. Similarly, expenditures on automobile purchases and furniture were deducted from development-oriented consumption to arrive at a measure of development-oriented consumption that excludes durable goods. Furthermore, high-value appliances and other durable goods were excluded from enjoyment-oriented consumption, resulting in a measure of enjoyment-oriented consumption that does not include durable goods.

3.3.2. Explanatory Variable: Digital Financial Usage

Currently, there are two main methods for measuring digital financial usage: the first method involves assessing respondents' subjective level of digital financial usage based on their familiarity with and utilization of digital financial products and services, while the second method evaluates the objective level of digital financial usage by scoring respondents' answers to core financial knowledge questions. In this study, the explanatory variable was digital financial usage, with a focus on analyzing rural households' engagement with internet lending, internet wealth management, internet insurance, and digital financial literacy. The measurement of digital financial usage was conducted through field surveys and questionnaires. The questionnaire included relevant questions about the respondents' usage of digital financial services, as detailed in Table 1. For each type of digital financial service, a value of 1 was assigned if the household uses the service, and 0 if they do

not. Similarly, a value of 1 was assigned for correct responses regarding digital financial knowledge, and 0 for incorrect responses, resulting in five dummy variables. Following this assignment scheme, factor analysis was employed to reduce the dimensionality of the data, resulting in an index for digital financial usage (Fin_factor). The assigned values for the five dummy variables were subjected to Bartlett's test and the KMO test. The KMO value was 0.677, and the significance value in the Bartlett spherical test was 0.000, meeting the criterion of being less than 0.01. These results indicate that the dataset was suitable for factor analysis. Additionally, following the approach of Abreu and Mendes, the total score for digital financial usage was measured by counting the number of correct responses to the aforementioned questions. This method, however, does not account for the varying importance of different digital financial usage questions, and will later be used as a robustness check.

Table 1. Indicators of digital financial usage and their descriptions.

Question	Option
Have you ever used internet consumer loans?	① YES; ② NO
Do you have experience with managing investments through internet channels?	① YES; ② NO
Have you purchased internet insurance?	① YES; ② NO
Can you distinguish between a credit card and a debit card?	① YES; ② NO
Do you know how to check your personal credit report online?	① YES; ② NO

3.3.3. Control Variables

Grounded in the research question and practical considerations, this study incorporates the following control variables: (1) Household head characteristics—age of the household head and its squared term divided by 100 (age and age²), gender, education level, marital status, self-rated health, and chronic illness status. (2) Economic characteristics of the household—household size, net household income, household debt, and household liquid cash. (3) Regional characteristics—village population and per capita net income of the village. Table 2 provides a detailed explanation of each variable.

Furthermore, Table 2 presents the preliminary statistical information for the variables. The average total consumption of farming households (Consum_total) was 28,297, with a maximum of 520,000 and a minimum of 100, indicating significant disparities in the consumption scale among farming households. In terms of consumption structure, the mean values for survival-type consumption and enjoyment-type consumption were lower than that for development-type consumption, with development-type and enjoyment-type consumption accounting for a relatively high proportion. Additionally, regarding the digital financial usage indicators, the maximum and minimum values were 4.626 and −0.325, respectively, highlighting considerable differences in digital financial capabilities among farmers. This indicates that the lack of digital computation skills and basic financial knowledge among farmers hinders their digital financial capabilities.

The average subsistence consumption of rural households was 5357.903, the average development-oriented consumption was 14,409.59, and the average enjoyment-oriented consumption was 8728.027. Development-oriented consumption had the highest mean value, which also confirmed that rural China is currently in a period of rapid development, with education, healthcare, and daily necessities constituting the primary components of household consumption expenditures.

Additionally, the average age of household heads was 56.755 years, reflecting the accelerating trend of aging in rural China. The average education level was only 8.044 years, indicating a relatively low level of labor quality in rural areas. These two factors collectively highlight a research direction: whether improving digital finance usage can enhance household economic conditions and promote consumption growth.

