The Impact of Digital Finance on the Livelihood Resilience of Poverty-Alleviated Farming Households

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Abstract

Improving the livelihood resilience of poverty-alleviated rural households is a core pathway for consolidating the achievements of poverty alleviation and establishing a long-term mechanism to prevent the risk of returning to poverty. Based on micro-survey data from 496 poverty-alleviated rural households in Ulanqab, Inner Mongolia Autonomous Region, in 2023, this study measures household livelihood resilience using the entropy method and comprehensive index method, and analyzes the effects and mechanisms of digital finance use and endogenous livelihood capital on the livelihood resilience of poverty-alleviated rural households through multiple linear regression, mediation effect models, propensity score matching (PSM), and instrumental variable methods. The results show that: (1) Livelihood resilience is the capacity of rural households to integrate risk resistance and loss recovery, and its core influencing factors include endogenous livelihood capital (personal health, household economy, and human capital) and external intervention (digital finance). (2) Among endogenous livelihood capital factors, a higher level of personal health and better household economic conditions significantly enhance livelihood resilience, while advanced age significantly inhibits it. (3) Digital finance use significantly enhances livelihood resilience through the dual mechanisms of promoting agricultural technology adoption to improve production efficiency and facilitating livelihood transformation to broaden income sources. (4) Endogenous livelihood capital and digital finance use need to form synergistic effects in order to overcome the structural constraints of "advanced age and low education" among poverty-alleviated rural households. The findings provide micro-level empirical evidence for optimizing household livelihood support policies in the context of preventing a return to poverty.

Full Text

The Impact of Digital Finance on the Livelihood Resilience of Poverty-Alleviated Farming Households

—An Investigation and Analysis Based on Ulanqab City

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Abstract: Enhancing the livelihood resilience of poverty-alleviated farming households is a core pathway for consolidating the achievements of poverty alleviation and establishing a long-term mechanism to prevent the risk of returning to poverty. Based on micro-survey data from 496 poverty-alleviated farming households in Ulanqab City, Inner Mongolia Autonomous Region, in 2023, this study uses the entropy method and the comprehensive index method to measure farmers' livelihood resilience. Through multiple linear regression, a mediating-effect model, propensity score matching (PSM), and an instrumental-variable approach, it analyzes the impacts and mechanisms of digital finance use and endogenous livelihood capital on the livelihood resilience of poverty-alleviated farming households. The results show that: (1) livelihood resilience is farmers' capacity to integrate risk resistance and loss recovery, and its core influencing factors include endogenous livelihood capital—personal health, household economy, and human capital—and external intervention, namely digital finance. (2) Among endogenous livelihood capital factors, higher levels of farmers' personal health and better household economic conditions significantly enhance livelihood resilience, while excessive age significantly inhibits it. (3) Digital finance use significantly enhances livelihood resilience through a dual mechanism: promoting the adoption of agricultural technologies to improve production efficiency and facilitating livelihood transformation to broaden income sources. (4) Endogenous livelihood capital and digital finance use must generate synergistic effects in order to break the structural constraints of "advanced age and low education" among poverty-alleviated farming households. The research findings provide micro-level empirical evidence for optimizing household livelihood-support policies in the context of preventing a return to poverty.

Keywords: prevention of return to poverty; poverty-alleviated farming households; livelihood resilience; digital finance; endogenous livelihood capital

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In 2020, China achieved a complete victory in the battle against poverty. The CPC Central Committee decided to establish a five-year transition period to promote the effective linkage between consolidating the achievements of poverty alleviation and rural revitalization. During the transition period, localities and departments fully leveraged the role of the monitoring and assistance system for preventing a return to poverty, taking timely and targeted measures for precise assistance, and no large-scale return to poverty occurred. However, farmers' livelihoods still face multiple challenges from natural, economic, and social dimensions[^1]. The risk of returning to poverty among poverty-alleviated farming households still exists[^2–^5], and livelihoods remain unstable. Existing studies mostly analyze farmers' livelihoods based on two types of frameworks. The first is the livelihood-vulnerability framework of "exposure level–sensitivity–adaptive capacity" (VSD), which focuses on risk identification; however, the concept of "adaptive capacity" is broad and difficult to quantify, and it lacks a systematic characterization of recovery mechanisms. The second is the livelihood-resilience framework of "buffering capacity–self-organization capacity–learning capacity," which emphasizes system recovery but neglects the assessment of risk exposure and sensitivity. Moreover, its core dimensions overlap with VSD; for example, both "buffering capacity" and "adaptive capacity" are based on the five major livelihood capitals[^6–^10]. This theoretical divergence makes existing tools unable to fully characterize the dynamic process of "risk shock–system response–

resilience formation," and makes it even more difficult to explain the multidimensional risks and sustainable-development contradictions faced by poverty-alleviated farming households during the transition period[^11].

In recent years, because the concept of livelihood resilience integrates the capacities of risk resistance and loss recovery, it has become an important tool for measuring the stability of farmers' livelihoods. Livelihood resilience refers to the dynamic capacity of poverty-alleviated farming households to achieve "risk resistance and loss recovery" when facing external risk shocks from nature, the economy, society, and other sources[^12]. The realization of this capacity depends on the joint effect of endogenous livelihood capital and external support measures. Endogenous livelihood capital refers to resources accumulated by farming households over the long term and capable of being autonomously mobilized; it is the "core household foundation" for coping with risks and includes the five major forms of capital: natural, physical, financial, human, and social. External support measures are external resources provided by the government, the market, social organizations, and other actors, mainly used to help farmers resist risks and recover losses, including policy support, economic support, service support, and so forth. Together, the two affect the level of livelihood resilience. However, existing research has not yet clarified the logical relationships among vulnerability, recoverability, and resilience, and framework construction remains fragmented. On this basis, this paper takes "risk input–

