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Research article

Research on the impact and mechanism of digital capabilities and digital finance on household wealth in the context of aging

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ABSTRACT

China has entered a period of synchronous development between digitalization and aging. Based on the data from the China Household Finance Survey (CHFS), the partial least squares structural equation model (PLS-SEM) and multi-group analysis were used to analyze the impact mechanism of digital capabilities and digital finance on the wealth of elderly households. The results indicate that digital capabilities and digital finance can improve the wealth level of households headed by the elderly through direct and indirect paths. The indirect effects of digital capabilities and digital finance on elderly household wealth are all exerted through the node of business and property income, and entrepreneurship/investment are mediating variables. Moreover, digital capabilities have a greater impact on the wealth of elderly households in the central and western China regions, while digital finance has a greater impact in the eastern China regions. In addition, there is no significant difference in the effect of digital capabilities on business and property income across regions, while digital finance has a larger effect in the eastern region. The above conclusions can provide theoretical and practical support for realizing active aging and common prosperity in different countries and regions.

1. Introduction

After four decades of rapid development, China has eradicated absolute poverty in 2020. At present, the main goal of China government has shifted from poverty eradication to national common prosperity in all regions of the country [1]. With the accelerated popularization of digitalization, the China National Informatization Plan of the 14th Five-Year Plan proposes to improve the accessibility of financial services to promote common prosperity. However, the elderly often have difficulties with the operation of smartphones and tend to be a vulnerable group in the digital society, due to their physical and intellectual backgrounds. Relevant policies have also proposed to address the digital divide faced by the elderly and defend their digital rights.

Over the past decade, digital finance in China has experienced unprecedented growth. Since in June 2013 Alibaba Group launched Yu'E Bao, an online money-market fund, various forms of digital financial services have emerged in China [2]. For example, mobile payment apps such as Alipay and WeChat Pay provide households with financial services such as purchase payments, money transfers, deposits, investments and loans. The total transaction value of mobile payments in China jumped from RMB 14.5 trillion in 2013 to RMB 526.98 trillion in 2020 [3], and the number of users increased to 904 million. Digital finance has reduced residents' reliance on traditional financial institutions, and unconsciously affected household economy [4]. Some scholars have studied the impact of digital

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finance on household wealth, and found that the development of digital finance can reduce poverty [5], promote household wealth growth [6], and increase the willingness of household entrepreneurship and investment [7,8]. However, their study was based on all age-group households, and there is still a lack of research on how digital finance affects the wealth of elderly households. Instead, some studies have analyzed the impact of digital finance on the consumption of the elderly [9].

Meanwhile, the issue of aging population in China is becoming increasingly prominent, with the proportion of people over 60 years old reaching 18.7% of China's total population. However, only 4.2% of the elderly in China return to the labor market after retirement due to their physical condition and the inadequacy of laws and regulations to protect their rights and interests to return to the labor market. Moreover, with the shrinking of family size and price inflation, the pressure on families to support the elderly is increasing, and "getting old before getting rich" has become a major challenge to China society [10]. In the proportion of elderly people, aged 60–69 accounted for 55.83% of the total number of elderly people, and an average of 20 million elderly people retire each year.[1] These low-aged elderly people often have higher rates of Internet use and greater digital capabilities than their predecessors, accompanied with higher education and incomes. With the China government's efforts, the proportion of older internet users have increased from 4.8% in 2017 to 14.3% in 2023,[2] which provides the possibility for digital finance to promote the common prosperity of the elderly population.

At the same time, the issue of uneven regional development in China is also becoming increasingly prominent. In terms of economic level, the per capita income levels of Shanghai, Beijing and Zhejiang is close to or above RMB 50,000, while the per capita income of most central and western regions, such as Henan, Guizhou and Sichuan, is less than RMB 30,000. In terms of network usage, the number of mobile phone users per 100 people in the eastern region is more than that in the central and western regions.[3] In terms of the level of financial development, the average distribution density of banking financial institutions in the eastern region is almost six times higher than that in the central and western regions.[4] These regional imbalanced development might cause different impact mechanisms on how digital finance affects the wealth of elderly households. However, little literature is found and further study is in need.

Based on the background and defects in the current research, the impact mechanism of digital capabilities and digital finance on the wealth of elderly households is still uncertain. In addition, whether the such impact mechanism varies among the regions also need further explored. Thus, this paper constructs PLS-SEM models to empirically test these impact mechanisms, by using 2019 China Household Finance Survey data. The motivations and possible contributions of this study are mainly reflected in the following three aspects:

First, in the dual context of digitization and aging, exploring the impact of digital finance on the household wealth of the elderly group has a positive impact on achieving common prosperity in China. However, most of the existing studies analyzing the impact of digital finance on household wealth use sample data of all ages households, and this paper takes households headed by the elderly as the object of study, which can supplement the existing shortcomings and provide some reference in this field.

Second, for the issue of unbalanced economic and network development across regions in China, this paper innovatively builds PLS-SEM models for the full sample and the sub-samples of eastern and central-western regions respectively, and conducts a comprehensive heterogeneity analysis of the differences in the impact mechanisms across regions. The research results can provide useful guidance for the government to formulate more targeted and differentiated policies.

Thirdly, this study involves China's digital finance, population structure, unbalanced regional development level, and related policy backgrounds, thus the research findings can provide some reference for other developing countries facing similar situations, such as those aimed at developing digital finance to increase household wealth, reduce wealth disparities, and address regional development imbalances.

2. Research development and model hypotheses

2.1. Digital capabilities and household wealth

Digital capabilities, the ability to use digital technology to make and implement personal or household economic decisions, includes the ability to use the Internet, understand and appropriately use digital financial services that benefit them [11]. Both personal and social factors influence older adults' digital capabilities. Older adults with characteristics such as younger age, higher education, good health, preference for social activities, and living in areas with higher levels of economic development, are more likely to use the Internet [12–14] and therefore have greater digital capabilities.

Currently, many China companies are vigorously moving their business online, and citizens can engage in various online activities, such as online shopping, mobile payments (payments and remittances), online investments, and online loans [15]. Anyone with a smartphone can open a mobile payment account via the Internet, which is a gateway to other digital financial services [16]. Digital capabilities have changed the traditional ways of information acquisition, information dissemination, investment and entrepreneurship, and consumption among residents, and it effectively reduces transportation, time and transaction costs, and improves the efficiency of payments [17,18], thus positively affecting household welfare. Existing studies based on households of all

[1] Data from China's Seventh National Population Census and the 2016 China Urban Labor Survey.

