

The impact of digital financial inclusion on household financial vulnerability in China: An empirical study based on CFPS



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ABSTRACT

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Digital Financial Inclusion (DFI) has developed rapidly worldwide and is considered an important tool to alleviate Household Financial Vulnerability (FV). However, most of the existing studies are limited to short-term effects and are based on single-time cross-sectional data, lacking a dynamic analysis of the impact of digital inclusive finance before and after. Therefore, based on the CFPS data from 2018 and 2022, employing an Ordered Probit regression model and its marginal effect analysis, combined with mediating effect tests, heterogeneity analysis, and robustness tests, the following hypotheses are verified: (1) DFI significantly reduces household financial vulnerability; (2) this effect is partly realized by increasing household income and easing credit constraints; (3) low-income households and economically underdeveloped areas rely more on DFI to alleviate financial vulnerability; (4) after the epidemic, the mitigation effect of DFI on household financial vulnerability is enhanced. The results show that digital financial inclusion plays a significant role in reducing household financial vulnerability, and digital inclusive finance can also reduce household financial vulnerability by increasing household income. At the same time, the role of digital inclusive finance is more significant in economically developed regions and low-income families. Additionally, the marginal effect of digital financial inclusion is stronger in 2022 after the pandemic compared to 2018.

Contribution/ Originality: This study uniquely employs dynamic CFPS panel data (2018–2022) to examine the evolving impact of digital financial inclusion on household financial vulnerability. It integrates mediating, heterogeneity, and post-pandemic analyses, offering a comprehensive, time-sensitive perspective often overlooked in prior cross-sectional studies.

1. INTRODUCTION

Household financial vulnerability describes the potential for a household to enter financial distress despite efforts to prepare for adverse economic events or unexpected financial stress (Yang & Zhang, 2022). Therefore, this problem directly translates into household economic security and social well-being and is one of the main research directions of economics at present. This is particularly true given the economic shocks associated with pandemics, which have furthered financial instability at the household level across the world (Asia-Pacific Financial Forum,

2023). However, even with the negative economic impact of the pandemic, the pace of digital financial inclusion development has reduced the financial vulnerability of households around the world to varying degrees. For low-income groups in particular, the relief would be more pronounced because they are more likely to fall into absolute poverty (Mansor et al., 2022). However, the specific impacts and pathways involved are not the same and will vary from region to region.

China's rapid rise in digital financial inclusion has resulted in a significant reduction in the vulnerability of household finances (Zhu, Xue, & Hu, 2023). Mobile payments, online lending platforms, and digital wealth management improve accessibility to financial services, particularly among rural communities and low-income populations. Products such as Alipay and Yu'e Bao have reduced the barriers to entry to traditional credit while offering flexible asset management tools. As of February 2021, approximately 87% of China's population had access to fintech applications such as WeChat Pay and Alipay, which together accounted for over 90% of electronic payments in the country. This widespread use of digital payment solutions has played a crucial role in improving financial access, especially in regions previously underserved by traditional banking services (Wang & Chen, 2022; X).

Similar to China's experience, digital financial inclusion has the same effect globally. In emerging economies with weak financial infrastructure, digital inclusive finance directly fills the gap in traditional financial services through technological substitution. In Kenya, for example, M-Pesa, a mobile payment platform, has reached more than 80% of the adult population through simple SMS technology (Jack & Suri, 2014; Sathik Mohamed Saliah, Nadarajan, & Teong, 2024), enabling low-income households to maintain basic consumption during the economic crisis (Hu, 2021). Similarly, India increased formal financial services coverage from 35 percent in 2014 to 78 percent in 2021 through its Aadhaar digital identity system and UPI payments network. However, such markets are generally subject to the risk of dependence on a single technology, such as the possibility of nationwide payment disruption due to the failure of the M-Pesa system.

China and other large developing countries have improved household financial resilience through the "digital ecology plus policy support" model. Alipay and WeChat Pay not only provide payment services but also integrate financial management, insurance, and credit evaluation to form a closed-loop ecosystem. This path relies on policy coordination, such as the Plan for Promoting Inclusive Finance Development (2016-2020), which requires banks to cooperate with technology companies to provide subsistence services, enabling rural digital payment usage to jump from 17 percent in 2015 to 65 percent in 2022. By contrast, a similar attempt in Indonesia has been limited by regulatory fragmentation, with a 21% default rate on online loans.

Despite these successes, the rapid expansion of digital financial inclusion has also exposed systemic risks that require urgent attention. While digital financial inclusion is achieving great results, it is also facing new challenges due to rapid development. Data privacy breaches are a real threat to big data credit evaluations. Users' personal consumption history, social behavior, financial status, and other data without adequate protection can be abused, leaked, and even used for unauthorized credit scoring, as well as lead to potential credit discrimination and privacy violations. While digital credit makes life easier in some cases, this convenience can mean household over-indebtedness. In particular, in the absence of strict regulation, some financial institutions may abuse user data, inducing risky lending practices and exacerbating financial vulnerabilities. For example, in some Southeast Asian countries, like India and Indonesia, while online lending has mitigated difficulties in accessing credit, it has also led to some over-indebtedness risks and some households falling into a cycle of debt. APUS, 2018; UOB Group, 2022). At the same time, the technological divide may leave older adults and residents in remote areas without access to equal services (Wang & Wang, 2016). The challenges highlight the need for risk mitigation and improvements in regulation and supervision as countries promote digital financial inclusion.

Based on theoretical research on digital inclusive finance and household financial vulnerability, this study first analyzes the theoretical mechanism of digital inclusive finance on household financial vulnerability. Then, the index

system of household financial vulnerability is constructed from the two aspects of excessive debt and emergency savings, which is embedded in the theory of financial inclusion (Ozili, 2020), and the current situation is analyzed. At the same time, this paper empirically analyzes the impact and mechanism of household financial vulnerability by constructing an ordered Probit model, and finally, it puts forward some suggestions to alleviate household financial vulnerability based on the analysis results.