Table 2. Variable description.

Variables	Values for the Variables	Mean	Std. Dev.
Consum_total	Total sum of various household consumption expenditures (in yuan)	28,297.32	31,371.55
Consum1	Total sum of household expenditures on food, daily necessities, utilities, and other goods and services (in yuan)	5357.903	6651.515
Consum2	Total sum of household expenditures on transportation, communication, education, medical care, and related services (in yuan)	14,409.59	19,061.38
Consum3	Total sum of household expenditures on public welfare, social gifts, entertainment, and related services (in yuan)	8728.027	14,931.79
Fin_factor	Index synthesis using factor analysis	0	0.719
Gender	Male = 1, Female = 0	0.675	0.469
Age	Take actual value (years)	56.755	11.235
Age ²	Respondent's age squared/100	33.472	12.486
Education	Illiterate or semi-literate = 0, Primary school = 6, Junior high school = 9, Senior high school or vocational school = 12, Associate degree = 15, Bachelor's degree = 16, Master's degree and above = 19	8.044	3.572
Marriage	Married = 1, Other statuses = 0	1.248	0.773
Health	Very unhealthy = 1, Unhealthy = 2, Average = 3, Fairly healthy = 4, Very healthy = 5	4.017	1.012
Chronic	Has chronic disease = 1, No chronic disease = 0	0.611	0.488
Size	Number of household members sharing actual income and expenses	3.18	1.499
Income	The actual amount of household total income minus total expenses (in yuan)	97,656.42	263,000
Debt	The actual amount of household debt (in yuan)	7824.074	21,051.74
Cash	The amount of current liquid assets in the household (in yuan)	29,675.93	24,866.4
Vill_income	The ratio of village net income to the current population of the village (in yuan)	16,295.93	6075.836
Vill_pop	Current population of the village (number of people)	900.861	616.307

Moreover, the average value of household heads with chronic illnesses was 0.611, indicating potential health risks among rural households. Therefore, this study will focus on whether increasing the number of community medical clinics can mitigate the compression of consumption demand caused by chronic illnesses.

4. Empirical Analysis

4.1. Basic Regression Analysis

Before conducting the baseline regression, it is essential to check for multicollinearity among the variables. The average variance inflation factor (VIF) was below the commonly accepted threshold of 10, indicating no severe multicollinearity issues. Column (1) of Table 3 presents the regression results corresponding to Model Specification (1), illustrating the impact of farmers' digital financial usage on total household consumption. Columns (2) to (4) correspond to Model Specification (2), detailing the effects of digital financial usage on survival-type consumption, development-type consumption, and enjoyment-type consumption, respectively. To account for potential heteroscedasticity in the error terms across different observations, robust standard errors were employed in the baseline regression estimation. The results of the baseline regression yielded the following three conclusions: First, from Column (1), the coefficient for digital financial usage was 3568.74 and was significantly positive at the 1% level, indicating that the usage of digital financial services by farmers promotes an increase in total household consumption, thereby validating Hypothesis 1.

Second, from Columns (2) to (4), it is evident that farmers' digital financial capabilities had a more pronounced effect on survival-type and enjoyment-type consumption, while the impact on development-type consumption was relatively minor. Third, the coefficients for digital financial usage suggest that its promotion of enjoyment-type consumption exceeded that of survival-type and development-type consumption, indicating an increasing proportion of development- and enjoyment-type consumption among farming households. This finding suggests that the consumption structure of farming households is continuously upgrading and optimizing.

Table 3. Impact of digital financial usage on household consumption scale and structure: baseline regression.