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takes the dynamic matching of "risk shocks—livelihood capacity responses" as its core logic, integrating the VSD [13] and Speranza [14] resilience frameworks. At the risk-input end, it retains VSD's "exposure level," which measures the frequency and intensity of natural disasters experienced by farmers, and "sensitivity," which measures the degree to which farmers' livelihood systems are prone to damage. At the capacity-response end, it reconstructs the "buffering capacity" of the resilience framework to measure static livelihood capital, such as land quality and household savings; distinguishes from VSD's broad "adaptive capacity"; uses "self-organization capacity" to measure livelihood-strategy adjustments driven by social networks; and uses "learning capacity" to measure long-term adaptation driven by cognitive upgrading, thereby supplementing the individual-cognition dimension of the resilience framework. These five dimensions form a logical chain of "risk shock (exposure level, sensitivity) → short-term resistance (buffering) → medium-term transformation (self-organization) → long-term adaptation (learning)," which not only resolves the problems of dimensional overlap and omission in the original framework, but also dynamically depicts the formation process of livelihood resilience.

Within this framework, the endogenous livelihood capital of poverty-alleviated farm households—such as health, economic, and human capital—constitutes the foundation of resilience. However, because it is difficult to change structural constraints such as advanced age and low education in the short term, improving the level of farmers' livelihood resilience depends not only on the supporting role of their endogenous livelihood capital, but also on the intervention of external measures to reduce the risk of returning to poverty. In the process of consolidating and expanding the achievements of poverty alleviation and effectively linking them with rural revitalization, the financial system plays an important bridging role. Digital finance, as a product of the integration of digital technology and financial services [15], can improve the efficiency and quality of financial activities and significantly lower the threshold and cost of financial services [16]. It can become an external empowerment tool for enlarging endogenous livelihood capital [17]. Its value lies in providing farmers with timely financial support, helping them absorb shocks more quickly, maintain the operation of basic livelihoods, and make up for the shortcomings caused by the slow recovery of traditional reserve capital. It can provide farmers with new channels for obtaining information, exchanging experience, engaging in collaborative production, joining online cooperatives, and seeking non-agricultural employment opportunities, thereby helping them improve their ability to use social capital to actively adjust livelihood strategies and strengthen self-organization capacity. Digital financial tools themselves are information carriers; farmers can more conveniently obtain knowledge of agricultural technologies, market conditions, financial knowledge, and policy information, thereby promoting cognitive upgrading and optimizing decision-making.

This paper selects Ulanqab City as the study area mainly for the following three reasons. First, the city is an inland arid and semi-arid region with frequent meteorological disasters. Farmers who mainly engage in traditional dryland farming and animal husbandry face prominent pressures in terms of exposure level and sensitivity, making it an appropriate setting for testing livelihood resilience in response to natural risks. Second, the interviewed households are mainly left-behind elderly people and exhibit the characteristics of "advanced age, low education, and poor health." Their livelihoods depend on a single source of agricultural income, and their endogenous livelihood capital has structural constraints, which is consistent with the theme of this paper: the coordinated improvement of resilience through endogenous livelihood capital and digital finance. Third, as a key area for consolidating the achievements of poverty alleviation, Ulanqab' s rural digital finance is still in its initial stage of development, farmers' utilization rate is relatively low, and relevant experience can provide micro-level reference for the formulation of poverty-return prevention policies in similar regions.

On this basis, this paper takes 496 poverty-alleviated farm households in Ulanqab City as the research objects and uses methods such as the entropy method, multiple linear regression, mediation-effect models, propensity score matching (PSM), and instrumental variables to focus on the following questions: What are the core influencing factors of the livelihood resilience of poverty-alleviated farm households? Through what mechanisms does the use of digital finance affect livelihood resilience? How should internal and external factors work together to prevent a return to poverty? The aim is to provide micro-level evidence for optimizing farmer livelihood-support policies under the background of poverty-return prevention.

1 Data and Methods

1.1 Overview of the Study Area

Ulanqab City is located in an inland arid and semi-arid region, with a total area of 5.45×10^4 km^2, an agricultural population of 6.108×10^5 people, and a cultivated land area of 9.07×10^5 hm^2. It is an area prone to meteorological disasters, mainly including drought, sandstorms, cold waves, rainstorms, blizzards, frost, and low temperatures. These disasters are frequent, regional, and seasonal, and multiple disasters often occur simultaneously (Figure 1). The survey shows that the interviewed farm households are mainly left-behind elderly people, who still engage in traditional rain-fed dryland farming—planting potatoes and wheat—and animal husbandry. This production mode faces multiple challenges, including low per-mu production benefits, livestock losses caused by winter cold waves, and forage shortages caused by drought. Livelihood vulnerability is high and self-recovery is difficult, creating an urgent need for external intervention to improve livelihood resilience. Meanwhile, the younger generation in each household mostly chooses to work away from home and is less engaged in agricultural work.

1.2 Data Sources and Questionnaire Survey

The data come from a field survey of poverty-alleviated farm households in Ulanqab City, Inner Mongolia, conducted from July to September 2023 by the "Farm Household Livelihoods" research group of Shanxi Normal University. A stratified multistage sampling method at the "township-village-household" levels was adopted. First, townships were divided into two strata—large villages and small villages—according to natural conditions, ensuring that the economic and demographic characteristics within each stratum were similar. Next, 2–3 townships were randomly selected from each stratum, and 2–3 villages were selected from each township, ultimately covering 18 sample villages in 7 counties/districts. Finally, one-on-one interviews were conducted with resident farm households in the sample villages. A total of 533 questionnaires were distributed; after screening for completeness and logical consistency, 496 valid questionnaires were obtained, with an effective response rate of 93.1%. Among them, 40 were from Zhuozi County, 170 from Fengzhen City, 132 from Qahar Right Front Banner, 40 from Qahar Right Middle Banner, 35 from Qahar Right Rear Banner, 38 from Jining District, and 41 from Liangcheng County.

