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HOW DIGITAL FINANCE DRIVES THE PERFORMANCE OF FINANCIAL ASSET ALLOCATION IN CHINESE URBAN HOUSEHOLDS

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Abstract
Rising Chinese household wealth has increased the demand for financial asset allocation. Digital finance has transformed traditional financial services, broadening participation in financial asset allocation to a wider spectrum of households through digital channels. However, the core objective of asset allocation is to enhance households' overall financial well-being. This study analyses the influence of digital finance drivers on the performance of financial asset allocation (PFAA) in urban Chinese households. The sample framework was designed using a multistage stratified random sampling method, in which the sampling probability was proportional to the stratum's size, ensuring randomness and independence. Field surveys were conducted in 19 first-tier Chinese cities, yielding 518 valid samples. Regarding data analysis techniques, this study initially employed exploratory factor analysis (EFA) to explore pertinent factors, followed by confirmatory factor analysis (CFA) to validate the measurement model. Subsequently, a structural equation model (SEM) was employed to estimate the path relationships and evaluate the research hypotheses. The study's outcomes revealed that all three independent variables–digital finance access, usage, and quality–positively influence PFAA. However, the relationship between the quality of digital finance and PFAA is relatively weak. These findings underscore the substantial value of digital finance for augmenting financial welfare and highlight the need for the government to refine policies associated with digital financial services. Financial institutions are encouraged to enhance the quality of their products and services, whereas households should bolster their financial literacy. Collectively, these efforts contribute to advancing family financial welfare, a critical aspect of economic prosperity.
Keywords: *Digital Finance, Performance of Financial Asset Allocation, Chinese Households*

1. Introduction

Chinese households have recently experienced a significant surge in private wealth. Based on findings from the China Household Financial Survey spanning 2011 to 2021, there has been a noteworthy compound annual growth rate in households' total assets, net wealth, and investable assets at 6.9%, 6.7%, and 9.4%, respectively. Understanding financial asset allocation is imperative for most families in today's complex and dynamic financial markets. With an ever-expanding array of investment options and fluctuating market conditions, households face significant challenges when making informed asset allocation decisions. Against the backdrop of declining interest rates and a contracting real estate market, it is imperative to maintain and increase wealth by reasonably allocating financial assets. Household financial asset allocation is a crucial component of personal finance management as it directly affects households' economic well-being and long-term financial stability. The performance of financial asset allocation (PFAA) is a crucial metric for evaluating the outcomes of financial asset allocation strategies (Gomes et al., 2021). By selecting an appropriate mix of assets, households can yield higher investment returns, thereby fostering wealth accumulation. Hence, the significance of household financial asset allocation lies in its capacity to aid households in wealth growth and risk management, ensure financial security, generate income, plan for retirement, accomplish long-term financial objectives, and augment overall well-being (Fan & Henager, 2022).

The widespread use of digital finance has also made it a potentially important factor affecting PFAA. Digital finance is a paradigm of finance in which traditional financial institutions and fintech companies deliver financial services via digital technologies. Thus, it represents a new trend, technology, and model arising from the convergence of digital technologies with traditional finance (Shen et al., 2022). Digital finance fulfills the rising financial demands of a growing population while expanding the scope and quality of customer service (Meng & Xiao, 2023). Digital financial services facilitated by digital technology differ significantly from traditional financing by efficiently lowering transaction costs and expanding their scope (Li et al., 2023). Digital finance fulfills household demand for financial services. Not only does it lower transaction costs, simplify transaction procedures, and enhance transaction efficiency, but it also improves the effectiveness and convenience of residents' financial usage (Lu et al., 2021). Additionally, digital finance mitigates information asymmetry by providing clients with comprehensive real-time financial information. Thus, it gives investors an effective decision-making basis (Kong et al., 2022).

The significant advantages stemming from the emergence of digital finance have led residents to increasingly rely on digital financial tools, such as digital payments, digital investments, and digital financing, to achieve household financial asset allocation. Particularly during the pandemic lockdown, enthusiasm for online financial investments remained consistently high. Digital finance profoundly reshapes the current financial industry structure. However, its impact on households remains an empirical question. Philippon (2015) argues that, over the past 130 years, the unit costs of financial intermediation have remained stable at approximately 2%. This indicates that households have not substantially benefited from advancements in IT over the past century. For households, the ultimate goal of financial asset allocation is to enhance their overall financial well-being by optimizing their investment portfolios. Therefore, further research is required to determine how digital finance drivers affect PFAA. Although a few studies have explored the effect of digital finance on household finance, most have used macro-level digital financial developments to analyze their impact on micro-household financial behavior. The marginal contribution of this study is that it evaluates the relationship between the drivers of micro-digital finance and asset allocation performance. However, research on this topic is currently lacking. In addition, our study constructed a comprehensive scale for PFAA based on the existing literature. The most recent findings were obtained by collecting primary questionnaire data. This study further contributes to a broader discussion on the societal welfare impact of digital finance. It also has implications for government departments refining digital finance policies, financial institutions strategically tailoring digital finance products, and households improving their financial situations.