Variables	(1)	(2)	(3)	(4)
	Consum_Total	Consum1	Consum2	Consum3
Fin_factor	3568.74 *** (1142.229)	961.24 *** (303.879)	1153.90 (804.790)	1419.96 *** (543.230)
Gender	4677.67 *** (1581.555)	1617.04 *** (420.758)	2298.83 ** (1114.330)	1794.00 ** (752.169)
Age	362.32 (514.371)	188.56 (136.844)	−358.73 (362.415)	706.89 *** (244.629)
Age ²	−738.48 (458.023)	−208.01 * (121.853)	−16.03 (322.713)	−650.80 *** (217.830)
Education	42.42 (220.561)	−95.66 (58.678)	72.12 (155.403)	−93.03 (104.896)
Marriage	840.59 (956.085)	145.56 (254.357)	779.47 (673.637)	157.26 (454.703)
Health	263.59 (892.127)	116.46 (237.342)	382.52 (628.574)	−225.50 (424.285)
Chronic	1547.52 (1866.928)	176.99 (496.679)	1004.14 (1315.397)	132.34 (887.889)
Size	5185.78 *** (539.489)	879.89 *** (143.526)	3326.58 *** (380.113)	973.34 *** (256.575)
Income	0.05 *** (0.003)	0.00 *** (0.001)	0.01 *** (0.002)	0.04 *** (0.001)
Debt	0.10 *** (0.035)	0.01 (0.009)	0.06 ** (0.025)	0.03 * (0.017)
Vill_income	0.14 (0.118)	0.12 *** (0.031)	0.05 (0.083)	0.03 (0.056)
Vill_pop	1.80 (1.209)	1.02 *** (0.322)	0.12 (0.852)	1.20 ** (0.575)
Constant	−571.85 (15,121.436)	−5477.80 (4022.916)	16,637.51 (10,654.240)	−17,817.52 ** (7191.575)
Observations	1080	1080	1080	1080
R-squared	0.467	0.161	0.283	0.468

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

4.2. Robustness Check Analysis

4.2.1. Based on the Cumulative Scoring Digital Financial Usage Indicator

Given the difficulty of accurately measuring the digital financial usage indicators for farmers and the potential for significant differences in regression results based on different measurement methods, this study adopted a cumulative scoring approach to measure digital financial usage (Fin_score), drawing on established research practices. Regression analyses were conducted on the total household consumption and consumption structure indicators. Table 4 presents the corresponding estimation results, showing that the digital financial capability measured by the cumulative scoring method had a significant positive impact on total household consumption in Column (1), as well as on survival-type

consumption and enjoyment-type consumption scales in Columns (2) and (4), respectively. These findings are consistent with the previous baseline regression results.

Table 4. Robustness Test I: digital financial usage indicator based on cumulative scoring.

Variables	(1)	(3)	(4)	(5)
	Consum_Total	Consum1	Consum2	Consum3
Fin_score	2812 *** (985.8)	762.2 *** (262.3)	980.8 (694.2)	992.4 ** (468.7)
Controls	YES	YES	YES	YES
Constant	−364.1 (15,185)	−5262 (4040)	16,375 (10,693)	−17,400 ** (7220)
Observations	1080	1080	1080	1080
R-squared	0.466	0.160	0.283	0.468

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

4.2.2. Changing the Measurement Indicator for the Dependent Variable

Due to the low frequency of durable goods consumption among farm households and the significant single-instance expenditure, it is challenging to allocate the actual depreciation of durable goods reasonably across different consumption periods. This could lead to an overestimation or underestimation of the impact of farm households' digital financial usage on actual consumption during the sample period. Therefore, this study excluded expenditures on home repairs, utility maintenance, vehicle purchases, and furniture to recalculate new measurement indicators for the total household consumption and consumption structure. The regression results after excluding durable goods consumption are shown in Table 5. It is evident that farm households' digital financial capabilities still significantly promote the expansion of total household consumption and the optimization and upgrading of the consumption structure, indicating that the estimation results remained robust and reliable even after excluding durable goods consumption. The low R-squared value in this paper can be attributed to the fact that rural household consumption behavior may be influenced by unquantifiable factors, such as cultural traditions and temporary shocks, which cannot be directly measured through proxy variables. On the other hand, a low R-squared value does not necessarily indicate an invalid model. The coefficients and significance of the theoretical model in this study align with theoretical expectations and have passed robustness tests, demonstrating strong explanatory power.