[2] Data from China Internet Network Information Center.

[3] Data from the National Bureau of Statistics of China.

[4] Data from Financial Operation Report of each province.

ages have found that the use of smartphones can increase household income through enhanced social networks, timely access to relevant information, and the provision of medical advice [19,20]. With the further development of digital capabilities, the use of mobile payments can increase the efficiency of consumption distribution to reduce household poverty [21], and can also make it easier for the elderly to receive financial support from their children and pensions remotely [22]. In addition, Li and Liu found that the use of mobile payments can increase per capita household income in China by RMB 4,200 [8]. In addition, households with greater digital capabilities can reduce their cost of living by obtaining goods and services at lower prices through online shopping [23].

In recent years, China has implemented a loose monetary policy with deposit rates at a relatively low level, and how to rationally allocate assets has important implications for households. Existing research has found that using Internet can reduce the information and transaction costs of purchasing stocks, thereby increasing stock investment rates and holdings [24], as well as increasing asset diversity and value [25]. Moreover, improving digital literacy will change the risk attitude of middle-aged and elderly people, thereby increasing their willingness to hold risky financial assets [26], this will also increase their property income. For entrepreneurial activities, mobile payments increase the accessibility of formal financial services by making transactions between buyers, sellers, and suppliers easier and safer [27], thus facilitating entrepreneurship among groups excluded from traditional financial services [28]. Combined with e-commerce platforms, entrepreneurial families can expand their customer base by opening online stores, and leverage the positive impact of digital capabilities on their entrepreneurial intentions. Especially for some small-scale individual businesses, this can increase their operating income [11,29].

The literature on the impact of digital capabilities on the wealth of elderly household was not retrieved, but based on the existing research, the following hypotheses are proposed:

Hypothesis 1: Enhancing digital capabilities can promote the growth of elderly household wealth.
Hypothesis 1a: Digital capabilities can increase residents' willingness to invest, which can increase business and property income, thus increasing the household wealth of the elderly.
Hypothesis 1b: Digital capabilities can promote entrepreneurial activities in households, which can increase business and property income, thus increasing household wealth of the elderly.

2.2. *Digital finance and household wealth*

Digital finance is the fusion of traditional financial services and Internet information technology, including digital payment, digital investment, digital financing and other services, which is characterized by universality and policy orientation. It directs the flow of financial resources to the weak links of economic development, improves economic conditions and contributes to household wealth accumulation [2,6,30]. Digital financial products have almost zero replication and transportation costs, free from the dependence on financial entities, allowing households living in rural, remote and areas with fewer financial institutions to enjoy financial services anytime, anywhere via the Internet [31]. With the effective and rich promotion of financial information provided by the internet and various social platforms, the transparency of financial products has increased, improving the match between supply and demand of financial services.

For families of all ages, existing research has found that with the increasing number of users and the continuous improvement of digital financial products, many products have launched intelligent investment advisory functions, which can recommend various asset portfolios based on income, assets, risk budgeting, and return goals [30], simplifying the process of participating in the financial market without the need for complex financial calculations and planning [4], which mitigates information asymmetries asymmetry. As a result, digital finance can significantly facilitate households' participation in financial investment [32], increase the types of financial assets held by households [6], and increase the proportion of risky assets allocated and the level of returns [4], thereby increasing residents' property income and promoting household wealth accumulation. Moreover, digital finance can also help elderly families better plan their pensions to increase family wealth [32,33]. In addition to investment, digital finance does not require collateral and relaxes the credit constraints of relatively poor areas and groups due to their own economic condition limitations and information asymmetry [1], stimulating the willingness of households to start their own businesses [6,34], and individual entrepreneurship also has a positive impact on reducing household poverty, narrowing the income gap, and increasing household wealth [6,35].

Furthermore, as communication technologies become more widespread globally, there is growing concern about the digital exclusion of older adults [36], and this rate increases with age. Therefore, it is a challenge to make digital dividends available to all seniors [9]. Chen et al. (2022) have found that digital finance can mitigate multidimensional indicators of relative poverty such as income and social security among the elderly population [37]. Like the other studies mentioned above, they did not involve digital capabilities variables. Although no literature considers digital capabilities and digital finance simultaneously on elderly household wealth, based on the existing findings, this paper proposes the following hypothesis:

Hypothesis 2: Digital financial development can promote the growth of household wealth among the elderly.
Hypothesis 2a: Digital financial development can increase residents' willingness to invest, leading to an increase in business and property income, thus increasing the wealth of elderly households.
Hypothesis 2b: Digital financial development can promote entrepreneurial activities, leading to an increase in business and property income, thus increasing the wealth of elderly households.

2.3. Regional differences in the impact of digital capabilities and digital finance on household wealth

Digital finance in China is still in the primary development stage, and the level of development is uneven across regions, with the level of development decreasing from the east coast to the central and western parts of the country, thus digital finance and digital capabilities might affect household wealth differently in regions. As urban-rural differences, the use of financial services can better increase the income of rural residents by alleviating financial exclusion [8], which can provide farmers with entrepreneurial resources and opportunities, and better promote rural households to engage in self-employment [38]. In terms of regional differences for all ages households among east, central and west, Shen et al. (2022) found that the boosting effect of digital finance on investment in risky financial assets was mainly found in high-income households and households in the east [39]. Using CFPS data, Zhou and Chen (2021) found that digital finance contributed more to household wealth growth in the central and western regions [40], while Lu and Wang (2021), using provincial panel data, found that digital financial inclusion had a greater poverty reduction effect in the eastern region compared to the relatively underdeveloped western region [41]. Regarding the other aspects of regional development, the role of digital finance in curbing the return to poverty is more significant for households in areas with higher levels of digital economy development [42], while the innovation-driven effect of digital finance on China firms is more significant in areas with lower levels of entrepreneurship [43].