Household financial vulnerability is an important indicator of the ability of households to cope with economic shocks. High financial vulnerability means that households lack sufficient financial buffers and are prone to fall into financial distress, or even lead to debt deterioration or financial bankruptcy when income declines or unexpected expenditures occur. According to the 2022 China Household Finance Survey (CFPS), more than 49.92% of households are in a state of moderate financial vulnerability, and another 23.15% are facing high financial vulnerability, indicating that households still have large financial risks under economic shocks. In recent years, digital financial inclusion has been identified as a key tool to improve household financial vulnerability. China's digital finance has developed rapidly. By 2022, the penetration rate of mobile payment in China had exceeded 86%. Peking University Digital Finance Research Center (2020) and the penetration rate of digital credit and online financial products has increased significantly. Studies have shown that digital financial inclusion can help low-income groups obtain more convenient credit services and improve financial resilience (Demirgüç-Kunt, Klapper, & Singer, 2018). However, there is still limited research on the impact of digital financial inclusion on household financial vulnerability, especially regarding whether there are dynamic changes before and after the pandemic.

Based on this, this study focuses on the following core issues: (1) Does digital financial inclusion significantly reduce household financial vulnerability? (2) Does DFI indirectly affect household financial vulnerability by raising household income or easing credit constraints? (3) Do low-income households and less economically developed regions rely more on DFI to mitigate financial vulnerability? (4) Has the pandemic changed the mechanism of DFI? Does it enhance the mitigating effect of DFI on household financial vulnerability?

Existing studies are mainly based on single-time cross-sectional data and lack dynamic analysis of the impact of DFI. Most current studies use cross-sectional data from a certain year to analyze the impact of DFI on household financial vulnerability. However, the development of digital inclusive finance is dynamic, and the popularity and usage habits of digital finance may have undergone structural changes after the pandemic, so the long-term impact of DFI needs to be considered. At the same time, the development of digital inclusive finance is dynamic, and the popularity and usage habits of digital finance may have undergone structural changes after the epidemic, so the long-term impact of DFI needs to be examined. Most studies only conclude that there is a negative correlation between DFI and household financial vulnerability through regression analysis, but there is a lack of systematic research on how DFI specifically reduces household financial vulnerability. Some studies suggest that low-income households and less economically developed areas may rely more on DFI. However, most empirical analyses only discuss the overall effect of DFI at the national level, without an in-depth analysis of the differences among different groups. For example, do high-income households benefit equally from DFI? Do economically developed regions utilize DFI more effectively than less developed regions? These questions have not been fully answered. Finally, the pandemic has changed the global economic behavior pattern and promoted the popularization of digital financial instruments (Gao, 2022) but whether the mechanism of action of DFI has changed due to the pandemic has not been fully studied.

2. LITERATURE REVIEW

2.1. Digital Financial Inclusion

The development of financial technology serves as a catalyst for digital financial inclusion, which is recognized as a novel solution to the coverage problems of traditional financial services. As described in the G20 High-Level Principles for Digital Financial Inclusion in 2016, digital financial inclusion is the expansion of inclusive finance

leveraging digital technology. It aims to accurately provide formal financial services to meet the demand of financially excluded groups in an affordable and sustainable manner.

Digital financial inclusion, widely recognized as a transformative force in financial accessibility, is defined by three key characteristics: technology-driven expansion, financial inclusivity, and multi-dimensional service functions (Demirgüç-Kunt et al., 2018; Dong & Si, 2022; Saliah, Nadarajan, & Teong, 2023). It leverages digital tools to reduce transaction costs, broaden financial service coverage, and offer tailored solutions to different demographic groups. Recent studies highlight its role in bridging financial gaps, particularly in rural areas, by enhancing accessibility and affordability (Peking University Digital Finance Research Center, 2020).

Drawing on existing studies, digital financial inclusion has been widely recognized for its transformative impact on financial accessibility, economic participation, and social equity. By reducing transaction costs and expanding service coverage, digital financial inclusion facilitates broader financial participation, particularly among low-income and underserved groups (Demirgüç-Kunt et al., 2018). Moreover, it has demonstrated potential in fostering economic opportunities, supporting small enterprises, and alleviating income inequality. However, its effectiveness varies across regions and demographic groups. While rural populations and individuals with lower education levels still face challenges in accessing digital financial services, such as a lack of digital skills, a lack of infrastructure, etc. These challenges require more targeted policy and training investments to bridge the digital divide and ensure that diverse populations can fully enjoy the convenience and security of digital finance. Women, especially in rural areas, have significantly increased their participation in financial activities through digital financial inclusion (Zhang, Wan, & Wu, 2021; Zhou, 2022). This highlights the dual role of digital financial inclusion: while it enhances financial accessibility, the existence of the digital divide and the uneven adoption across regions and income levels present ongoing challenges.

2.2. Household Financial Vulnerability

Household financial vulnerability means that even after trying to cope with the problem, households remain at risk of financial distress (Yang & Zhang, 2022). These issues include loss of income, increased expenses, or declining asset values, and it examines households' ability to manage their finances and handle risk (Gao, 2022).

In the process of studying family financial vulnerability, because it cannot be measured directly, scholars have proposed different methods to measure family financial vulnerability. These methods include financial ratio analysis, emergency savings assessment, and subjective assessment. Financial ratio analysis uses indicators such as debt-to-asset ratios and liquidity ratios to examine a family's financial health (Xu, Ma, & Du, 2023), and emergency savings assessment examines whether a family has enough savings to cope with emergencies and focuses on their ability to cope with crises. The subjective assessment collects households' perceptions of their financial situation through surveys that show their expectations and confidence in future stability. Each method has its advantages and disadvantages. The first two methods provide clear and objective data but may lose subjective experience. Subjective assessments are flexible, but may be influenced by respondents' biases (An, 2021).

There are many factors affecting the financial vulnerability of households. Internal factors include income levels, financial literacy, and macroeconomic environments. The income level is the main factor. Low-income families are more vulnerable because they have fewer financial resources. In contrast, better financial literacy and stronger social networks can reduce financial stress and improve risk management (Yang & Zhang, 2022). External factors include the macroeconomic environment, such as regional economic development and participation in financial markets. These factors affect how easy it is for households to access good financial services. In less developed regions, weak financial markets and uneven economic growth can increase the financial pressure on households (Gao, 2022). To reduce household financial vulnerability, the academics have made several policy recommendations. One is to improve financial literacy. Better financial education can help families manage their finances more effectively and use financial tools wisely. The other is to strengthen the social safety net to provide

families with a more reliable financial safety net. Similarly, using technology and supportive policies to encourage financial inclusion can help provide greater access to financial services for low-income and vulnerable households (An, 2021). These measures can reduce financial risk, enable households to better withstand economic changes, and strengthen the overall stability of the financial system.