Table 5. Robustness Test II: excluding durable goods' consumption.

Variables	(1)	(2)	(3)	(4)
	Consum_Total	Consump1	Consum2	Consum3
Fin_factor	3223.74 *** (1042)	274.9 *** (89.75)	35.83 (732.2)	741.8 * (441.7)
Controls	YES	YES	YES	YES
Constant	−634 (14,283)	−2131 * (1188)	16,214 * (9693)	−14,580 ** (5847)
Observations	1080	1080	1080	1080
R-squared	0.467	0.264	0.135	0.537

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

4.2.3. Excluding Samples of Households with Self-Reported High Financial Literacy

In real life, some households have accumulated more digital financial operation experience and knowledge through participation in financial market investments and economic activities, or through a “learning by doing” approach in their work practices. These farmers typically have higher financial literacy levels and are more proficient in using digital finance.

Including this group in the sample may lead to an overestimation or underestimation of the consumption effects of digital finance usage. Based on responses to the survey question “Please evaluate your overall level of financial knowledge”, where responses range from “Very Poor = 1” to “Very Good = 5”, this study excluded samples where respondents rated their knowledge as “Good = 4” or “Very Good = 5”, resulting in the exclusion of 81 samples. Thus, this section conducts robustness checks by excluding these high self-reported financial literacy samples, with results presented in Table 6. Compared to the baseline regression results in Table 3, the regression results remained robust even after excluding these samples. Furthermore, the coefficient for the impact of digital finance usage on total household consumption was larger than in the baseline regression results in Table 4, indicating that digital finance had a greater stimulative effect on consumption for households with average financial literacy, yielding higher marginal effects for this demographic.

Table 6. Robustness Test II: exclusion of samples with high self-reported financial literacy.

Variables	(1)	(2)	(3)	(4)
	Consum_Total	Consum1	Consum2	Consum3
Fin_factor	4294 *** (1231)	1025 *** (335.9)	1817 ** (853.6)	1617 *** (597.5)
Controls	YES	YES	YES	YES
Constant	−16,144 (15,476)	−6281 (4223)	6530 (10,730)	−20,797 *** (7511)
Observations	999	999	999	999
R-squared	0.473	0.160	0.285	0.484

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

4.3. Handling Endogeneity Issues

From the perspective of practical issues, the estimated results of digital financial usage may be subject to endogeneity. On one hand, farmers’ usage of digital finance is intrinsically influenced by their financial context. The use of different types of internet finance—such as lending, investment, and insurance—is an accumulative process, particularly in the current environment, where consumer products and services are deeply integrated with digital financial products. This integration may lead farmers to consciously enhance their knowledge of digital finance, affecting their consumption decisions and resulting in a potential reverse causality that contributes to endogeneity. On the other hand, the concept of digital financial usage is broad, encompassing internet lending, investment, and insurance, which can introduce measurement bias. Furthermore, the usage of digital finance is closely related to an implicit, unmeasurable “ability”, leading to endogeneity in the previous models due to measurement errors and omitted variables.

Based on the above analysis, this study adopts the instrumental variable method and ultimately selects smartphone usage proficiency as the instrumental variable. This variable meets the two fundamental requirements for instrument variables: relevance and exogeneity. Firstly, farmers’ usage of digital finance typically relies on smartphones, making proficiency in smartphone operation a prerequisite for accessing digital financial products and services, thereby satisfying the relevance requirement. Secondly, farmers’ consumption behaviors do not significantly influence their ownership and usage of smartphones, indicating there is no necessary causal relationship between the two, thus fulfilling the exogeneity requirement. Additionally, this study employed farmers’ membership in village internet communities as a second instrument variable. As previously analyzed, farmers’ consumption decision-making behaviors may drive them to consciously enhance their knowledge of digital finance, and the prevalence of social interactions in rural communities facilitates the sharing of digital finance experiences through these internet communities, satisfying the relevance criterion. Furthermore, whether farmers join a village internet community does not impact their household consumption scale, thereby meeting the exogeneity criterion.