However, there is no literature that examines regional differences in the impact of digital capabilities and digital finance on elderly household wealth simultaneously. Considering that the economic level, financial accessibility, and development of digital finance in the central and western regions are lower than those in the eastern regions, this paper proposes the following hypotheses:

Hypothesis 3: The effect of digital capabilities on the wealth of elderly households differs significantly across regions.
Hypothesis 3a: Digital capabilities are more likely to increase the investment intentions of elderly households in the eastern region.
Hypothesis 3b: Digital capabilities are more likely to promote entrepreneurial activities in the central and western regions.
Hypothesis 3c: The impact of digital capabilities on the business and property income of elderly households varies significantly across regions.
Hypothesis 4: The impact of digital finance on the wealth of elderly households differs significantly across regions.
Hypothesis 4a: Digital finance is more likely to increase the willingness to invest in the eastern region.
Hypothesis 4b: Digital finance is more likely to promote entrepreneurial activities in the central and western regions.
Hypothesis 4c: The impact of digital finance on the business and property income of elderly households varies significantly across regions.

2.4. Other factors affecting household wealth

The factors that influence household wealth have been studied extensively by scholars. Regarding individual characteristics, Vo and Ho (2022) found that education can promote wealth accumulation [44]. Karla et al. (2022) found that pensions narrow the net worth gap between men and women in Germany [45]. Casasnovas and Saez (2020) found that the health status of middle-aged and elderly people is closely related to household wealth [46]. In terms of economic factors, Headey et al. (2005) showed that income, saving behavior and risk preference are significantly related to household wealth [47], and Ashman and Neumuller (2021) further found that income inequality is the most important cause of household wealth disparity in the United States [48].

While the existing research provides a reference for this paper, it still has the following shortcomings: First, in examines the impact of digital finance on the elderly, most of the existing literature take consumption structure as explained variables [9]. While in investigating the impact of digital finance and digital capability on household wealth, most of their samples are all ages households, and fewer have older adults as their subjects. Second, most of the existing studies used OLS regressions, logistic regressions, mediation effect models, and moderation effect models to analyze the related issues. However, linear models have the problem of multicollinearity among variables, and these models cannot test all paths simultaneously [49]. Few studies have established structural equation modeling to systematically investigate the influence mechanism of household wealth. Third, in existing heterogeneity analysis studies, the differences in their impact mechanisms are not analyzed comprehensively enough, and their conclusions are divergent, which still needs further discussion [5,33].

3. Data, variable and methods

3.1. Data source

There are two main data sources used in this paper. The micro data comes from the China Household Finance Survey (CHFS), which was conducted nationwide by the China Household Finance Survey and Research Centre of Southwest University of Finance and Economics in 2019. CHFS data covers information on assets, income, liabilities and personal characteristics of 34643 households in 29 provinces and 343 districts and counties across the country. Given that it is difficult for longevous elderly people to use digital services (such as mobile payment), this paper takes the household with head of household aged 60–85 as sample. After removing outliers and interpolating missing values, 12653 valid observations were obtained. Macro data only involves digital finance indexes, which abstracts from The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) published by Peking University

Table 1
Variable definition.

	Variable	Definition	Sources
Explained variable	Household net worth	Calculated from total household assets minus total household debt, then divided into 5 levels according to the 20%, 40%, 60% and 80% percentiles, coded from 1 to 5, with higher values representing more household wealth	[6,51]
Explanatory variables	Digital capabilities: Smartphone	1 = Use, 0 = No use	[11,20]
	Digital capabilities: Mobile payment	Whether to use third-party payment accounts such as Alipay, WeChat Pay, Baidu Wallet, etc., coded as 1 = yes, 0 = no	[8,11]
	DFI: index aggregate	Provincial Digital Financial Inclusive Index: index aggregate (in logarithms)	[1,4]
	DFI: coverage breadth	Provincial Digital Financial Inclusive Index: coverage breadth (in logarithms)	[1,4]
General control variables	Region	1 = Central and western regions; 0 = Eastern region	[52]
	Education	Coded education level of householder from lowest to highest: 1 = Elementary school and below, 2 = Middle school, 3 = High school and above	[44,51]
	Social security	The type of social endowment insurance for the householder, coded from the lowest to highest amount received: 1 = Low (no insurance), 2 = Medium (includes: new rural social endowment insurance for rural residents, social endowment insurance for non-working urban residents), 3 = High (basic endowment insurance for the urban working group)	[45]
	Social interaction	Household spending on holidays, weddings and funerals is divided into 5 levels according to the 20%, 40%, 60% and 80% percentiles, coded from 1 to 5, with higher values meaning more frequent socialization	[15,53]
	Health	Householder self-rated health. An ordinal variable with values of 1, 2, 3, 4, and 5, with higher values being healthier	[6,46]
	Household savings	Calculated by adding household cash, mobile payment account cash, demand deposits, and time deposits, then dividing by the number of people in the household, divided into 5 levels corresponding to the percentiles of 20%, 40%, 60% and 80%, coded from 1 to 5, with higher values indicating more deposits	[15,46]
	Agriculture and wage Income	It is calculated by adding the household's agricultural income and wage income, and then is divided into 3 levels according to 33% and 66% percentiles, with higher values indicating more income	[34,54]
	Entrepreneurship	Whether the family runs a business or project, coded as 1 = Yes, 0 = No	[11,42]
	Investment	Whether the household invests in risky financial assets (including: wealth management products, stocks, funds, bonds, derivatives, non-RMB assets, gold, other financial assets), 1 = Yes, 0 = No	[4,25,26]
	Business and property income	Sum of household business income and property income, coded as 1 = Income less than 0 yuan, 2 = Income equals 0, 3 = Less than 1000 yuan), 4 = 1000 yuan to 5000 yuan, 5 = 5000 yuan and above	[8]

[50]. Since the city-level code of CHFS data is not accessed, this paper uses the provincial digital financial index (DFI) to match the CHFS data.

3.2. Variable description

For the explained variables, following existing studies [6,51], this paper chooses household net worth to measure household wealth, which is calculated by subtracting total household assets from total household liabilities. Among them, total assets include financial assets and non-financial assets (agricultural assets, business assets, land, shop and house assets, vehicles and other assets), and total liabilities include financial liabilities, business liabilities and house liabilities.

This paper involves two aspects of explanatory variables: digital capabilities and digital finance. The digital capabilities variables are about whether or not to use devices and software related to digital finance, which is the basis of household access to digital financial services. "Whether or not to use a smartphone" is used to measure network access, and "whether or not to use mobile payment" is used to measure the use of digital finance. The digital financial variables involve two macro indexes: DFI-index aggregate, and DFI-coverage breadth. DFI is based on the micro business data composition of Ant Group, whose market share of digital business is large enough that their data can truly reflect the use of digital finance in China. As high representativeness and reliability, DFI is widely used to study the economic impact of digital finance in China, especially on issues such as regional disparities [50].