2.3. The Relationship Between Digital Financial Inclusion and Household Financial Vulnerability

Current research mainly focuses on two aspects of how digital financial inclusion affects household financial vulnerability. First, it examines the mechanisms involved. Second, it looks at how these effects take place. Scholars have found that digital financial inclusion can lower the cost of financial services and improve resource allocation efficiency. This creates more economic opportunities for households and businesses. On one hand, it relaxes credit constraints and stimulates consumption, thereby reducing household financial vulnerability and enhancing financial stability (Abubakr et al., 2024; Chen & Gong, 2021; Qu & Li, 2023). On the other hand, it provides convenient financing for small and medium-sized enterprises. This financing promotes technological innovation and industrial upgrades, helping to solve the "low-end lock-in" issue (Dong & Si, 2022). Digital financial inclusion also promotes fairness in income distribution. By delivering more services to low-income and disadvantaged groups, it narrows the gap in financial access (Demirgüç-Kunt et al., 2018).

Existing research demonstrates that digital inclusive finance mitigates household financial vulnerability through a three-pronged mechanism of technology-driven information integration, risk diversification, and enhanced financial literacy. First, by leveraging big data and mobile internet technologies, digital inclusive finance alleviates the issue of information asymmetry prevalent in traditional financial markets (Gomber, Kauffman, Parker, & Weber, 2018), thereby enabling households to access cost-effective risk management tools such as credit and insurance (Demirgüç-Kunt et al., 2018). Mobile payment platforms like M-Pesa and Alipay offer tailored microfinance services based on transaction data analysis (Jack & Suri, 2014). Second, digital inclusive finance broadens the reach of financial services, including remote insurance and P2P lending, thereby enhancing households' risk-sharing capabilities (Alt, Beck, & Smits, 2018). Households with access to these services have experienced a 20%-35% reduction in liquidity constraints when facing shocks such as illness or unemployment (Suri & Jack, 2016). Additionally, interactive services provided by digital inclusive finance, such as financial education apps, promote rational financial decision-making through experiential learning (Annamaria Lusardi & Mitchell, 2014) and discourage irrational debt behavior (Karlan, McConnell, Mullainathan, & Zinman, 2016). While some studies suggest that the digital divide may exacerbate vulnerability disparities, the majority of the literature supports the consistent and pervasive inhibitory effect of digital inclusive finance on household financial vulnerability.

Pan and Zhang (2024) point out that large-scale digital financial inclusion can ease problems of over-indebtedness and under-saving. Access to digital wallets and credit products is highly convenient. It helps households build emergency funds and increases financial stability. Quick approval and flexible repayment terms serve as a lifeline in emergencies, relieving stress among vulnerable groups. Digital platforms with budget reminders and savings targets guide families in managing their incomes and expenses. They discourage unnecessary spending and prevent sudden financial crises. Research also shows that digital financial inclusion can raise household incomes and diversify income sources (Bin Hithir, Khan, Junoh, Yusof, & Ahmad, 2025; Ye & Luo, 2023). These indirect effects strengthen a household's ability to cope with financial shocks.

At the same time, studies reveal that digital financial inclusion has varying impacts across urban and rural areas, income levels, educational backgrounds, gender, and other personal characteristics. Many scholars find that rural areas see higher marginal benefits. However, due to limited digital skills and infrastructure, coverage remains constrained (Chen, 2021; Zhou, 2022). Low-income groups benefit the most, while the impact on middle-income groups is relatively smaller (Zhang et al., 2021). Yet, individuals with lower education often struggle to effectively

use digital services, which can deepen the digital divide in developing countries (Zhang et al., 2021). From a gender perspective, digital financial inclusion has notably reduced the gap in accessing a variety of financial services, particularly among rural women (Demirgüç-Kunt et al., 2018).

Even though digital financial inclusion is widely regarded as a tool to alleviate financial exclusion, recent studies have gradually revealed its negative impact of exacerbating systemic risks and social inequality. First, the difference in technology access thresholds and digital literacy may expand the "digital divide," in which vulnerable groups are excluded from digital financial services due to equipment, network, or skill limitations, but deepen the Matthew effect of financial resource allocation (Rojas Torrijos, 2021). Secondly, the convenient credit supply of digital inclusive finance may induce excessive debt (Mader, 2018). In addition, the issues of data privacy and algorithm discrimination are prominent; the monitoring of user behavior by digital financial platforms may violate privacy, and the bias of algorithm models based on historical data may reinforce the exclusion of marginal groups (Zetzsche, Birdthistle, Arner, & Buckley, 2020). The regulatory lag further implies risks, and some countries find it difficult to curb digital financial fraud, abuse of capital pools, and other chaos due to imperfect legal frameworks (Arner, Buckley, Zetzsche, & Veidt, 2020). Although scholars have called for hedging risks through "inclusive regulation" and financial education, the negative effect of digital financial inclusion remains an important challenge for the sustainable development of inclusive finance.

Existing research shows that digital inclusive finance significantly reduces household financial vulnerability, but the existing literature has three limitations: first, it relies too much on short-term cross-sectional data, ignores the long-term dynamic effect of digital inclusive finance, and lacks tracking and comparison of urban-rural differences and the impact caused by the pandemic (Zhang, Fang, & Huang, 2024); Second, the quantitative analysis of negative risks (such as data privacy abuse and algorithm discrimination) is insufficient, especially the empirical test of the "technology-system" interaction (such as how the credit investigation system of the central bank regulates the credit bias of platform algorithms). Third, the impact of external shocks and social structure is underestimated; for example, the trust threshold and debt stigma of rural households towards digital tools may offset the policy dividend of digital inclusive finance (Wu & Peng, 2024). These limitations call for future research that integrates long-term tracking data, interdisciplinary methods (such as behavioral economics and computational social sciences), and regional heterogeneity frameworks to more comprehensively assess the inclusive boundaries and risk thresholds of digital financial inclusion in China.

Based on the preceding literature evaluation, this study presents the following hypothesis:

H₁: The development of digital financial inclusion significantly reduces household financial vulnerability.

H₂: Digital financial inclusion indirectly reduces household financial vulnerability by increasing household income levels.

H₃: Digital financial inclusion indirectly reduces household financial vulnerability by easing credit constraints.

H₄: The effect of digital financial inclusion on alleviating household financial vulnerability is more pronounced in economically underdeveloped regions compared to developed regions.

H₅: Compared with high-income groups, low-income groups are more likely to rely on digital financial inclusion to reduce family financial vulnerability.