To ensure the reliability of the estimation results, the cumulative scoring of digital finance usage was also tested as another endogenous variable. This study utilized the two-stage least squares method for regression analysis, with the results presented in Table 7. Panel A examines the case where factor-based digital finance usage was treated as an endogenous variable, while Panel B considers the cumulative scoring of digital finance usage as the endogenous variable.

Table 7. Endogeneity test of digital finance usage and household consumption of farmers.

Panel A: Factor Digital Finance Usage as an Endogenous Variable				
Variables	(1)	(2)	(3)	(4)
	Fin_Factor	Consum_Total	Fin_Factor	Consum_Total
	Phase One	Phase Two	Phase One	Phase Two
Phone	0.167 *** (0.0447)			
Fin_factor		21,362 * (11,072)		42,352 *** (14,890)
Community			0.0342 *** (0.00948)	
Controls	YES	YES	YES	YES
Constant	3.355 *** (0.390)	−63,379 (41,787)	3.544 *** (0.389)	−136,523 ** (55,934)
F-value		13.91		13.03
DWH Chi ²		1.75		14.205
p-value		(0.0747)		(0.0002)
Observations	1080	1080	1080	1080
R-squared	0.277	0.345	0.277	0.274
Panel B: Cumulative Scoring of Digital Finance Usage as an Endogenous Variable				
Variables	(1)	(2)	(2)	(4)
	Fin_Score	Consum_Total	Fin_Score	Consum_Total
	Phase One	Phase Two	Phase One	Phase Two
Phone	0.236 *** (0.0517)			
Fin_score		15,094 ** (7565)		32,853 *** (10,966)
Community			0.0441 *** (0.0110)	
Controls	YES	YES	YES	YES
Constant	3.968 *** (0.451)	−51,610 (35,035)	4.229 *** (0.451)	−125,350 ** (49,665)
F-value		22.34		42.12
DWH Chi ²		16.23		15.245
p-value		(0.0000)		(0.0001)
Observations	1080	1080	1080	1080
R-squared	0.288	0.388	0.285	0.283

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

In Panel A, where factor digital finance usage was treated as an endogenous variable, the variable “phone” (indicating whether farmers are proficient in using smartphones) was selected as an instrumental variable. We conducted a regression analysis using the two-stage least squares (2SLS) method and applied the Durbin–Wu–Hausman (DWH) test to compare the differences between OLS and 2SLS estimates. The results of the DWH test showed a *p*-value of 0.0747, indicating a significant endogeneity issue at the 10% significance level. However, at the 5% significance level, the endogeneity problem was not significant. To ensure the robustness of the estimation results, we chose 2SLS as the

primary estimation method. In the first-stage regression, the F-statistic for the variable “phone” was 13.91, which is greater than 10, indicating that there was no weak instrument problem. In the second-stage regression, the factor digital finance usage continued to show a positive and significant effect on the scale of household consumption, affirming the reliability of our conclusions. Similarly, we also selected the variable “community” (indicating whether farmers have joined village internet communities) as an instrumental variable and performed a regression analysis using the 2SLS method. The DWH test results showed a Chi-squared statistic of 14.205 with a p -value of 0.0002. This result was significant at the 1% level, allowing us to reject the null hypothesis that digital finance capability is an exogenous variable. The first-stage F-statistic was 13.03, indicating that there was no weak instrument problem. The conclusions drawn from Panel B, where cumulative scoring of digital finance usage was treated as an endogenous variable, remained reliable. Ultimately, the estimation results indicated that the positive impact of digital finance usage on household consumption persisted even after controlling for endogeneity, supporting the significant role of digital finance in promoting household consumption among farmers.