The control variables reflect other types of factors that influence household wealth, involving three main areas: personal characteristics of the household head (education level, social security level, health status), household characteristics (social interaction, household savings, agricultural and wage income, place of residence) and business investment decisions (investment, entrepreneurship, business and property income). Descriptions and treatment of relevant variables are shown in Table 1.

As shown in Table 1, to avoid the influence of extreme values on the model results, variables (e.g., household net worth, household savings) with large standard deviations in the raw data were categorized by percentiles. For comparison of the regional impacts of digital capabilities and digital finance on the household wealth, the data were divided into two subgroups: east region, and central-western region. The central and western regions are combined into one group, as their level of economic, financial, and business development are comparable and both are lower than the level of eastern region [52]. Also, the two subgroups have similar sample sizes.

3.3. Partial least squares structural equation modeling (PLS-SEM)

This paper uses PLS-SEM to synthesize the impact mechanisms of digital capabilities and digital finance on household wealth, and to analyze the heterogeneity of the impact mechanisms across regions. Compared with the linear model, the PLS-SEM model can analyze all paths simultaneously and reduce the standard error of estimation [49], allowing for a more systematic and complete analysis of the impact mechanism. In addition, the measurement model in this paper contains two types of structures, reflective and formative, which are more suitable for using the PLS-SEM model. Moreover, PLS-SEM is a nonparametric method that does not require the assumption of a normal distribution of the data. The corresponding calculations in this paper are performed by SmartPLS package.

The PLS-SEM consists of two parts: the measurement model and the structural model. The measurement model describes the relationship between the structure (latent variables) and their corresponding indicators, and the structural model uses path coefficients to describe the relationship between the exogenous and endogenous latent variables.

The measurement model is expressed by equations (1) and (2) [55]:

For reflective measurement:

$$X_h = \pi_{h_0} + \pi_h \xi + \varepsilon_h \tag{1}$$

For formative measurement:

$$\xi = \sum_h W_h X_h \tag{2}$$

X_h is the indicator. When ξ is the reflective structure, ξ is the latent variable measured by the indicator X_h, π_h is the outer loading corresponding to ξ, ε_h is the measurement error. When ξ is the formative structure, W_h is the outer weight corresponding to ξ.

The structural model of PLS-SEM is expressed in equation (3) [55]:

$$\xi_j = \beta_{j_0} + \sum_i \beta_{ji} \xi_i + \upsilon_j \tag{3}$$

where ξ_j is the j^{th} latent variable with i number of latent variables, β_{ji} is the path coefficient from ξ_i to ξ_j, and υ_j is the error term.

Parameter estimation in PLS-SEM is divided into two steps. First, the latent variable scores are estimated using partial ordinary least squares regression according to the above equations after iterations. Then, OLS is used to compute the final estimates of outer weight and load and the path coefficients of the structural model [56].

Further, in order to study the differences in impact mechanisms across regions, a multigroup analysis is used in this paper. The differences in the path coefficients $\left(\beta^{(1)}, \beta^{(2)}\right)$ between the two groups are tested by the Hypothesis equation (4) and (5) [57]:

$$H_0 : \left|\beta^{(1)} - \beta^{(2)}\right| = 0 \tag{4}$$

$$H_1 : \left|\beta^{(1)} - \beta^{(2)}\right| > 0 \tag{5}$$

Considering that the signs of the path coefficient differences across groups may be different, this paper adopts the permutation test to create the two-tailed confidence intervals.

4. Results and discussion

4.1. Descriptive statistics

As the large sample size and the skewed distribution of the data, the Chi-square test and the Mann-Whitney test are applied for analysis. As shown in Table 2, significant differences exist between the eastern and central-western regions for all indicators except the ‘entrepreneurship’ indicator. Specifically, for elderly household wealth, household net worth in the eastern region is significantly higher than in the central-western region by about an order of magnitude. In terms of digital capabilities, 51.2% of elderly households in the full sample own a smartphone, and the smartphone penetration rate in the eastern region is 12.1% higher than that in the central and western regions; 27% of elderly households in the full sample use mobile payment, and the usage rate in the eastern region is 8.5% higher than that in the central and western regions, indicating significant differences in digital capabilities across the different regions. The two DFI indexes also reflect the higher level of digital finance development in the eastern region.

4.2. Evaluation of measurement models

After modification and calculation on the sample, the SEM model diagram is built and shown in Fig. 1. Based on the evaluation criteria of Hair et al. [58], the reliability and validity of the model are evaluated. For the reflective construct (Digital capabilities, Digital finance and Personal factors), the CR values of all latent variables in Table 3 are greater than 0.7, and Cronbach’s alpha is greater than 0.6, indicating that the reliability of the model meets the requirements. The AVE values of all latent variables for the full

Table 2
Descriptive statistics.

Variable		Mean(SD)/N(%) Full sample	Eastern region	Central and western regions	χ^2 value/Z value
Household net worth (1–5)		3.009(1.417)	3.469(1.449)	2.631(1.272)	−33.189***
Smartphone	Use	6473(51.2%)	3297(57.8%)	3176(45.7%)	181.970***
	No use	6180(48.8%)	2410(42.2%)	3770(54.3%)	
Mobile payment	Use	3411(27.0%)	1806(31.6%)	1605(23.1%)	115.999***
	No use	9242(73.0%)	3901(68.4%)	5341(76.9%)	
DFI-index aggregate (Min: 5.644, Max: 6.017)		5.801(0.099)	5.872(0.099)	5.743(0.050)	−69.490***
DFI-coverage breadth (Min: 5.609, Max: 5.952)		5.745(0.095)	5.812(0.098)	5.690(0.044)	−67.157***
Education (1–3)	Elementary school and below	5438(43.3%)	1989(34.9%)	3494(50.3%)	−18.512***
	Middle school	3872(30.6%)	1876(32.9%)	1996(28.7%)	
	High school and above	3298(26.1%)	1842(32.3%)	1456(21.0%)	
Social security	Low	1566(12.4%)	673(11.8%)	893(12.9%)	−14.293***
	Medium	6111(48.3%)	2344(40.9%)	3777(54.4%)	
	High	4976(39.3%)	2700(47.3%)	2276(32.8%)	
Social interaction (1–5)		2.984(1.423)	3.318(1.447)	2.710(1.341)	−23.892***
Health (1–5)		3.073(0.992)	3.176(0.956)	2.987(1.031)	−10.163***
Household savings (1–5)		3.020(1.412)	3.332(1.406)	2.763(1.365)	−22.546***
Agriculture and wage Income (1–3)		2.011(0.819)	2.162(0.818)	1.887(0.799)	−18.830***
Entrepreneurship	Yes	688(5.4%)	288(5.0%)	400(5.8%)	3.091
	No	11965(94.6%)	5419(95.0%)	6546(94.2%)	
Investment	Yes	1652(13.1%)	1099(19.3%)	553(8.0%)	352.140***
	No	11001(86.9%)	4608(80.7%)	6393(92.0%)	
Business and property income (1–5)		3.017(1.012)	3.153(1.085)	2.906(0.934)	−13.141***