The questionnaire adopted a structured format and covered five core mod-

(a) Elevation of the study area

Map labels: Chahar Right Rear Banner; Chahar Right Middle Banner; Jining District; Zhuozi County; Liangcheng County; Fengzhen City; Chahar Right Front Banner.

Legend: county/district boundary; elevation/m: 2300–1148. Scale: 0–30 km. North arrow.

(b) Distribution of survey sites

Map labels: Chahar Right Rear Banner; Baiyinchagan Town; Kebuer Town; Chahar Right Middle Banner; Sancha Kou Township; Malianqu Township; Jining District; Zhuozi County; Zhuozishan Town; Bayinhai Town; Chahar Right Front Banner; Tugu Wula Town; Longshengzhuang Town; Hongshaba Town; Fengzhen City; Guantunbao Township; Jubaotun Town; Liangcheng County; Hongmao Town.

Legend: county/district boundary; townships where survey sites are located. Scale: 0–30 km. North arrow.

Fig. 1 Overview of the study area

···modules. Among them, in order to systematically examine the multidimensional role of digital finance in the livelihood system of farming households, the questionnaire did not establish an independent module for measuring the use of digital finance; instead, it treated it as a core thread and embedded it within the five modules above for cross-observation. The questionnaire reliability and validity tests show that Cronbach' s Alpha coefficient is 0.718, greater than 0.7, indicating good internal consistency of the scale; the Kaiser-Meyer-Olkin (KMO) value is 0.757, greater than 0.7, and Bartlett' s test has $P < 0.001$, indicating that the data are suitable for subsequent analysis.

1.3 Research methods

1.3.1 Measurement of farming households' livelihood resilience

The livelihood resilience evaluation index for poverty-alleviated farming households is constructed from five dimensions: "exposure level, sensitivity, buffering capacity, self-organization capacity, and learning capacity," to evaluate whether they face a risk of returning to poverty[^9]. First, the entropy method and the composite index method are used to calculate the livelihood vulnerability index and the livelihood recovery-capacity index; second, the livelihood recovery-capacity index is subtracted from the livelihood vulnerability index to obtain the livelihood resilience index. If the livelihood resilience index is less than 0, it indicates that the livelihood recovery-capacity index is smaller than the livelihood vulnerability index, and poverty-alleviated farming households face a risk of returning to poverty; otherwise, they do not face such a risk.

The specific selection of indicators at each dimension is as follows: (1) "exposure level" is represented by the degree to which drought, wind disasters, hail disasters, frost, snow disasters, and desertification affect agricultural production; (2) "sensitivity" is represented by the share of agricultural income and the share of agricultural labor; (3) "buffering capacity" is represented by land quality, labor quantity, agricultural machinery and equipment, and household savings; (4) "self-organization capacity" is represented by the political outlook of household members, social trust, participation in community activities, participation in cooperatives, and social relations; (5) "learning capacity" is represented by financial literacy, economic decision-making capacity, and information-screening capacity[^18]. The specific indicator information is shown in Table 1.

The calculation process for each indicator is as follows.

(1) Because differences in indicator properties, magnitudes, and dimensions exist among the original questionnaire data, the data are standardized.

Positive indicators:

$$X'_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Negative indicators:

$$X'_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}} \tag{2}$$

where X'_{ij}, X_{ij}, $X_{\max}$, and $X_{\min}$ are, respectively, the standardized value, original value, maximum value, and minimum value of the j-th indicator for the i-th farming household.

(2) The entropy method is used to determine indicator weights.

$$p_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}} \tag{3}$$

$$e_j = -k \sum_{i=1}^{n} \left(p_{ij} \times \ln p_{ij}\right) \tag{4}$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} \left(1 - e_j\right)} \tag{5}$$

where p_{ij} is the proportion of the standardized value of the j-th indicator for the i-th farming household; e_j and w_j are, respectively, the entropy value and weight of the j-th indicator; $k = 1/\ln n$, is the entropy

Table 1 Connotations and weights of evaluation indicators for the vulnerability and resilience of farmers' livelihoods

Tab. 1 Connotations and weights of evaluation indicators for the vulnerability and resilience of farmers' livelihoods

Element layer	Indicator layer	Indicator connotation	Weight
Exposure level	Degree of drought impact	Degree of drought impact on agricultural production	0.043
Exposure level	Degree of wind-disaster impact	Degree of wind-disaster impact on agricultural production	0.025
Exposure level	Degree of hail-disaster impact	Degree of hail-disaster impact on agricultural production	0.023
Exposure level	Degree of frost impact	Degree of frost impact on agricultural production	0.019
Exposure level	Degree of snow-disaster impact	Degree of snow-disaster impact on agricultural production	0.004
Exposure level	Degree of sandification impact	Degree of sandification impact on agricultural production	0.034
Sensitivity	Share of agricultural income	Proportion of agricultural income in total household income	0.120

Element layer	Indicator layer	Indicator connotation	Weight
Sensitivity	Share of agricultural labor	Proportion of agricultural labor in the household’ s total labor force	0.144
Buffering capacity	Land quality	Comprehensive judgment based on soil fertility and field-road conditions	0.053
Buffering capacity	Quantity of labor	Number of working-age laborers in the household	0.043
Buffering capacity	Agricultural machinery and equipment	Whether the household owns agricultural machinery and equipment	0.034
Buffering capacity	Household savings	Sum of the household members’ current savings	0.037
Self-organization capacity	Political status of household members	Political status of household members	0.034
Self-organization capacity	Social trust	Respondent’ s degree of trust in other villagers	0.065
Self-organization capacity	Participation in community activities	Whether household members participate in community activities	0.055
Self-organization capacity	Participation in cooperatives	Whether household members have joined a cooperative	0.042

Element layer	Indicator layer	Indicator connotation	Weight
Self-organization capacity	Social relations	Whether there are relatives working in the government or in banks	0.039
Learning capacity	Financial literacy capacity	Respondent' s understanding of credit policies	0.071
Learning capacity	Economic decision-making capacity	Type of investment project preferred by the respondent	0.070
Learning capacity	Information-screening capacity	Whether the respondent can compare deposit interest rates across different periods and different banks	0.045

standardization coefficient; n is the total number of sampled farming households; m is the total number of evaluation indicators.