4.4. Impact Mechanism Test

This section further explores the impact mechanisms of digital financial capability on farmers’ household consumption behavior from three dimensions: alleviating credit constraints, enhancing risk prevention ability, and improving financial management returns. This study examined the effects of digital financial capability on credit constraints (Credit), risk prevention ability (Risk), and financial management returns (Profit). Both credit constraints (Credit) and risk prevention ability (Risk) were treated as binary variables, and Probit models were used for their mechanism tests, while financial management returns (Profit) were still examined using OLS models. Additionally, the cumulative scoring digital financial usage index was used as a control, with results presented in Table 8.

Table 8. Impact mechanism test of digital financial usage on farmers’ household consumption behavior.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Credit	Risk	Profit	Credit	Risk	Profit
Fin_factor	0.526 *** (0.0696)	0.213 ** (0.0860)	764.1 *** (127.4)			
Fin_score				0.443 *** (0.0587)	0.212 *** (0.0726)	923.9 *** (107.9)
Controls	YES	YES	YES	YES	YES	YES
Constant	−0.207 (0.967)	−1.371 (0.993)	1263 (1687)	−0.143 (0.963)	−1.545 (1.000)	85.68 (1662)
Observations	1080	1080	1080	1080	1080	1080
R-squared			0.079			0.110

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

This study used the presence of outstanding bank loans in households to represent the credit constraints faced by rural families. If rural households can obtain loans from banks or other formal financial institutions, their credit constraints are relatively small. The estimates in Columns (1) and (4) of Table 8, based on the Probit model, indicate that the various measures of digital financial usage had a positive impact on the credit accessibility of rural households, thus validating Research Hypothesis 2.

The study measured risk prevention capability through whether households purchased commercial insurance. If a household’s expenditure on commercial insurance was greater than zero, the risk prevention capability (Risk) was assigned a value of 1; if the expenditure was zero, the value was assigned as 0. The estimates in Columns (2) and (5) of Table 8, also based on the Probit model, show that both measures of digital financial usage positively influenced the households’ risk prevention capabilities. This indicates that as the level of digital financial usage increased, the probability of households participating in

commercial insurance and their risk prevention capabilities significantly improved, thus validating Research Hypothesis 3.

The study used the indicator of “financial investment returns of rural households” to examine the mechanism through which digital financial capability affects household consumption scale. According to the results in Columns (3) and (6) of Table 8, digital financial capability significantly enhanced the financial investment returns of rural households, validating Hypothesis 4.

4.5. Heterogeneity Analysis

4.5.1. Analysis Based on Differences in Income Levels and Education Levels

To reveal the relationship between digital financial use and household consumption levels among families with different income endowments, this study categorizes households into three groups: low income, middle–high income, and high income. The subsample tests based on household income classifications are presented in Columns (1) to (3) of Table 9. The results indicate that increased digital financial usage significantly positively affected overall consumption levels for middle- and high-income families, while it had a positive but insignificant impact on low-income families. This suggests that the promoting effect of digital financial use on household consumption is influenced by the family’s income level. Furthermore, this study examined the heterogeneity in the impact of digital financial use on household consumption based on education levels. Respondents’ educational attainment was divided into three categories: low, medium, and high educational levels, with results shown in Columns (4) to (6) of Table 9. The influence of digital financial use on household consumption was greater among individuals with lower to medium education levels. For each unit increase in digital financial usage, household consumption expenditure rose by 6499 yuan and 8607 yuan, respectively.

Table 9. Heterogeneity Test I: based on differences in income and education levels.