Note: ***, **, * indicate statistical significance at the levels of 0.1%, 1% and 5%, respectively.

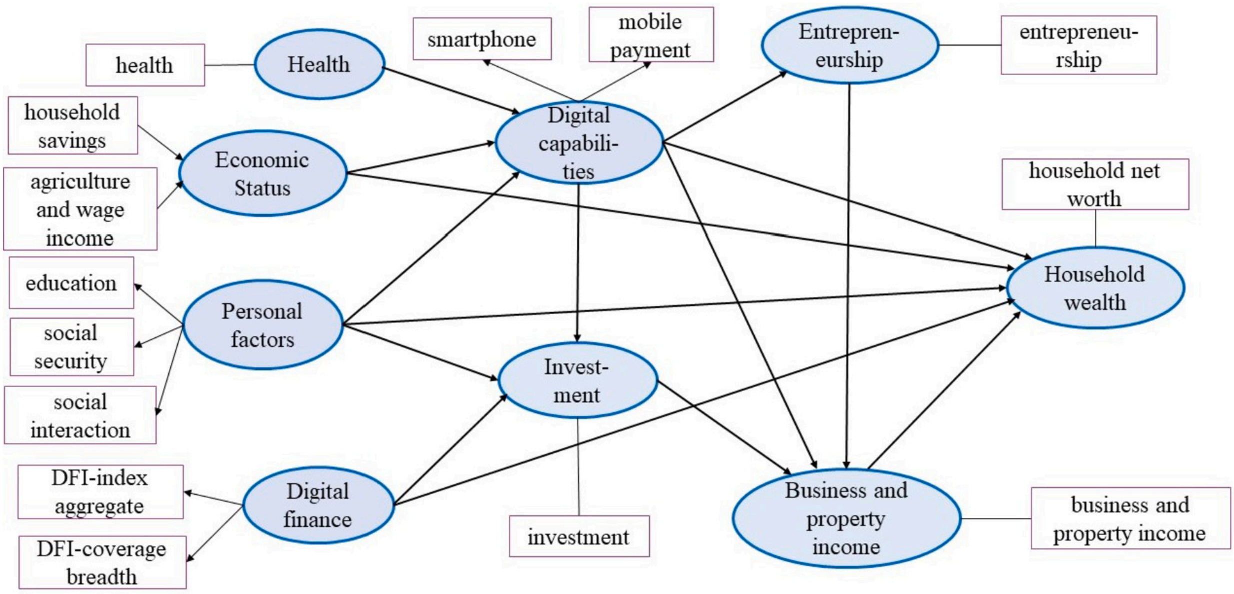

Fig. 1. Structural equation model.

sample and subsamples are greater than 0.5 and the outer loadings are greater than 0.7 and statistically significant, indicating that the indicators used to measure the latent variables are reliable. In addition, the HTMT values for all latent variables in Table 4 are below 0.85, indicating that the different constructs measure different factors those affect household wealth. For the formative construct (Economic Status), the path coefficients of the latent and redundant variables for both the full sample and the subsample are greater

Table 3
Measurement model of PLS-SEM modelling.

Construct	Indicator	Full sample		Eastern region		Central and western regions	
		Loading/Weight	Reliability and validity	Loading/Weight	Reliability and validity	Loading/Weight	Reliability and validity
Household wealth	household net worth	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000
Digital capabilities (Reflective)	smartphone mobile payment	0.845*** 0.853***	Cronbach's $\alpha = 0.613$ CR = 0.838 AVE = 0.721	0.848*** 0.848***	Cronbach's $\alpha = 0.610$ CR = 0.837 AVE = 0.720	0.841*** 0.852***	Cronbach's $\alpha = 0.604$ CR = 0.835 AVE = 0.716
Digital finance (Reflective)	DFI-index aggregate DFI-coverage breadth	0.992*** 0.992***	Cronbach's $\alpha = 0.984$ CR = 0.992 AVE = 0.984	0.998*** 0.998***	Cronbach's $\alpha = 0.995$ CR = 0.998 AVE = 0.995	0.960*** 0.931***	Cronbach's $\alpha = 0.884$ CR = 0.944 AVE = 0.894
Business and property income	business and property income	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000
Economic Status (Formative)	household savings agriculture and wage income	0.438*** 0.764***	path = 0.797 $VIF_1 = 1.126$ $VIF_1 = 1.126$	0.400*** 0.798***	path = 0.786 $VIF_1 = 1.112$ $VIF_1 = 1.112$	0.447*** 0.768***	path = 0.787 $VIF_1 = 1.104$ $VIF_1 = 1.104$
Personal factors (Reflective)	education social security social interaction	0.759*** 0.763*** 0.776***	Cronbach's $\alpha = 0.650$ CR = 0.810 AVE = 0.587	0.745*** 0.768*** 0.761***	Cronbach's $\alpha = 0.631$ CR = 0.802 AVE = 0.575	0.756*** 0.758*** 0.768***	Cronbach's $\alpha = 0.637$ CR = 0.805 AVE = 0.579
Investment	investment	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000
Entrepreneurship	entrepreneurship	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000
Health	health	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000	1.000***	Cronbach's $\alpha = 1.000$ CR = 1.000 AVE = 1.000

Note: (1) ***, **, * indicate statistical significance at the levels of 0.1%, 1% and 5%, respectively.
(2) The global variable of "Economic status" is financial assets per capita, which is calculated by dividing household financial assets by household size, and is divided into three levels according to 33% and 66% percentiles, and the higher the value denotes the better the economic status. Path is the path coefficient between the "Economic status" and global variable.

than 0.7, indicating that the validity of the measurement model is fulfilled. The VIF values of all indicators of the formative construct are less than 5, indicating no collinearity problems. Finally, from the bootstrap method, the confidence intervals of all indicators do not contain 0, so the outer weights of all indicators are significant. In all, the measurement model meets the requirements for the full sample and subsamples, thus the structural model analysis can proceed.