(3) The composite index method is used to calculate the livelihood resilience of farming households.

Livelihood vulnerability:

$$E_i = \sum_{j=1}^{6} \left(w_j \times X'_{ij}\right) \tag{6}$$

$$M_i = \sum_{j=7}^{8} \left(w_j \times X'_{ij}\right) \tag{7}$$

$$V_i = E_i + M_i \tag{8}$$

Livelihood recovery capacity:

$$B_i = \sum_{j=9}^{13} \left(w_j \times X'_{ij}\right) \tag{9}$$

$$S_i = \sum_{j=14}^{17} \left(w_j \times X'_{ij} \right) \tag{10}$$

$$L_i = \sum_{j=18}^{20} \left(w_j \times X'_{ij} \right) \tag{11}$$

$$R_i = B_i + S_i + L_i \tag{12}$$

Livelihood resilience:

$$\mathrm{LR}_i = R_i - V_i \tag{13}$$

In the formulas: E_i and M_i are respectively the exposure index and sensitivity index of the i-th farming household; B_i, S_i, and L_i are respectively the buffering capacity, self-organization capacity, and learning capacity of the i-th farming household; V_i is the livelihood vulnerability index of the i-th farming household; R_i is the livelihood recovery capacity index of the i-th farming household; and LR_i is the livelihood resilience index of the i-th farming household.

1.3.2 Research model

A multiple linear regression model is used to analyze the impact of digital financial use on the livelihood resilience of farming households. The following benchmark model is constructed:

$$\mathrm{LR}_i = \alpha_0 + \alpha_1 \mathrm{Fina}_i + \alpha_2 \mathrm{Control}_i + \varepsilon_i \tag{14}$$

In the formula: LR_i is the explained variable, representing the livelihood resilience index of the i-th farming household; Fina_i is the explanatory variable, representing the digital financial use of the i-th farming household; $\mathrm{Control}_i$ is the control variable, representing the individual characteristics and household characteristics of the i-th farming household; α_0 is the constant term; α_1 and α_2 are the corresponding regression coefficients; and ε_i is the random error term.

With reference to Moser’ s asset-dynamics framework [19] and Ellis’ s capital dynamic-transformation framework [20], the endogenous livelihood capital of farming households, as a stock, is unlikely to change significantly in the short term. By contrast, as an external intervention measure, digital financial use can enable farming households to quickly obtain externally injected financial capital in the short term, support them in adopting more appropriate agricultural production technologies or carrying out non-agricultural entrepreneurial activities. To verify whether the use of agricultural production technologies and livelihood transformation play a mediating role in the process by which digital financial use affects the livelihood resilience of farming households, on the basis of the benchmark regression model and with reference to Jiang Ting' s two-step method [21], a mediation-effect model is constructed:

$$\text{Mediator}_i = \beta_0 + \beta_1 \text{Fina}_i + \beta_2 \text{Control}_i + \mu_i \tag{15}$$

where: Mediator_i denotes, respectively, agricultural production technology use and livelihood transformation for the ith farmer household; β_0 is the constant term; β_1 and β_2 are the corresponding regression coefficients; and μ_i is the random error term.

1.3.3 Variable setting

(1) The explained variable is the livelihood resilience index, measured using the entropy method and the comprehensive index method.

(2) The explanatory variable is "digital finance use," measured by whether the farmer household uses third-party payment services (such as Alipay or WeChat Pay) or Internet lending (such as Ant Credit Pay or JD Finance). Use is assigned a value of 1, and non-use a value of 0.

(3) The mechanism variables are agricultural production technology use and livelihood transformation. The former is measured by whether the farmer household uses any agricultural technology such as soil improvement or water-saving irrigation; the latter is measured by whether the farmer household engages in non-agricultural activities such as running a small shop or an online store. Yes and no are assigned values of 1 and 0, respectively.

(4) For control variables, household head age, gender, education level, and health level are selected as individual-level control variables; the number of household members, number of houses, contracted land, and land area are selected as household-level control variables.

Descriptive statistics for the relevant variables are shown in Table 2.

As can be seen from Table 2, the minimum value of the livelihood resilience index is −0.209 (<0). According to the statistics, among the surveyed households that have been lifted out of poverty, 41.14% have a livelihood resilience level below "0." Although they have been lifted out of poverty, they still face a relatively high risk of returning to poverty. In terms of the individual characteristics of households lifted out of poverty, the average age reaches 64 years, the average education level does not reach senior high school, only 15.93% of households are in good health, each household has on average only one house and cannot use it for mortgage or productive purposes, and the digital finance usage rate is only 33.36%. These characteristics—advanced age, low education level, low health level, and low material capital—indicate that structural obstacles remain in livelihood recovery.

2 Results and Analysis

2.1 Benchmark regression results

The benchmark model regression results are shown in Table 3. Columns (1)-(3) show that, after progressively taking into account control variables at the individual and household levels, the use of digital finance as an external measure helps improve the livelihood resilience level of farmer households. In the multicollinearity test, the variance inflation factors (VIF) are all less than 10, indicating that the multicollinearity among the selected variables is within an acceptable range.