Variables	(1) Low Income	(2) Middle Income	(3) High Income	(4) Low Education	(5) Middle Education	(6) High Education
Fin_factor	637.0 (1871)	5594 * (2980)	5096 ** (2211)	6499 * (3532)	8607 ** (3327)	3250 ** (1556)
Controls	YES	YES	YES	YES	YES	YES
Constant	20,464 (19,744)	−453.9 (36,850)	−92,632 ** (43,005)	−39,847 (35,700)	−13,374 (40,090)	8899 (21,470)
Observations	270	270	540	111	208	761
R-squared	0.349	0.138	0.481	0.553	0.728	0.335

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

4.5.2. Based on Differences in Community Basic Service Levels

When enhancing the level of digital financial usage and financial literacy in households through financial education programs, special attention should be paid to the scientific design of policies and the precision of their implementation. This leads to a new question: how do the construction and promotion of foundational and developmental facilities and services in villages, such as community building, skills training, logistics delivery, and medical services, create group differences in the impact of digital financial usage on household consumption? In the context of rural revitalization, how can villages enhance the role of digital financial usage in promoting household consumption? To address this, we examined the differences in community information group chat, skills training, logistics delivery, and medical services, with results presented in Table 10, Part A and Part B.

Among them, Columns (1) and (2) represent the grouped differences based on the number of community information group chats, with groups having three or fewer and more than three. Columns (3) to (5) illustrate the group differences based on the annual

number of training participants in villages, categorized as 0–10, 10–30, and over 30 individuals. Columns (6) and (7) show the differences between groups where delivery services can and cannot reach the doorstep. Finally, Columns (8) to (10) reflect the group differences based on the number of standardized medical clinics in villages, categorized as 0, 1, and more than 1 clinic.

Table 10. Heterogeneity Test II: the effects of community building.

Part A: Based on Community Building and Skills Training					
Variables	(1)	(2)	(3)	(4)	(5)
	Low Community	High Community	Low Train	Meddle Train	High Train
Fin_factor	13,505 *** (1955)	11,378 *** (1651)	13,786 *** (1976)	12,497 *** (1830)	7195 ** (3217)
Controls	YES	YES	YES	YES	YES
Constant	27,065 *** (1344)	29,749 *** (1238)	28,326 *** (1331)	28,092 *** (1530)	28,370 *** (1993)
Observations	560	520	600	320	160
R-squared	0.079	0.084	0.075	0.128	0.031
Part B: Based on Logistics and Medical Services					
Variables	(6)	(7)	(8)	(9)	(10)
	Delivery_YES	Delivery_NO	0_Clinic	1_Clinic	2_Clinic
Fin_factor	13,377 *** (1961)	11,450 *** (1679)	6382 ** (2737)	11,553 *** (1487)	22,457 *** (3968)
Controls	YES	YES	YES	YES	YES
Constant	31,959 *** (1588)	26,250 *** (1114)	22,141 *** (1586)	28,847 *** (1111)	32,098 *** (2774)
Observations	380	700	160	780	140
R-squared	0.110	0.062	0.033	0.072	0.188

Note: *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively, and values in parentheses are standard errors.

From Columns (1) and (2) in Table 10, it can be observed that households with higher levels of digital finance usage were better able to enhance their consumption levels when the number of community information group chats was limited. With fewer community information group chats, channels for information exchange and resource sharing are constrained, reducing farmers' opportunities to access market information (such as product prices and consumption opportunities) and financial services. Digital finance, through tools such as mobile payments, online credit, and e-commerce, provides farmers with direct access to market and financial resources, thereby compensating for the lack of community information. In villages with fewer participants in skill training, the promoting effect of digital finance usage on consumption expenditure was the strongest. However, as the number of training participants increased, the influence of digital finance usage gradually diminished, though it still maintained a significant positive impact on consumption.