3. METHODOLOGY

3.1. Data Source

This study employs Stata 18.0 as the primary tool for data analysis. The micro-level data used in this research are derived from the 2018 and 2022 China Family Panel Studies (CFPS), organized and managed by the China Social Science Survey Center at Peking University. The reason for choosing 2018 is that it is the pre-pandemic base year. China's digital inclusive finance had formed a relatively mature format in 2018, with a penetration rate of mobile payment reaching 73%. However, it was not disrupted by the impact of COVID-19 on economic behavior in 2020, such as the contraction of offline consumption, the surge of online finance, and policy interventions such as

large-scale rescue loans. The data from 2018 can be selected to remove the confounding effect of the epidemic shock and to more clearly identify the longer-term structural impact of DFI on household financial vulnerability.

3.2. Definition of Variables

3.2.1. Dependent Variable

The primary focus of this study is household financial vulnerability. To measure this construct, two key indicators are employed: the debt-to-asset ratio and the amount of emergency savings. For the debt-to-asset ratio, numerous studies suggest that a debt-to-income ratio exceeding 30% is commonly regarded as a critical threshold for over-indebtedness (Anderloni, Bacchiocchi, & Vandone, 2012; D'Alessio & Iezzi, 2013; Disney, Bridges, & Gathergood, 2008). Regarding emergency savings, previous research similarly indicates that households with emergency savings amounting to less than three months of expenses are at a high risk of financial vulnerability, particularly in cases of income disruptions or unexpected medical costs (Lusardi, Schneider, & Tufano, 2011). Based on these two dimensions of household financial vulnerability, this study categorizes households with a debt-to-asset ratio exceeding 30% as 1, and those with a ratio below 30% as 0. Likewise, households with emergency savings amounting to less than three months of expenses are coded as 1, while those exceeding this threshold are coded as 0. Combining these two dimensions, a composite index of household financial vulnerability (FV) is constructed.

Table 1: The measurement of the variables.

Table 1. Dependent variable measurement.

Variable	Name	Dimension	Associated Question and Coding
FV	Household financial vulnerability	FV	Asset debt ratio more than 30% and emergency savings less than three months of household expenses = 2; (High vulnerability)
			Asset debt ratio more than 30% or emergency savings less than three months of household expenses = 1; (Medium vulnerability)
			In neither case = 0 (Low vulnerability)
	Asset debt ratio	DEBT	Asset debt ratio over 30%=1; Asset debt ratio less than 30%=0
	Emergency savings	SV	Emergency savings are less than Three months of household expenses = 1; Emergency savings greater than Three months of household expenses = 0

The results in Table 2 showed that households of moderate financial vulnerability made up the largest proportion of the sample, about 49.92%. This indicates that nearly half of the households surveyed face significant financial vulnerabilities and may face considerable financial stress in coping with economic fluctuations and unexpected events. High vulnerability households accounted for 23.15% of the sample, indicating that a significant proportion of households showed very high levels of financial vulnerability. Low vulnerability households accounted for only 23.15% of the sample, indicating that a smaller proportion of households were able to maintain a relatively stable financial situation, reflecting the generally low level of financial health in the sample population.

Table 2. Proportions of household vulnerability.

Variable	Value	Sample	Proportions
FV	0 (Low)	178	26.9%
	1 (Medium)	330	49.9%
	2 (High)	153	23.1%

3.2.2. Independent Variable

The core explanatory variable explored in this paper is Digital Inclusive Finance (DFI), which originates from the Digital Inclusive Finance index developed by the Digital Finance Center of Peking University. To align with the explained variables, the annual provincial index is selected. However, due to the broad scope of digital financial inclusion, this study further examines the impact of three first-level indicators: coverage breadth, usage depth, and digitization degree, on household financial vulnerability. Although the digital inclusive financial index is processed without dimensionality reduction, there are magnitude differences between it and other variables; therefore, the digital inclusive financial index and its sub-indices are used as proxy variables after logarithmic transformation. It is important to note that the digital financial index is primarily constructed based on microtransaction data from Ant Financial (Alipay), focusing on explicit behavioral indicators such as payments, money funds, and credit. However, it does not fully encompass the use of household risk management tools such as insurance, equity investments, and pension finance (Lee, Lou, & Wang, 2023).

3.3. Model Construction

3.3.1. Panel Data Model

Since the dependent variable in this study ranges from 0 to 2 and is ordinal, an ordered probit (Oprobit) regression model is employed to explore the relationship between household financial vulnerability and digital financial inclusion. The model setting of this paper refers to the study of Annamaria Lusardi and Mitchell (2014) on the impact of financial literacy on the level of pension planning and capturing the nonlinear response of ordinal dependent variables through ordered Probit. Compared with the linear probability model (LPM), ordered Probit is more consistent with the economic meaning of vulnerability level and avoids predicting values beyond a reasonable range.

The model is constructed as follows:

$$Oprobit\ FV_i = \beta_0 + \beta_1 DFI_i + \beta_2 X_i + e_i \quad (1)$$

Where:

FV_i represents household financial vulnerability.

DFI_i denotes the provincial-level Digital Financial Inclusion Index for each province.

X_i represents the control variables.

e_i represents the variance.

3.3.2. Mediation Effect Model

To explore the mechanism through which digital financial inclusion affects household financial vulnerability, this study employs a three-step method to construct a mediation effect model. However, considering that the mediating variable is not an ordinal discrete variable, OLS regression is used to process the mediating variable, while the ordered probit model is applied to other variables. The mediation model is constructed as follows:

$$Oprobit\ FV_i = \beta_0 + \beta_1 DFI_i + \beta_2 X_i + e_i \quad (2)$$

$$M_i = \beta_0 + \beta_1 DFI_i + \beta_2 X_i + e_i \quad (3)$$

$$Oprobit\ FV_i = \beta_0 + \beta_1 DFI_i + \beta_2 M_i + \beta_3 X_i + e_i \quad (4)$$

Where:

FV_i represents household financial vulnerability.

DFI_i denotes the provincial-level Digital Financial Inclusion Index for each province.

X_i represents the control variables.

e_i represents the variance.

M_i represents the mediating variable.

When analyzing the impact of digital inclusive finance on household financial vulnerability, this study introduces two types of control variables: household characteristics and household head characteristics, to control for potential confounding effects and enhance the causal inference power of the estimation.