It can also be seen from column (3) that health level and education level significantly improve the livelihood resilience level of farmer households, whereas age and the number of household members have a negative impact on livelihood resilience (Table 3). Usually, older people have poorer health, and the two together reflect the importance of personal health and physical condition in improving livelihood resilience. In general, households with more family members suffer less negative impact from risk shocks. However, the regression result is the opposite. A possible reason is that the greater the number of laborers in a farmer household, the more likely they are to choose migrant work, resulting in the dispersion of household members and reducing the livelihood resilience of farmer households. This phenomenon still requires further study. The higher the education level of farmer households, the stronger their ability to accept new things and their cognitive ability, which helps improve their long-term adaptability and livelihood resilience.

Table 2 Descriptive statistics of relevant variables

Variable category	Variable name	Variable meaning	Mean	Standard deviation	Minimum	Maximum
Explained variable	Livelihood resilience	Measured according to the comprehensive index method	0.029	0.094	−0.209	0.303
Explanatory variable	Digital finance use	Use = 1; non-use = 0	0.331	0.471	0.000	1.000

Variable category	Variable name	Variable meaning	Mean	Standard deviation	Minimum	Maximum
Mechanism variable	Agricultural production technology use	Yes = 1; no = 0	0.653	0.476	0.000	1.000
Mechanism variable	Livelihood transformation	Yes = 1; no = 0	0.105	0.307	0.000	1.000
Control variable	Age/years	Household head age	64.119	11.920	26.000	90.000
Control variable	Gender	Household head: male = 1; female = 0	0.451	0.498	0.000	1.000

Variable category	Variable name	Variable meaning	Mean	Standard deviation	Minimum	Maximum
Control variable	Education level	Household head’ s education level: junior high school or below = 1; senior high school = 2; bachelor’ s degree = 3; master’ s degree = 4; doctorate = 5	1.502	0.799	1.000	5.000
Control variable	Health level	Poor = 1; relatively poor = 2; average = 3; good = 4; excellent = 5	3.133	1.256	1.000	5.000

Variable category	Variable name	Variable meaning	Mean	Standard deviation	Minimum	Maximum
Control variable	Number of household members	1 person = 1; 2 persons = 2; 3 persons = 3; 4 persons = 4; 5 persons and above = 5	2.913	1.205	1.000	5.000
Control variable	Number of houses	None = 1; 1 house = 2; 2 houses = 3; 3 houses and above = 4	2.026	0.314	1.000	4.000
Control variable	Contracted land	Yes = 1; no = 0	0.617	0.487	0.000	1.000
Control variable	Land area/hm^2	Land area (logarithm)	1.638	1.519	0.000	5.707
Instrumental variable	Owns a smartphone	Yes = 1; no = 0	0.521	0.500	0.000	1.000

Table 3 Benchmark regression results

Variable	(1)	(2)	(3)
Digital finance usage	0.056^{***}(0.009)	0.032^{***}(0.010)	0.036^{***}(0.010)
Age	-	-0.000^{***}(0.001)	-0.001^{**}(0.000)

Variable	(1)	(2)	(3)
Gender	–	$0.017^{**}(0.009)$	0.013(0.009)
Education level	–	$0.016^{***}(0.006)$	$0.014^{***}(0.006)$
Health status	–	$0.007^{*}(0.004)$	$0.008^{**}(0.004)$
Number of household members	–	–	$-0.013^{***}(0.004)$
Number of houses	–	–	0.028(0.014)
Contracted land	–	–	−0.001(0.016)
Land area	–	–	0.000(0.005)
Constant	$0.103^{**}(0.005)$	$0.020^{***}(0.038)$	0.014(0.047)
Sample size	496	496	496
VIF value	–	1.340	1.950
R^2	0.078	0.149	0.183

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively; VIF is the variance inflation factor; R^2 is the model goodness of fit; values in parentheses are robust standard errors. The same applies below.

2.2 Endogeneity test

Considering that there may be a bidirectional causal relationship between digital finance usage and farmers' livelihood resilience, this paper selects whether the farm household owns a smartphone as an instrumental variable to test for endogeneity (Table 4). As a necessary hardware carrier for digital payment and online financial services, the smartphone is directly related to the adoption of digital finance and satisfies the relevance requirement for an instrumental variable, while whether a farmer owns a mobile phone does not directly affect the farmer' s livelihood resilience.

In the first stage, the estimated coefficient of farmers' ownership of smartphones is significant at the 1% significance level, satisfying the relevance principle. In the second stage, the estimated coefficient of digital finance usage is significant at the 1% significance level. This result indicates that, after controlling for the problem of bidirectional causality, digital finance usage still has a positive impact on the livelihood resilience of farm households. The Lagrange multiplier test (LM) statistic is 14.796, rejecting the null hypothesis that "the instrumental variable is underidentified" ; the weak instrumental variable F value is 15.180 > 10, indicating that there is no problem of weak instruments, thereby verifying the robustness of the benchmark regression results.

2.3 Robustness test

For the robustness test, households are grouped according to "whether the household uses digital finance" : those using digital finance are assigned to the treatment group, and otherwise to the control group. PSM is used to match the treatment group and the control group, thereby enhancing their comparability. First, based on the logit model, the propensity score for each farmer entering the treatment group is calculated; second, according to the propensity score, nearest-neighbor matching with $k = 4$ is used to match treatment-group households with the most similar control group in terms of characteristics; finally, to ensure the matching effect, balance tests are conducted on the two groups of samples (Tables 5–6).

Table 4 Results of endogeneity analysis of digital finance usage

Variable	First stage of digital finance usage	Second stage of livelihood resilience
Digital finance usage	-	$0.140^{***}(0.060)$
Owns a smartphone	$0.185^{***}(0.047)$	-
Control variables	Controlled	Controlled
Constant	$0.472^{**}(0.238)$	$-0.043(0.068)$
LM statistic	14.796	14.796
Weak-instrument variable F value	15.180	15.180

Note: LM is the Lagrange multiplier test.