In villages where logistics delivery was available, the promoting effect of digital finance usage on household consumption was greater. These villages typically have well-developed road infrastructure, allowing for smooth transportation and warehousing logistics, enabling farmers to engage in broader online shopping and e-commerce activities through digital finance. Conversely, in villages without medical clinics, the impact of digital finance usage on household consumption expenditure was relatively small. This may be due to insufficient health security suppressing some consumption demands, as farmers prioritize preventive savings for health reasons, which restrains current consumption. However, as the number of medical clinics increased, the positive influence of digital finance usage on consumption expenditure significantly enhanced.

5. Research Conclusions and Implications

Expanding resident consumption demand is a crucial requirement to meet the growing aspirations for a better life and to achieve domestic circulation. Effectively unleashing resident consumption potential and promoting consumption upgrades are key strategic bases for accelerating the construction of a new development pattern. This study, based on micro-survey data from households and villages collected by the research team in 2022, investigated the impact mechanisms and effects of digital finance usage on the household consumption scale and structural upgrades.

The results indicated that (1) digital finance usage significantly promoted the expansion of the household consumption scale and the upgrading of the consumption structure, particularly in fostering development of enjoyment-based consumption. Robustness checks—using cumulative scoring for digital finance usage, excluding durable goods consumption indicators, eliminating samples of households with self-reported high financial literacy, and employing instrumental variable methods to address endogeneity—confirmed that the results remained robust. (2) Mechanism testing revealed that alleviating credit constraints, enhancing risk prevention capabilities, and increasing financial investment returns are the primary pathways through which digital finance usage drives the expansion and quality improvement of household consumption. (3) The analysis of the heterogeneous consumption effects of digital finance usage showed that it was more effective in unlocking consumption potential among middle- and high-income households, and its promoting effect was more pronounced among those with lower education levels. Additionally, heterogeneity tests at the village level indicated that community building and skills training significantly amplified the consumption-promoting effects of digital finance usage, while improvements in logistics delivery and basic medical clinic services also enhanced the capacity and efficiency of consumption effects.

Based on the above research, this paper proposes the following policy recommendations: First, strengthen digital financial education and promotion. Targeted and tiered education programs should be implemented for different groups. For farmers with lower levels of education, accessible and straightforward training on digital financial literacy should be provided, focusing on the use of basic financial tools, such as mobile payments, online loans, and digital savings. Additionally, community information group chats should be leveraged at the village level to share case studies on the use of digital financial tools and best practices for making consumption decisions. This approach aims to enhance trust and willingness to adopt digital finance solutions. Second, optimize the rural digital financial ecosystem. Efforts should be made to develop a diverse range of digital financial products. For middle- and high-income groups, more consumption-oriented credit products, such as specialized loans for education, healthcare, and tourism, should be designed. At the same time, low-income groups should be provided with low-interest, low-threshold microcredit products. Additionally, the convenience of digital financial services should be enhanced by promoting the adoption of smart terminal devices and related software applications, enabling farmers to access digital financial services with ease. Simplifying the operational processes of digital financial tools is also essential to reduce technical barriers. Third, strengthen village infrastructure development. Efforts should be made to promote community building and skills training by encouraging villages to organize regular training courses on topics such as e-commerce operations and financial management. This will enhance residents' abilities to use digital financial tools, thereby amplifying the role of digital finance in driving consumption. Additionally, the logistics distribution network should be improved by establishing efficient logistics channels between rural and urban areas to reduce transportation costs for consumer goods and promote e-commerce consumption. Policy support should also be provided to e-commerce logistics enterprises to address the "last-mile"-delivery challenge in rural areas. Furthermore, medical and health security should be enhanced by improving the infrastructure of rural medical clinics. This will provide farmers with reliable healthcare services, reduce their precautionary savings needs, and unlock greater consumption potential.

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Notes

- ¹ Source: National Bureau of Statistics, https://www.stats.gov.cn/xxgk/jd/sjd2020/202101/t20210119_1812623.html (accessed on 12 September 2024).
- ² Source: National Bureau of Statistics, “2020 Resident Income and Consumption Expenditure,” https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900970.html (accessed on 12 September 2024).

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