Household characteristics include credit constraints, that is, whether they face financing constraints. Credit accessibility directly affects the risk buffer capacity of households, and constrained households rely more on informal borrowing and increase their vulnerability (Demirgüç-Kunt et al., 2018). Controlling for this variable separates the independent effect of DFI in mitigating formal credit exclusion. As well as household expenditure, high consumption expenditure may crowd out savings and insurance investments, amplifying the negative impact of income shocks (Lusardi & Mitchell, 2014). The inclusion of the expenditure variable can distinguish whether DFI reduces FV through the "revenue increase" or "expenditure saving" channel. At the same time, the family size, the elderly dependency ratio, and the child dependency ratio are introduced. These variables are directly related to rigid expenditures (education, pension, health care), squeezing liquidity reserves. Studies have shown that for every 1-unit increase in the dependency ratio, the probability of a family falling into a financial crisis increases by 12%-15% (World Bank, 2019). Household head characteristics include age, marriage, and education level. Age affects risk preference, while gender and marriage regulate financial resilience through income stability and decision-making power allocation (Alt et al., 2018). For example, married households may spread risk through spousal assistance, and young people are more likely to be over-indebted. The above variables may be related to both DFI penetration level and FV; for example, households in remote areas are more likely to face credit constraints and have low DFI coverage. If not controlled, this will lead to missing variable bias.

4. RESULTS AND DISCUSSION

4.1. Data Test

To enhance the reliability of the regression estimate, this paper calculates the VIF values of the variables presented in Table 3. The VIF values of the variables are all below 10, indicating the absence of multicollinearity among them.

Table 3. VIF test results.

	VIF	1/VIF
EDU	1.54	0.65
AGE	1.53	0.65
SIZE	1.46	0.68
MARRIGE	1.40	0.71
LNCONSUME	1.33	0.75
WEAK	1.27	0.78
CHILD_P	1.25	0.79
DFI	1.22	0.81
RES	1.19	0.89
FIN_ASS	1.11	0.93
GEN	1.07	0.96
Mean VIF	1.04	

In order to verify the Proportional Odds Assumption (POA) of the ordered Probit model, this study adopts the Wald test. The test results in Table 4 show that the chi-square statistic is 16.823, the degrees of freedom are 12, and the corresponding P value is 0.102. As the P value is greater than 0.05, we cannot reject the null hypothesis, indicating that the data does not provide sufficient evidence to show that the regression coefficients are significantly different among the different categories. Therefore, this study concludes that the hypothesis of the Ordered Probit model is valid, and ordered Probit can be used for estimation without employing the Generalized Ordered Probit (goprobit) or the Partial Proportional Odds Model (gologit2). This result demonstrates that the selected model adequately fits the data structure, and the regression results are robust.

Table 4. Wald test results.

Chi ² Statistic	Degrees of Freedom	P-Value
16.823	12	0.10

Although the paper has verified the reliability of the model through VIF test, Wald test, and robustness analysis, this study is limited by the fact that the CFPS data in 2022 cannot be visited on the spot, and the sample size is reduced compared with that in 2018, which may lead to sampling bias. Small samples may affect statistical significance, especially for the analysis of subgroups such as low-income, rural, etc. As a result, the sample size is reduced and regional coverage is uneven, and the data mainly relies on mobile payment transaction data to construct the DFI index, which may miss households that do not use digital financial instruments, resulting in the underestimation of the digital finance penetration rate. In the future, it is necessary to further verify the universality of the conclusions through a larger and more balanced sampling design.

4.2. Order Probit Regression Model

The ordered probit model is used to regress the relationship between digital financial inclusion and the financial vulnerability of Chinese households. Column 1 in Table 5 analyzes the impact of digital inclusive finance on the financial vulnerability of Chinese households when control variables are not added, with a coefficient of -0.1510098, which is significant at the 1% level. After adding control variables, digital inclusive finance can have a negative impact on household financial vulnerability, which is significant at the 1% level, indicating that digital inclusive finance will significantly alleviate household financial fragility. Therefore, Hypothesis 1 is not rejected.

The reason why digital inclusive finance can reduce household financial vulnerability is that this financial model breaks knowledge barriers through digital information platforms, systematically improves household financial management cognition and financial decision-making ability, promotes microeconomic subjects to establish a scientific asset allocation mechanism, and finally realizes the structural optimization of household balance sheets and the substantial enhancement of financial risk resistance.

Table 5. Order probit test results.

Variable	FV (1)	FV (2)
DFI	-0.15*** (0.04)	-0.13*** (0.04)
FIN_ASS		-0.62*** (0.05)
LNCONSUME		0.11* (0.05)
AGE		0.00* (0.00)
EDU		-0.02** (0.01)
MARRIGE		-0.16 (0.13)
GENDER		0.06 (0.08)
WEAK		0.11 (0.08)
SIZE		0.03 (0.03)
ELDER_P		-0.01 (0.13)
CHILD_P		0.22** (0.09)
R ²	0.01	0.13

Note: “*”, “**” and “***” indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

The remaining control variables can be classified into two categories. Age, education, marriage, and gender can be categorized as the characteristics of the household head, while the rest, such as financial assets, household consumption, weakness, household size, elder presence, and children present, can be classified as the characteristics of the family. Regarding the characteristics of the household head, the financial asset ratio has a negative impact on the financial vulnerability of the family at the significance level of 1% because, based on the modern portfolio theory framework, families with a higher degree of financial asset diversification usually demonstrate stronger financial literacy. Through asset portfolio optimization and the application of risk hedging tools, they can achieve Pareto improvement of financial resources across periods and thereby build a dual defense mechanism of income growth and risk mitigation (Calvet, Campbell, & Sodini, 2009). Family expenditure has a positive effect at the significance level of 10% because families with higher expenditure are more likely to have insufficient savings, which makes it difficult for them to cope with shocks. The remaining significant variables at the family characteristic level are the child dependency ratio, which is significant at the 5% level and has a positive impact on the financial vulnerability of the family. This is because families with infants and children tend to have higher expenditures on medical care and education, resulting in heavier financial burdens. In contrast, the elderly dependency ratio is not significant. The reason is that China's social welfare and medical insurance system for the elderly are relatively complete, so the influence of having elderly members in the family on financial vulnerability is not significant.