Before matching, except for contracted land, the absolute standardized deviations of the covariates are all greater than 10%, and the t-test results are significant, indicating that most covariates differ significantly between the treatment group and the control group. After matching, the standardized deviations of the covariates shrink and their absolute values are all less than 10%; the t-test results are not significant, indicating that there are no significant differences in covariates between the treatment group and the control group. The comparability of the two groups of samples is enhanced and meets the requirements of a randomized experiment.

Compared with before matching, after matching, the goodness of fit of the propensity score model (Ps R^2), the mean standardized bias (Mean Bias), the median standardized bias of all covariates (Med Bias), and the sum of squares of the standardized bias of the sample (B) all decrease significantly; the significance of the likelihood-ratio chi-square statistic (LR chi^2) declines; and the ratio of the covariate variances between the treatment group and the control group (R) approaches 1. This indicates that, after matching, the independence between variables and the balance of their distributions are significantly improved. Therefore, the sample matching results are reliable (Table 6).

In the preceding empirical analysis, nearest-neighbor matching with $k = 4$ was adopted for propensity score matching. This paper further uses caliper matching, kernel matching, and radius matching to enhance the robustness of the benchmark regression results (Table 7). The regression results under different matching methods are basically consistent with those above: the effect of digital finance usage on improving farmers' livelihood resilience is significant, and the average treatment effects of the above matching methods are all positive and relatively close, all passing the significance test at the 1% level. The regression results of the benchmark model are therefore relatively reliable.

2.4 Mechanism test

2.4.1 Adoption of adaptive agricultural technologies

Column (2) verifies the impact of digital finance usage on the adoption of agricultural technologies (Table 8). The impact of digital finance usage on the use of agricultural technologies is positive and significant at the 10% significance level, indicating that digital finance usage promotes farmers' use of agricultural technologies and improves production efficiency

. Compared with traditional finance, digital finance, on the basis of providing financial support, has unique advantages in information transmission; it can not only help farmers obtain knowledge related to agricultural technologies

Table 5 Comparison of the sample experimental group and the control group before and after propensity score matching (PSM)

Tab. 5 Comparison of the sample experimental group and the control group before and after PSM

Variable	Treatment	Experimental-group mean	Control-group mean	Standardized bias/%	Reduction/%	t-test
Age	Before matching	57.095	67.362	−88.7	97.7	0.000
Age	After matching	59.577	59.819	−2.1		0.859
Gender	Before matching	0.563	0.390	35.0	79.1	0.001
Gender	After matching	0.549	0.513	7.3		0.545

Variable	Treatment	Experimental-group mean	Control-group mean	Standardized bias/%	Reduction/%	t-test
Education level	Before matching	1.823	1.340	57.0	99.9	0.000
Education level	After matching	1.620	1.620	−0.1		0.997
Health status	Before matching	3.601	2.930	55.6	90.0	0.000
Health status	After matching	3.486	3.553	−5.5		0.633
Number of family members	Before matching	3.298	2.749	47.1	79.8	0.000
Number of family members	After matching	3.239	3.189	4.3		0.460
Number of houses in the household	Before matching	2.086	2.006	25.9	90.9	0.009
Number of houses in the household	After matching	2.078	2.107	−9.4		0.717
Contracted land	Before matching	0.601	0.632	−6.3	−7.4	0.520
Contracted land	After matching	0.627	0.594	6.7		0.573

Variable	Treatment	Experimental-group mean	Control-group mean	Standardized bias/%	Reduction/%	t-test
Land area	Before matching	1.511	1.733	−14.8	82.1	0.133
Land area	After matching	1.567	1.527	2.7		0.822

Table 6 Balance test

Tab. 6 Balance test

Sample	Ps R^2	LR χ^2	$P > \chi^2$	Mean Bias	Med Bias	B	R
Before matching	0.223	134.49	0.000	41.3	41.1	118.2	1.74
After matching	0.006	2.21	0.974	4.8	4.9	17.6	1.07

Note: Ps R^2 is the goodness of fit of the propensity-score model; LR χ^2 is the likelihood-ratio chi-square statistic; $P > \chi^2$ is the P value of the above LR χ^2 test; Mean Bias is the mean standardized bias; Med Bias is the median standardized bias of all covariates; B is the sum of squared standardized biases of the sample; and R is the ratio of the covariate variances between the experimental group and the control group.

Table 7 Average treatment effects under different matching methods

Tab. 7 Average processing effects under different matching methods

Variable	Nearest-neighbor matching	Caliper matching	Radius matching	Kernel matching
Use of digital finance	0.038^{***}(0.010)	0.039^{***}(0.010)	0.035^{***}(0.009)	0.035^{***}(0.010)
Control variables	Controlled	Controlled	Controlled	Controlled
Constant term	−0.084(0.055)	−0.087(0.055)	0.023(0.050)	0.015(0.048)

Variable	Nearest-neighbor matching	Caliper matching	Radius matching	Kernel matching
Sample size	317	314	388	405
R^2	0.161	0.159	0.130	0.145
Average treatment effect	0.033^{**}(0.013)	0.033^{**}(0.013)	0.023^{**}(0.029)	0.027^{***}(0.012)

Table 8 Mechanism test results

Tab. 8 Mechanism test results

Variable	(1) Livelihood resilience	(2) Agricultural technology	(3) Livelihood transformation
Use of digital finance	0.036^{***}(0.010)	0.099^{*}(0.052)	0.095^{***}(0.037)
Control variables	Controlled	Controlled	Controlled
Constant term	0.014(0.047)	0.407(0.261)	0.022(0.154)
Sample size	496	496	496
R^2	0.183	0.316	0.099

knowledge; it also provides additional market information through financial-service platforms, helping farmers better understand and respond to market changes and improving their livelihood resilience[^23].