4.3. Evaluation of structural model

In this paper, the same indicators, data processing and algorithm settings are used for measurement models of full sample and the two subsamples. According to the MICOM procedure, all c-values fall within the 95% confidence intervals, thus the compositional invariance of the model is established [57]. The latent variables of the model have the same meaning in different regions, which provides the basis for heterogeneity analysis.

As shown in Table 5, in terms of the explanatory power of the models, from R^2, the models explain and 38.5%–45.3% of the variance of household wealth, 22.7%–24.2% of the variance of digital capabilities, 13.3%–14.0% of the variance of business and property income, 12.4%–23.4% of the variance of investment, and 2.7%–3.5% of the variance of entrepreneurship. Regarding the out-of-sample predictive power of the models, the Q^2 values are obtained using the blindfold method. All Q^2 values are larger than 0, indicating that the predictive relevance of the models is sufficient. Furthermore, the SRMR values of all models are below 0.1, indicating that the goodness of fit of all models meets the criteria [59].

Table 4
Assessment of discriminant validity using HTMT.

Construct	1	2	3	4	5	6	7	8
1. Digital finance								
2. Digital capabilities	0.180 (0.234,0.148)							
3. Investment	0.249 (0.258,0.011)	0.488 (0.530,0.416)						
4. Business and property income	0.151 (0.147,0.011)	0.312 (0.308,0.289)	0.220 (0.242,0.156)					
5. Personal factors	0.317 (0.374,0.119)	0.697 (0.691,0.682)	0.421 (0.464,0.323)	0.293 (0.295,0.252)				
6. Health	0.071 (0.025,0.012)	0.208 (0.181,0.209)	0.098 (0.081,0.092)	0.142 (0.117,0.146)	0.268 (0.197,0.299)			
7. Entrepreneurship	0.012 (0.004,0.014)	0.224 (0.213,0.244)	0.034 (0.034,0.044)	0.281 (0.261,0.310)	0.074 (0.102,0.061)	0.063 (0.063,0.066)		
8. Household wealth	0.361 (0.375,0.033)	0.543 (0.505,0.546)	0.360 (0.354,0.303)	0.328 (0.309,0.307)	0.690 (0.696,0.634)	0.194 (0.146,0.201)	0.096 (0.057,0.149)	

Note: Table 4 shows the HTMT values for the full sample, with the first number in parentheses showing the HTMT values for samples from the eastern region and the second number showing the HTMT values for samples from central and western regions.

Table 5
The validity of the structural model.

Construct	Evaluation indicators	Full sample	Eastern region	Central and western regions
Household wealth	Adjusted R^2 Q^2	0.453 0.450	0.426 0.423	0.385 0.382
Digital capabilities	Adjusted R^2 Q^2	0.242 0.173	0.233 0.166	0.227 0.161
Business and property income	Adjusted R^2 Q^2	0.140 0.137	0.135 0.133	0.133 0.132
Investment	Adjusted R^2 Q^2	0.206 0.205	0.234 0.231	0.124 0.122
Entrepreneurship	Adjusted R^2 Q^2	0.030 0.030	0.027 0.027	0.035 0.035
SRMR		0.076	0.081	0.075

4.4. Main results and discussion of PLS-SEM modelling

To ensure the robustness of the conclusions, this paper uses bootstrap to obtain BCa bootstrap confidence intervals and calculate the p-values of the path coefficients. And the nonparametric permutation test is used to evaluate whether the differences of the path coefficients are significant. Table 6 shows the results of the path coefficients and multiple group analysis, and Table 7 shows the total indirect effects with the total effect values. All path coefficients, indirect effects, and total effects for the full sample and subsamples are significant, indicating that the measures of the structural model are statistically significant.

In terms of total effect on full sample, the top 5 total effects of each latent variable on elderly household wealth from highest to lowest are economic status (0.299), personal factor (0.298), digital finance (0.189), digital capability (0.172), and business and property income (0.114). Following economic implications among latent variables and the impact path map of Fig. 1, digital capabilities, digital finance, and business and property income are the three important path nodes to elderly household wealth, and thus the effects of these three nodes are main contents of explanation.

For digital capabilities and digital finance, as shown in Table 6, they both can directly boost elderly household wealth (digital capabilities: $\beta = 0.146, \beta_1 = 0.116, \beta_2 = 0.178$; digital finance: ($\beta = 0.186, \beta_1 = 0.180, \beta_2 = 0.020$), which are corresponding to Hypotheses 1 and 2. In terms of indirect effects, as shown in Fig. 1 and Table 7, digital capabilities and digital finance can indirectly enhance household wealth through the paths: digital capabilities → investment/entrepreneurship → business and property income → household wealth, and digital finance → investment → business and property income → household wealth. The above results verify Hypotheses 1a, 1b and 2a. For direct effects, digital capabilities and digital finance can increase the wealth of the digitally capable elderly by enabling them to shop at cheaper online stores and facilitating them to receive financial support from family members who do not live with them. For indirect effects, digital finance can help seniors access diversified financial services (e.g., insurance, stocks), and complete the process of account opening, transactions, and withdrawals online, thus they can make financial investments beyond low interest rate fixed deposits and increase their property income. In the other way, digital capabilities can stimulate family entrepreneurship and increase their business income. Households with business can use easy-to-use e-commerce platforms (e.g. TaoBao) to expand their scope and channels of sales, thus reducing transaction costs and improving management efficiency. However, at present the household income of most of China elderly comes from pensions, and the proportion of elderly people who

Table 6
Results of path coefficients and Multiple-Group Analysis.