Regarding the aspect of household head characteristics, age and education level have a significant impact on household financial vulnerability. In terms of age, this variable has a negative impact on household financial vulnerability at the 10% significance level. This might be because most enterprises in China prefer to hire fresh graduates, and after the pandemic, due to the reduction in business, corresponding positions have also been reduced. Enterprises tend to lay off older employees (Zhaopin, 2024). Regarding the education level aspect, this variable has a negative impact on household financial vulnerability at the 5% significance level. The reason is that the higher the education level, the higher the possibility of having a high income, and households with higher education levels can better plan and allocate family assets and have stronger risk-resistance capabilities.

4.3. Marginal Effects

Since the coefficients of the ordered probit model do not directly represent changes in probabilities but rather changes in latent variables, interpreting them directly can be challenging. According to Table 6, a one-unit increase in digital financial inclusion raises the probability of low and medium household financial vulnerability by 2.43% and 2.06%, respectively, at the 1% significance level, while reducing the probability of high vulnerability by 4.49%.

Table 6. Marginal effects results.

Variable	Low	Medium	High
DFI	0.02*** (0.00)	0.02*** (0.00)	-0.04*** (0.01)
FIN_ASS	0.11*** (0.01)	0.09*** (0.00)	-0.20*** (0.01)
LNCOMSUME	-0.02* (0.01)	-0.01* (0.00)	0.03* (0.01)
AGE	-0.00* (0.00)	-0.00* (0.00)	0.00* (0.00)
EDU	0.00** (0.00)	0.00** (0.00)	-0.00** (0.00)
MAR	0.02 (0.02)	0.02 (0.02)	-0.05 (0.04)
GEN	-0.01 (0.01)	-0.00 (0.01)	0.02 (0.02)
WEAK	-0.01 (0.01)	-0.01 (0.01)	0.03 (0.02)
SIZE	0.00	0.00	-0.01

Variable	Low	Medium	High
	(0.00)	(0.00)	(0.01)
ELDER_P	0.00 (0.02)	0.00 (0.02)	-0.00 (0.04)
CHILD_P	-0.03** (0.01)	-0.03** (0.01)	0.07** (0.03)

Note: **, *** and **** indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

Among other control variables, a one-unit increase in the proportion of financial assets increases the probability of low and high household financial vulnerability by 11.09% and 9.4%, respectively, at the 1% significance level, while decreasing the probability of high vulnerability by 20.49%.

A one-unit increase in consumption decreases the probability of low and medium household financial vulnerability by 2.01% and 1.71%, respectively, at the 10% significance level, while increasing the probability of high vulnerability by 3.72%. A one-unit increase in age decreases the probability of low and medium household financial vulnerability by 0.15% and 0.13%, respectively, at the 10% significance level, while increasing the probability of high vulnerability by 0.28%.

A one-unit increase in education level increases the probability of low and medium household financial vulnerability by 0.51% and 0.43%, respectively, at the 5% significance level, while decreasing the probability of high vulnerability by 0.28%. Finally, a one-unit increase in the child dependency ratio decreases the probability of low and medium household financial vulnerability by 3.93% and 3.33%, respectively, at the 5% significance level, while increasing the probability of high vulnerability by 7.25%.

4.4. Mediation Effects

This paper employs the stepwise regression method to analyze the relationships among digital financial inclusion, household income, credit constraints, and household financial vulnerability. The mediating effect test empirically examines the mechanism through which digital financial inclusion influences household income and credit constraints, thereby affecting household financial vulnerability.

The results are presented in Table 7. The second column illustrates the significant relationship between digital financial inclusion and both household income and credit constraints at the 1% significance level. The third column shows the results after incorporating the two mediating variables, indicating that both have a negative impact on household financial vulnerability at the 1% significance level. These findings support Hypotheses 2 and 3.

Table 7. Mediation effects results.

Variable	FV	DFI	FV
DFI	-0.151*** (0.04)		-0.06*** (0.00)
LNINCOME		0.15*** (0.02)	-0.52*** (0.06)
CONTROL VARIABLE	YES	YES	YES
R ²	0.01	0.40	0.17
DFI	-0.15*** (0.04)		-0.06*** (0.00)
limit		-0.36*** (0.01)	0.09*** (0.03)
Control variable	Yes	Yes	Yes
R ²	0.01	0.48	0.17

Note: **, *** and **** indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

According to the results in the table, in regional heterogeneity, the impact of digital financial inclusion on the financial vulnerability of households located in the eastern region of China is weaker than that in the non-eastern

region. As a result, the impact of digital financial inclusion on them is less obvious than that in non-Eastern regions. Based on income, we can see that digital financial inclusion has no significant impact on families with high income but has a very significant mitigation effect on families with low income. This is because households with low incomes have higher emergency funding needs and are more likely to encounter credit constraints, which digital inclusion can help alleviate.

From the perspective of urban and rural areas, the financial vulnerability of digital financial inclusion to urban or rural households is less than 5%. There is a negative effect on the household. For this, in order to further study the differences in the impact of digital financial inclusion on the financial vulnerability of different groups, this paper analyzes its marginal utility.

4.5. Robustness Test

In order to ensure the reliability of the benchmark regression results, this paper first tests through the core explanatory variable replacement method. In view of the fact that the digital inclusive financial index is composed of three first-level dimensions, namely, coverage breadth, depth of use, and degree of digitalization, which are independent and have different construction logics (Guo et al., 2020), the three sub-dimension indexes are respectively included in the model as alternative variables. It can be seen from the table that the direction of the estimated coefficients after replacing the variables is basically consistent with the coefficient size, significance level, and direction of the benchmark model. Therefore, the triple first-level dimension test in Table 8 confirms that the inhibitory effect of digital financial inclusion on household financial vulnerability has the characteristics of multi-dimensional driving, rather than the statistical illusion dominated by a single dimension, and the model results are robust.

Table 8. Variable replacement Oprobit regression results.

Variable	FV	FV	FV
Coverage breadth	-0.10** (0.04)		
Coverage depth		-0.15*** (0.04)	
Digitization level			-0.11** (0.93)
Control variable	YES	YES	YES
R ²	0.13	0.13	0.13

Note: “*”, “**” and “***” indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

In order to further verify the robustness of the model setting, this study uses the ordered Logit model to replace the benchmark ordered Probit model for re-estimation. Although the two types of models are based on the latent variable assumptions of the Logistic distribution and normal distribution, respectively, their connection functions have different fat-tailed characteristics (Greene, 2018). Table 9 shows that the coefficient direction of the digital financial inclusion index is positively consistent with the ordered probit results under the ordered Logit setting.