2.4.2 Promoting the livelihood transformation of households lifted out of poverty

The regression results in column (3) indicate that the use of digital finance helps promote farmers' livelihood transformation[^24-25] (Table 8). Digital finance not only alleviates the credit constraints faced by farmers in livelihood transformation, but also, by providing market information, credit support, and payment convenience, lowers the threshold for entrepreneurship and stimulates farmers'

entrepreneurial potential, thereby helping farm households diversify income and spread risks, and strengthening their livelihood resilience[26].

3 Discussion

3.1 Theoretical significance of framework integration

From the perspective of existing research, Wu Benjian et al.[6] point out that resilience-analysis frameworks still follow the analytical framework of poverty vulnerability, or study and discuss individual livelihoods on the basis of a recovery-capacity framework, lacking a certain degree of comprehensiveness and objectivity. For example, in Zhang Yongli et al.' s[10] vulnerability-based study of preventing a return to poverty, although risks can be identified through exposure risk and sensitivity, and resistance capacity can be measured using the five major livelihood capitals, the examination of learning capacity is neglected. Long-term resistance capacity is not only about using existing resources to cope with current risks, but also about improving the ability to adapt to future risks through learning. In Liu Wei et al.' s[9] assessment of livelihood vulnerability among relocated poverty-alleviation migrants, the risks faced by farm households were measured through the dimensions of exposure and sensitivity; however, adaptive capacity was measured only as a single dimension, integrating multiple indicators such as the five major livelihood capitals, subjective self-evaluation, and policy support. This leads to blurred boundaries among measurement dimensions and makes it difficult to quantify the dynamic recovery process. In applications of the recovery-capacity framework, Sun Yan et al.[7] and Meng Ziyu et al.[8] measured recovery capacity through three dimensions—buffering capacity, self-organization capacity, and learning capacity—but neglected assessments of risk-exposure intensity and livelihood-system sensitivity, creating the problem that it is difficult to judge whether the level of recovery capacity can cope with risk shocks.

Therefore, the framework integrated in this paper— “exposure level–sensitivity–buffering capacity–self-organization capacity–learning capacity” —forms a closed loop in the dynamic logic of “risk input–capacity response,”resolving, to a certain extent, divergences among existing frameworks. First, it resolves the problem of overlapping dimensions by clearly defining buffering capacity as static livelihood-capital reserves, such as land and savings, distinguishing it from the broadly defined adaptive capacity in the VSD framework; it treats self-organization capacity and learning capacity as independent dimensions, thereby avoiding conceptual overlap with buffering capacity. Second, it retains the risk identification of VSD—exposure level and sensitivity—while remedying the defect of the recovery-capacity framework, which discusses only recovery and not risk, and introduces self-organization and learning capacities. Finally, it expands the meanings of self-organization capacity and learning capacity. From the temporal perspective of “short-term resistance (buffering capacity absorbs shocks)–medium-term change seeking (self-organization capacity adjusts strategies)–long-term adaptation (learning capacity upgrades cognition),” it presents the process by which farm households cope with risks. For example, when farm households in Ulanqab City face drought shocks, they first maintain their livelihoods through household savings (buffering), then connect to markets through cooperatives (self-organization), and ultimately acquire technical knowledge through digital finance (learning) to achieve long-term adaptation. Using the VSD framework can only measure the level of livelihood vulnerability of farm households in the region, but cannot explain whether some households with similar vulnerability will ultimately fall back into poverty. If the recovery-capacity framework is adopted, it can measure that some farm households have stronger recovery capacity, but cannot explain whether the functioning of that recovery capacity matches the intensity of risk. By contrast, this paper' s framework, through the calculation method "resilience index = recovery capacity − vulnerability," can identify groups of farm households with "high risk and high recovery capacity" and "high risk and low recovery capacity," thereby providing a theoretical tool for targeted assistance.

3.2 The practical logic of digital finance empowering endogenous livelihood capital

In the analysis of digital-finance use, digital-finance use by households lifted out of poverty has a significant enhancing effect on livelihood resilience. This is similar to the findings of Wang et al.[27]: the use of digital finance can strengthen farm households' social capital and non-agricultural income, helping alleviate poverty vulnerability[28].

Combining benchmark regression and field investigation, it was found that among the farm households participating in the survey, the average age was 64; households with primary-school and junior-middle-school education accounted for 64.72%, and the average educational level was not even senior high school; 37.30% of households had undergone treatment for a serious illness in recent years; and only 15.93% of households were in good health. They thus exhibit the demographic characteristics of "advanced age, low education, and poor health." In response to the livelihood constraints brought about by these three types of characteristics, digital finance demonstrates precise adaptability. Elderly households mainly face the problem of limited mobility. Traditional borrowing and access to funds require collateral, offline signatures, and other complicated procedures, which are time-consuming and labor-intensive. Digital finance, by contrast, relies on credit data for rapid approval, enabling elderly households to obtain emergency funds in a short time. This matches the needs of elderly households whose mobility is limited and who require a rapid response to risks, and alleviates the financial pressure they face when purchasing agricultural inputs and equipment for disaster prevention and risk resistance[13,22]. Low-education households mainly face weak text-comprehension ability and difficulties in processing complex information. Digital finance can transform abstract financial knowledge and knowledge related to agricultural technology into intuitive content, reducing cognitive difficulty and thereby promoting the adoption of agricultural technology and improving livelihood resilience. Digital-finance software provides farm households with pathways for resource sharing and risk sharing through cooperatives or online platforms, improving production efficiency and stress resistance; this helps enhance farm households' social capital and organizational capacity. In terms of learning capacity, digital finance significantly improves farm households' ability to obtain information and accelerates their learning and adaptation to new technologies and new markets. Through online education and remote training, farm households can quickly master modern agricultural technologies and management knowledge, improving production efficiency[22-23]. Households in poor health mainly face the inability to engage in high-intensity planting or difficulty undertaking heavy manual labor. Digital finance helps them break through health constraints and achieve livelihood transformation by assisting livelihood transition. In the survey, some farm households increased diversified income through light and low-intensity non-agricultural work, such as opening small shops, doing transport, opening online stores, and engaging in micro-commerce. This reduced their dependence on a single agricultural income and thereby lowered sensitivity; at the same time, during the course of operation, it strengthened communication and collaboration, enhancing self-organization capacity.