Path relation	Full sample		Eastern region		Central and western regions		Multi-group analysis		
	Path coef. (β)	t-value	Path coef. (β_1)	t-value	Path coef. (β_2)	t-value	Diff ($\triangle\beta$)	p-value	Significant diff
Digital finance → Household wealth	0.186***	26.272	0.180***	16.417	0.020*	2.162	0.160***	0.000	Yes
Digital finance → Investment	0.163***	17.240	0.142***	11.682	0.051***	3.746	0.091***	0.000	Yes
Digital capabilities → Household wealth	0.146***	18.927	0.116***	10.074	0.178***	15.897	−0.062***	0.000	Yes
Digital capabilities → Business and property income	0.139***	15.483	0.126***	9.397	0.140***	11.507	−0.014	0.450	No
Digital capabilities → Investment	0.283***	28.773	0.305***	21.969	0.265***	18.857	0.040*	0.036	Yes
Investment → Business and property income	0.159***	12.775	0.182***	10.545	0.099***	5.652	0.083***	0.000	Yes
Digital capabilities → Entrepreneurship	0.174***	18.481	0.166***	12.731	0.188***	13.886	−0.022	0.247	No
Entrepreneurship → Business and property income	0.252***	21.882	0.234***	15.507	0.279***	16.331	−0.045*	0.045	Yes
Business and property income → Household wealth	0.114***	16.345	0.112***	11.324	0.127***	12.228	−0.015	0.276	No
Economic Status → Household wealth	0.251***	25.304	0.221***	14.855	0.285***	21.269	−0.064**	0.002	Yes
Economic Status → Digital capabilities	0.281***	25.800	0.285***	17.215	0.272***	18.811	0.013	0.562	No
Personal factors → Household wealth	0.253***	27.155	0.280***	19.684	0.225***	17.478	0.055**	0.004	Yes
Personal factors → Digital capabilities	0.242***	22.253	0.228***	13.743	0.240***	16.676	−0.012	0.584	No
Personal factors → Investment	0.172***	18.381	0.194***	14.960	0.149***	10.733	0.045*	0.017	Yes
Health → Digital capabilities	0.050***	6.389	0.060***	5.182	0.042***	3.835	0.018	0.253	No

Note: (1) ***, **, * indicate statistical significance at the levels of 0.1%, 1% and 5%, respectively.
(2) Diff = path coefficient for samples from the eastern region - path coefficient for samples from the central and western regions.

increase their income through investment, entrepreneurship, and business is not high enough, which is also reflected in the low proportion of indirect effects in the model results.

As shown in Table 6 and Table 7, both direct effects and total effects show that digital capabilities can better enhance household wealth in the central and western regions ($\triangle\beta = -0.062, \triangle total\ effect = -0.065$), while the enhancing effect of digital finance in the eastern region is larger than in the central and western regions ($\triangle\beta = 0.160, \triangle total\ effect = 0.162$). This finding supports Hypotheses 3 and 4. For regional difference, in central and western regions, especially in rural areas, the coverage of financial institutions is relatively low, so digital financial APPs such as mobile payment and mobile banking are stronger substitutes for traditional finance and can help elderly people to access financial services and financial information without time and place restrictions. Thus, digital capabilities can better contribute to household wealth in this region. However, the digital infrastructure in this region is not well developed and the amount of funds available to households is small. This leaves households with limited use to digital financial services, which also means that the wealth-boosting effect of digital finance is weaker in this area.

As can be seen in Table 7, the indirect effect of digital capabilities on household wealth accounts for 13.59%–17.73% of the total effect in the above two paths, but with no significant difference across different regions. While, the indirect effect of digital finance on household wealth in the central and western is significantly higher than that in eastern region. As shown in Fig. 1, the indirect effects of digital capabilities and digital finance on elderly household wealth are all exerted through the node of business and property income, since investment and entrepreneurship have a direct impact on business and property income, which are the main sources of household wealth except family wages. As shown in Table 7, the impact paths from digital capabilities and digital finance to business and property income are all significant, but across regions no significant difference exists in both direct and total indirect impact

Table 7
Total effect and total indirect effect.

		Full sample	Eastern region	Central and western regions	Multi-group analysis		
					Diff	p-value	Significant diff
Digital finance → Household wealth	Total effect	0.189***	0.183***	0.021*	0.162***	0.000	Yes
	Total indirect effect	0.003*** (1.59%)	0.003*** (1.64%)	0.001** (4.76%)	0.002**	0.003	Yes
Digital finance → Investment	Total effect	0.163***	0.142***	0.051***	0.091***	0.000	Yes
Digital finance → Business and property income	Total effect	0.026***	0.026***	0.005**	0.021***	0.000	Yes
Digital capabilities → Household wealth	Total effect	0.172***	0.141***	0.206***	−0.065***	0.000	Yes
	Total indirect effect	0.026*** (15.12%)	0.025*** (17.73%)	0.028*** (13.59%)	−0.003	0.415	No
Digital capabilities → Business and property income	Total effect	0.228***	0.221***	0.219***	0.002	0.917	No
	Total indirect effect	0.089*** (39.04%)	0.094*** (42.53%)	0.079*** (36.07%)	0.016	0.105	No
Digital capabilities → Investment	Total effect	0.283***	0.305***	0.265***	0.040*	0.036	Yes
Digital capabilities → Entrepreneurship	Total effect	0.174***	0.166***	0.188***	−0.022	0.247	No
Business and property income → Household wealth	Total effect	0.114***	0.112***	0.127***	−0.015	0.276	No
Investment → Business and property income	Total effect	0.159***	0.182***	0.099***	0.083***	0.000	Yes
Investment → Household wealth	Total effect	0.018***	0.020***	0.013***	0.008*	0.047	Yes
Entrepreneurship → Business and property income	Total effect	0.252***	0.234***	0.279***	−0.045*	0.045	Yes
Entrepreneurship → Household wealth	Total effect	0.029***	0.026***	0.036***	−0.009*	0.042	Yes
Economic status → Household wealth	Total effect	0.299***	0.261***	0.341***	−0.080***	0.000	Yes
	Total indirect effect	0.048*** (16.05%)	0.040*** (15.33%)	0.056*** (16.42%)	−0.016**	0.007	Yes
Economic status → Digital capabilities	Total effect	0.281***	0.285***	0.272***	0.013	0.562	No
Economic status → Investment	Total effect	0.080***	0.087***	0.072***	0.015	0.090	No
Economic status → Entrepreneurship	Total effect	0.049***	0.047***	0.051***	−0.004	0.541	No
Economic status → Business and property income	Total effect	0.064***	0.063***	0.059***	0.003	0.665	No
Personal factors → Household wealth	Total effect	0.298***	0.316***	0.277***	0.040*	0.031	Yes
	Total indirect effect	0.045*** (15.10%)	0.036*** (11.39%)	0.051*** (18.41%)	−0.015**	0.005	Yes
Personal factors → Digital capabilities	Total effect	0.242***	0.228***	0.240***	−0.012	0.584	No
Personal factors → Investment	Total effect	0.240***	0.264***	0.212***	0.051**	0.004	Yes
	Total indirect effect	0.068*** (28.33%)	0.070*** (26.52%)	0.064*** (30.19%)	0.006	0.405	No
Personal factors → Entrepreneurship	Total effect	0.042***	0.038***	0.045***	−0.007	0.205	No
Personal factors → Business and property income	Total effect	0.082***	0.086***	0.067***	0.018*	0.026	Yes
Health → Household wealth	Total effect	0.009***	0.009***	0.009***	0.000	0.967	No
Health → Digital capabilities	Total effect	0.050***	0.060***	0.042***	0.018	0.253	No
Health → Investment	Total effect	0.014***	0.018***	0.011***	0.007	0.110	No
Health → Entrepreneurship	Total effect	0.009***	0.010***	0.008***	0.002	0.482	No
Health → Business and property income	Total effect	0.011***	0.013***	0.009***	0.004	0.270	No