At the same time, the significance level also maintains the statistical strictness of $p < 0.01$. In addition, the direction and significance of the coefficients of the control variables are also basically consistent. Therefore, it can be considered that the model results are robust.

Table 9. Model replacement Ologit regression results.

Variable	FV	FV
DFI	-0.25*** (0.06)	-0.24*** (0.07)
FIN_ASS		-1.03*** (0.09)
LNCONSUME		0.21** (0.10)
AGE		0.01* (0.00)
EDUC		-0.04** (0.01)
MAR		-0.29 (0.23)
GEN		0.10 (0.15)
WEAK		0.19 (0.13)
SIZE		-0.06 (0.05)
ELDER_P		-0.05 (0.23)
CHILD_P		0.38** (0.16)
R ²	0.13	0.12

Note: “*”, “**” and “***” indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

4.6. Comparison Before and After the Pandemic

Digital financial inclusion is an important tool to alleviate household financial vulnerability, and its mechanism of action may change dynamically due to external shocks. Based on the micro survey data from 2018 and 2022, this paper analyzes the difference in the impact of DFI on household financial vulnerability before and after the pandemic by using the ordered Probit model. We find that although DFI significantly reduces household vulnerability before and after the epidemic, its effect is slightly stronger after the epidemic, as shown in Table 10. At the same time, the buffering effect of financial assets (fin_ass) has been significantly enhanced after the pandemic. However, the role of education level (edu) diminished after the pandemic; this may be due to the depreciation of academic qualifications and the rapid increase in the number of Chinese graduates in recent years. The impact of variables such as the proportion of children (child_p) also shows structural changes; the child dependency ratio has no significant effect before the pandemic. This may be because the economy was doing well before the pandemic, preventing family members from being laid off due to corporate downsizing, so child support was affordable.

While the family's unhealthy vulnerability and family size, which were not significant after the pandemic, were significant before the pandemic, both have a positive impact on family financial vulnerability. Before the pandemic, health problems in family members (e.g., chronic diseases, sudden illnesses) could lead to a sharp increase in healthcare expenditures, directly increasing financial vulnerability. However, after the epidemic, the increased pressure on the public health system, the run on medical resources, or the government's temporary medical subsidies, such as free testing and treatment fee reductions, may have partially alleviated the direct impact of health shocks on household finances, resulting in a decline in the significance of this variable. Additionally, households may have been more focused on health risk management (such as saving emergency funds) during the pandemic, weakening the marginal effect of health vulnerability. Furthermore, before the epidemic, a larger family size correlated with higher rigid expenditures (such as education and living costs), making it more significant for financial vulnerability. However, after the pandemic, the number of family members may have a dual effect through the "risk-sharing" mechanism: on one hand, the superimposed risk of multiple people losing their jobs or incomes increases vulnerability; on the other hand, multi-member families can enhance their ability to resist risks through

internal resource allocation (such as joint savings, division of labor, and care). The hedging effect of these two factors may cause the net effect of the family size variable to be no longer significant.

Table 10. Compare 2018 and 2022 (Oprobit regression results).

Variable	2018	2022	2018	2022
DFI	-0.13*** (0.03)	-0.15*** (0.04)	-0.12*** (0.04)	-0.13*** (0.04)
FIN_ASS			-0.34*** (0.11)	-0.62*** (0.05)
LNCONSUME			0.17*** (0.05)	0.11* (0.05)
AGE			0.00 (0.00)	0.00* (0.00)
EDU			-0.03*** (0.01)	-0.02*** (0.01)
MAR			-0.02 (0.12)	-0.16 (0.13)
GEN			-0.01 (0.08)	0.06 (0.08)
WEAK			0.20*** (0.06)	0.11 (0.08)
SIZE			0.06** (0.28)	0.03 (0.03)
ELDER_P			0.12 (0.12)	-0.018 (0.13)
CHILD_P			0.05 (0.09)	0.22*** (0.09)
R ²	0.01	0.01	0.04	0.13

Note: “*”, “**” and “***” indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

Subsequently, the marginal effects between the two years are compared in Table 11. Before the epidemic, each unit increase in digital financial inclusion could increase the probability of a family becoming a moderately vulnerable family by 3.71% and a family becoming a low-vulnerability family by 1.75%. After the epidemic, for every unit increase in digital financial inclusion, there will be a 2.43% probability of a family becoming a low-stability family, which indicates that after several years of development, digital financial inclusion will help more families develop into low-vulnerability families.

Regarding the control variables, the proportion of financial assets significantly increases the probability of low and medium vulnerability, while reducing the probability of high vulnerability, which aligns with the post-epidemic data. However, the probability after the epidemic is relatively higher because, post-epidemic, the buffering effect of financial assets is more prominent, especially as high-asset households diversify risks through investment diversification, which significantly reduces the probability of high vulnerability. Before the epidemic, consumption increases and reduces the probability of low and medium vulnerability, while increasing the probability of high vulnerability. In terms of age, age before the epidemic is not significant, but age after the epidemic increases the probability of becoming a highly vulnerable family because the firm effect develops normally before the epidemic, and there will be no layoffs due to downsizing. Regarding education, the direction remains consistent before and after the epidemic, but the magnitude and significance level after the epidemic are not as strong as before the epidemic.

In terms of control variables, the proportion of financial assets will significantly increase the probability of medium and low vulnerability, while reducing the probability of high vulnerability, which is consistent with the trend of post-pandemic data. However, the probability after the pandemic is relatively large because, after the pandemic, the buffering effect of financial assets is more prominent, especially for high-asset households that diversify their risks by diversifying their investments, which significantly reduces the probability of high vulnerability. Before the epidemic, consumption will increase and decrease the probability of low and medium

vulnerability, while increasing the probability of high vulnerability, but the effect will be more obvious than after the epidemic because, under the impact of the macro environment, household consumption is concentrated from optional consumption (such as tourism and entertainment) to necessities. The price elasticity of demand for necessities is low and less affected by income fluctuations. In terms of age and child dependency ratio, the age and child dependency ratio before the epidemic are not significant, but after the epidemic, they will increase the probability of becoming a highly vulnerable family because the enterprise effect is normal before the epidemic, and there will be no layoffs due to layoffs, and it is also easier to afford the cost of raising children.

Table 11. Compare 2018 and 2022 (Marginal effects results).