The use of digital finance not only helped farmers with poor health maintain agricultural production, but also prevented them from completely losing their sources of agricultural income because of health problems. This adaptive empowerment and synergistic enhancement enable digital finance, when facing the demographic characteristics of rural households in Ulanqab City, both to avoid the "technological idling" that results from being detached from endogenous livelihood capital and to precisely make up for shortcomings, ultimately achieving an effective improvement in livelihood resilience.

3.3 Unresolved Issues and Future Directions

The negative correlation between the number of household members and livelihood resilience runs counter to the traditional notion that "there is strength in numbers." Based on the survey data, it may be inferred that migrant work is a "double-edged sword" : on the one hand, it increases short-term income; on the other hand, when risks occur, only elderly people may remain at home, resulting in a lack of "family mutual assistance." In addition, migrant workers are often concentrated in low-skilled industries such as construction and catering, and their income is greatly affected by economic cycles. If wage income from migrant work is interrupted, livelihood vulnerability may instead be intensified. This mechanism needs to be further verified in subsequent research using tracking data. Moreover, future studies should further analyze the livelihood resilience of farmers with different livelihood types, so as to enhance the reliability and pertinence of the research conclusions.

4 Conclusions and Recommendations

4.1 Conclusions

(1) By integrating a livelihood-resilience analysis framework of "exposure level–sensitivity–buffering capacity–self-organization capacity–learning capacity," it is possible to form a dynamic closed loop of "risk input–capacity response," thereby remedying the defect of existing analytical frameworks that they have difficulty fully depicting the formation of and response to resilience.

(2) The livelihood resilience of poverty-alleviated farmers is jointly affected by endogenous livelihood capital and external intervention measures. Higher levels of individual health and education significantly improve resilience, whereas advanced age significantly suppresses resilience. The use of digital finance is a key external tool for improving resilience, and the conclusion remains robust after controlling for endogeneity. Digital finance improves livelihood resilience through a dual mechanism: first, by promoting the adoption of agricultural technologies, such as water-saving irrigation and pest and disease control, thereby improving production efficiency; and second, by promoting livelihood transformation, such as opening online stores and engaging in transportation, thereby broadening income sources. The synergistic effect of internal and external factors is the key to preventing a return to poverty. In the short term, endogenous livelihood capital has difficulty breaking through structural constraints such as advanced age, low education, and poor health; it therefore requires empowerment by external tools such as digital finance. Yet if digital finance is detached from endogenous livelihood capital, its mechanism cannot be implemented. Neither of the two can be lacking.

4.2 Recommendations

(1) Improve the inclusiveness and adaptability of digital finance. For semi-arid and arid areas such as Ulanqab City, special "digital finance + agricultural technology" products should be developed, such as technology-adoption loans and disaster-emergency loans, so as to lower the threshold for credit; "digital-literacy training" should be carried out, focusing especially on elderly and less-educated farmers—for example, by teaching farmers step by step how to use WeChat Pay and agricultural apps—so as to narrow the digital divide.

(2) Strengthen the foundational role of endogenous livelihood capital. Improve the rural medical-security system, reduce the inhibiting effect of health shocks on resilience, and increase the reimbursement ratio for serious illnesses; promote rural vocational education and carry out training in "agricultural technology + non-agricultural skills" according to farmers' needs, such as potato-growing techniques and e-commerce operations.

(3) Optimize support for household livelihood strategies. Guide households with migrant workers to "find employment nearby," support local characteristic industries, absorb labor, and balance income with family mutual assistance; establish a "risk-security mechanism for wage income," carry out skills training for migrant workers, provide temporary unemployment subsidies, and alleviate income instability.

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Impact of digital finance on the livelihood resilience of poverty alleviated farmers: A survey analysis based on Ulanqab City

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Abstract: Enhancing the livelihood resilience of poverty alleviation households is central to consolidating poverty reduction outcomes and preventing long-term poverty recurrence. Based on 2023 micro-survey data from 496 poverty alleviation households in Ulanqab, Inner Mongolia, China, this study measures farmers' livelihood resilience using the entropy method and the comprehensive index method. Multiple linear regression, mediation effect modeling, propensity score matching, and instrumental variable methods were employed to examine the effects and mechanisms of digital finance use and endogenous livelihood capital on household livelihood resilience. The findings are as follows: (1) Livelihood resilience reflects farmers' capacity to withstand risks and recover from livelihood shocks. Its key determinants include endogenous livelihood capital (personal health, household economic, human capital), as well as external support (digital finance). (2) Among the endogenous factors, better personal health and stronger household economic conditions significantly improve livelihood resilience, whereas advanced age significantly constrains it. (3) The use of digital finance significantly enhances livelihood resilience through two pathways: promoting agricultural technology adoption to improve production efficiency and facilitating livelihood diversification to expand income sources. (4) The endogenous livelihood capital and digital finance operate synergistically, helping to overcome structural constraints associated with advanced age and low educational attainment among poverty alleviation households. These results provide micro-level empirical evidence for optimizing livelihood support policies aimed at strengthening rural resilience and reducing the risk of poverty recurrence.

Keywords: poverty recurrence prevention; poverty alleviation households; livelihood resilience; digital finance; endogenous livelihood capital

Note: Figure translations are in progress. See original paper for figures.