Note: (1) ***, **, * indicate statistical significance at the levels of 0.1%, 1% and 5%, respectively.
(2) The percentage of indirect effects in total effects are in parentheses. Some paths have only a direct effect or an indirect effect whose value is equal to the total effect, and only their total effect is shown in the table.
(3) Diff = effect values for the eastern region - effect values for the central and western regions.

paths of digital capabilities, while the paths from digital finance to business and property income have larger effects in the eastern region. The indirect effect of digital capabilities on business and property income has a relative high share of 36.07%–42.53%, and entrepreneurship and investment are two important mediating variables. For the indirect paths to business and property, shown in Table 6, the promotion of digital capabilities on entrepreneurship is not significantly different across regions, but the effects of entrepreneurship on business and property income vary significantly across the regions, with higher effect in central and western regions ($\triangle\beta = -0.045$). However, the promotion effects of digital capabilities ($\triangle\beta = 0.040$) and digital finance ($\triangle\beta = 0.091$) on investment are significantly larger in east region than those in central and west regions. The above results support Hypothesis 3a, 4a, 4c, and reject Hypothesis 3b and 3c. Based on the above results, households earn business and property income in different ways across regions. In the eastern region, traditional financial institutions are denser, thus residents are better understanding and more concerned about various types of financial investments, especially for elderly people with pensions, whose households are likely to invest more money and earn more substantial returns. In the central and western regions, as the cost of starting a business is relatively low, and the logistics system is improving, their entrepreneurship brought more household wealth than in the east.

In addition, the paths between digital finance and entrepreneurship were also examined. The path coefficients were positive but insignificant in both eastern and central-western regions, suggesting that digital finance cannot significantly enhance entrepreneurial intentions (the path was removed from the formal model). Hypothesis 2b, 3b, and 4b were rejected, which is contrary to the previous studies' results on all ages sample [15,43]. According to 2019 CHFS data, fewer households used loans and most households with loans used offline bank loans instead of internet loans, which may be related to older people prefer robust business decisions. Thus, the ability of digital finance to alleviate credit constraints is not fully exploited, which explains the insignificance of the path.

5. Conclusions and policy implications

Using CHFS and PKU-DFIIC data, this paper systematically analyzes the impact mechanism of digital capability and digital finance on the household wealth of the elderly and investigates the regional difference in impact mechanism by PLS-SEM modelling. The results show that digital finance and digital capabilities can both directly promote the growth of household wealth. They can also enhance household wealth through indirect effects, the paths are as follows: digital capabilities → investment/entrepreneurship → business and property income → household wealth, digital finance → investment → business and property income → household wealth, and all path coefficients are positive and significant. Moreover, according to the results of the multigroup analysis, for direct and total effects, digital capabilities have a greater effect on households in the central and western regions, while digital finance has a larger boost in the eastern region. In addition, there is no significant difference in the impact of digital capabilities on business and property income for both direct and total indirect effect, while digital finance, with indirect effects only, has a greater impact in the eastern region. In particular, the promotion of digital capabilities on entrepreneurship is not significantly different across regions, while digital capabilities and digital finance are more effective in enhancing investment willingness in the eastern region.

The findings of this paper have the following policy implications: First, improve the digital capabilities of the elderly population. Priority should be given to expanding network infrastructure coverage in central and western regions, eliminating the digital exclusion of families in remote areas, and encouraging volunteers in communities and villages to provide regular network technology tutoring for the elderly. Second, differentiated policies should be formulated according to the different impact mechanisms in different regions. When conducting online technology training for the elderly in the eastern region, the focus should be on how to make deposits, purchase financial products, invest in stocks and other related operations in the digital financial APP. In the central and western regions, more emphasis should be placed on instructing the elderly in operations related to receiving and transferring money online, and running an online store. Combined with local entrepreneurship training and industrial policies, it will increase the entrepreneurial willingness of families. These policy recommendations are not only applicable to China, but also provide references for other developing countries to promote digital finance and solve the problems of unbalanced regional economic development.

In addition, there are also shortcomings in this paper. First, the development of digital finance is changing rapidly, and the impact of digital finance on household wealth is also changing. Due to the limitation of data availability, the change of its impact effect should be tracked dynamically based on the follow-up survey data. Second, the DFI data used in this paper was compiled by the Institute of Digital Finance Peking University based on Ant Group's microdata, which may not be fully representative of the development of digital finance because traditional financial institutions are also developing digital financial services, which requires future researchers to use more comprehensive information to conduct studies.

CRediT authorship contribution statement

Yingxin Li: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Renhao Jin:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Xiaohui Li:** Writing – original draft, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

CHFS data can be downloaded for free from https://chfser.swufe.edu.cn/datas/, and PKU-DFIIC data can be downloaded through https://idf.pku.edu.cn. Data will be made available on request.

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