Variables	2018			2022		
	Low	Medium	High	Low	Medium	High
DFI	0.01*** (0.00)	0.03*** (0.01)	-0.05*** (0.01)	0.02*** (0.00)	0.02*** (0.00)	-0.04*** (0.01)
FIN_ASS	0.04*** (0.01)	0.08*** (0.02)	-0.12*** (0.04)	0.11*** (0.01)	0.09*** (0.00)	-0.20*** (0.01)
LNCOMSUME	-0.02*** (0.00)	-0.04*** (0.01)	0.06*** (0.01)	-0.02* (0.01)	-0.01* (0.00)	0.03* (0.01)
AGE	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00* (0.00)	-0.00* (0.00)	0.00* (0.00)
EDU	0.00*** (0.00)	0.00*** (0.00)	-0.01*** (0.00)	0.00** (0.00)	0.00** (0.00)	-0.00** (0.00)
MAR	0.00 (0.01)	0.00 (0.03)	-0.00 (0.04)	0.02 (0.02)	0.02 (0.02)	-0.05 (0.04)
GEN	0.00 (0.01)	0.00 (0.02)	-0.00 (0.03)	-0.01 (0.01)	-0.00 (0.01)	0.02 (0.02)
WEAK	-0.02*** (0.00)	-0.05*** (0.01)	0.07*** (0.02)	-0.01 (0.01)	-0.016 (0.01)	0.03 (0.02)
SIZE	0.00** (0.00)	0.01** (0.00)	-0.02** (0.01)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)
ELDER_P	-0.00 (0.01)	-0.01 (0.03)	0.02 (0.04)	0.00 (0.02)	0.00 (0.02)	-0.00 (0.04)
CHILD_P	-0.00 (0.01)	-0.01 (0.02)	0.021 (0.03)	-0.03** (0.01)	-0.03** (0.01)	0.07** (0.03)

Note: **, ***, and **** indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

For education, the direction is consistent before and after the pandemic, but the magnitude and significance level after the pandemic are not as strong as before the pandemic, which may be due to the depreciation of academic qualifications caused by the rapid increase in the number of Chinese graduates in recent years. Regarding the number of unhealthy people and family size, both are significant in 2018 but not in 2022.

This is because household health problems significantly increased financial vulnerability before the pandemic. However, the pandemic prompted the government to improve the healthcare benefit system, with government subsidies available in 2022. Since households are more inclined to save, their emergency funds help them manage risks.

At the same time, regarding family size, although an increase in family members may add to the risk of unemployment, it also stimulates the "risk sharing" mechanism (such as resource sharing and joint savings), and the positive and negative effects offset each other.

Table 12. Compare 2018 and 2022 (Test of heterogeneity).

Variable	FV	FV	FV	FV	FV	FV
	2022					
	Non-eastern region	Eastern region	Low income	High income	Rural	Non-rural
DFI	-0.10*** (0.03)	-0.17* (0.09)	-0.15*** (0.05)	-0.06 (0.11)	-0.12** (0.05)	-0.28** (0.11)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.14	0.12	0.13	0.12	0.12	0.20
	2018					
	Non-eastern region	Eastern region	Low income	High income	Rural	Non-rural
DFI	-0.04* (0.02)	-0.32*** (0.09)	-0.16*** (0.05)	-0.05 (0.10)	-0.09* (0.06)	-0.17*** (0.05)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.06	0.04	0.04	0.07	0.05	0.04

Note: **, *** and **** indicate significance at the 10%, 5% and 1% levels respectively, and the values in brackets are the Standard deviation.

The impact of digital financial inclusion on household financial vulnerability shows significant heterogeneity before and after the epidemic in Table 12. From the perspective of regional differences, the significance of DFI in the non-eastern region in 2022 is very high, while the significance in the eastern region is weak, which may lead to a decreasing policy dividend due to the high early penetration rate of digital finance in the latter. In contrast, the eastern part in 2018 was more significant. In terms of income stratification, low-income families have significantly benefited from DFI before and after the epidemic, while the effect on high-income families has always been insignificant, highlighting the continuous protective effect of DFI on vulnerable groups. The urban-rural comparison shows that the effect of DFI in non-rural areas has been greatly enhanced after the epidemic, reflecting the acceleration of the digitalization process. In rural areas, the significance in 2022 is significantly higher than in 2018, indicating that infrastructure improvement releases the potential of inclusive finance.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This study investigates the impact mechanism of digital financial inclusion (DFI) on household financial vulnerability (FV) using ordered probit regression, marginal effect analysis, and tests for mediation, heterogeneity, and robustness. The findings confirm that DFI significantly alleviates household financial vulnerability by increasing income and reducing credit constraints, with stronger effects observed among low-income households, economically underdeveloped regions, and in the post-pandemic period.

The study highlights the differentiated impacts across demographics and geographies, demonstrating DFI's growing importance in mitigating financial risks and promoting household financial stability in a rapidly digitizing economy. These findings suggest that policymakers should prioritize expanding digital financial infrastructure and improving digital literacy, especially among vulnerable populations, to enhance the inclusiveness and effectiveness of financial systems.

To enhance the role of digital financial inclusion (DFI) in reducing household financial vulnerability, policymakers should prioritize expanding access for low-income and rural populations, narrow the digital divide through targeted literacy programs, and ensure robust regulation to protect consumers. Additionally, promoting diversified, low-threshold financial products and innovative digital tools can strengthen households' financial resilience and support inclusive, sustainable economic development. Collaborative efforts between government, financial institutions, and technology providers are essential to create a more equitable and resilient digital financial ecosystem that leaves no group behind.

6. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite its valuable insights, this study has several limitations. First, the sample size for 2022 is smaller than in previous years due to COVID-19-related restrictions, which may impact the robustness and generalizability of the findings. Second, the study lacks data on financial literacy, a key factor influencing household financial behavior and vulnerability, which limits the understanding of underlying behavioral mechanisms. Third, the research mainly focuses on the short-term effects of digital financial inclusion (DFI), without delving into long-term impacts such as intergenerational wealth stability or sustained financial resilience. Lastly, the study does not deeply explore the digital literacy gap, especially among the elderly, rural residents, and low-income groups, who may face barriers in accessing and effectively using digital financial services. Future research should explore the long-term effects of DFI on household economic stability and resilience, including its role in asset accumulation, wealth mobility, and intergenerational transfer. Studies should also incorporate financial literacy as a mediating or moderating factor and investigate effective strategies to bridge the digital divide.

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