2. Literature Review and Hypotheses Development

2.1 Digital Finance

Digital financing involves digital technology and innovation to deliver various financial services. These services include but are not limited to banking, investing, payments, insurance, and lending (Siddik & Kabiraj, 2020). Digital financing offers many benefits to financial service users. From a literature perspective, digital finance has several drivers that determine the digital finance concept as a whole. Thathsarani and Jianguo (2022) categorize the features of digital finance into three aspects: access, usage, and quality. For instance, access to digital finance refers to a household's ability and opportunities to use digital financial services and products. It encompasses the availability and affordability of digital devices, Internet connectivity, and the accessibility of digital financial platforms and applications (Durai & Stella, 2019). Digital finance access ensures that people can conveniently and securely perform financial transactions, access banking services, make payments, transfer money, and manage their finances online (Shen et al., 2022). Furthermore, digital finance usage has expanded the range of household investment options. This enables families to participate in diverse investment avenues, including stocks, bonds, and funds, while also providing more adaptable investment options, like peer-to-peer lending and virtual currencies. Diverse choices cater to various risk preferences of households and assist in spreading their investment risks, improving asset allocation's diversity and flexibility. Reducing information search and transaction costs in financial services has led more users to adopt digital finance (Li et al., 2022). Additionally, the quality of digital finance is vital to ensure PFAA. The safety, reliability, and service quality of digital financial platforms directly affect households' investment experiences and risk control. If digital financial platforms have security risks, households may be exposed to having their funds stolen or abnormal transactions (Thathsarani & Jianguo, 2022). Therefore, good-quality digital finance can provide a secure transaction environment and efficient customer service to help households respond to market fluctuations promptly, adjust their investment portfolios, and maximize asset appreciation.

2.2 Performance of Financial Asset Allocation

Asset allocation is a crucial aspect of financial planning and investment management as it directly affects a household's investments' overall performance and risk profile (Li et al., 2022). Modern portfolio theory suggests that diversified investments can effectively reduce risk, making them the optimal choice for household financial asset allocation under uncertain conditions (Qu, 2019). The PFAA comprehensively evaluates how well an investment portfolio is structured to achieve a household's financial objectives while managing risk effectively and efficiently. This requires a careful balance between risk and return, aligned with the household's unique financial situation and goals (Gomes et al., 2021). A well-allocated portfolio should aim to achieve optimal returns for a given level of risk, considering the household's risk tolerance and investment horizon (Li et al., 2022). Household investors can mitigate risk and enhance returns by diversifying their investments into risk-free assets. Diversification serves as a crucial strategy for risk mitigation, dispersing risks, and mitigating the potential impact of underperformance on individual investments, as Lu et al. (2022) emphasized. Hence, asset allocation performance reflects diversification across asset classes and within each class. It is essential to incorporate sustainable and long-term financial well-being into asset allocation strategies, as the performance of these investments involves assessing both financial returns and their alignment with households' financial goals (Gomes et al., 2021).

2.3 Digital Finance and Performance of Financial Asset Allocation

Some studies have presented evidence supporting the impact of digital finance on PFAA. Li et al. (2022) established this relationship, both theoretically and empirically. They integrated the Expected Utility Theory and Modern Portfolio Theory, incorporating digital finance and investable amounts into the intertemporal return model for risky household investments. The derived optimal solution indicates a potentially influential connection between digital financing and financial asset returns. Subsequent empirical examinations using data from the China Household Finance Survey not only validated the proposed theoretical assumptions but also demonstrated that digital finance significantly and positively influences investment returns. Guo et al. (2022) quantified PFAA using the Sharpe ratio, which assesses the ratio of excess financial asset returns to the assumed risk level, reflecting the allocation efficiency. The Tobit model estimations indicate that digital finance positively impacts asset allocation efficiency. Li and Qian (2021) use the index substitution method to compute portfolio returns and risks. They employ the one-year deposit interest rate announced by central banks as the risk-free rate to calculate the Sharpe and Sortino ratios. Empirical testing also confirms that digital finance has a positive effect on PFAA. Zhang and Zheng (2023) conducted a comparative analysis of the influence of digital and traditional finance on PFAA. Their findings revealed that digital finance substantially impacts PFAA more than traditional finance.

The empirical literature review demonstrates that digital finance increases investor convenience in time and space. Unlike traditional finance, digital finance transcends dependence on physical financial branches in traditional trading patterns, transforming offline into online transactions in digital finance. Households can open accounts, conduct investment transactions, and more via smartphones anytime and anywhere, reducing transaction costs, enhancing investment convenience, and improving the PFAA. The research framework proposed in this study is illustrated in Figure 1. The framework emphasizes the drivers of digital finance and establishes relationships based on this framework. Accordingly, we formulated the following three research hypotheses:

Hypothesis H1: The access to digital finance positively influences PFAA.

Hypothesis H2: The usage of digital finance positively influences PFAA.
Hypothesis H3: The quality of digital finance positively influences PFAA.

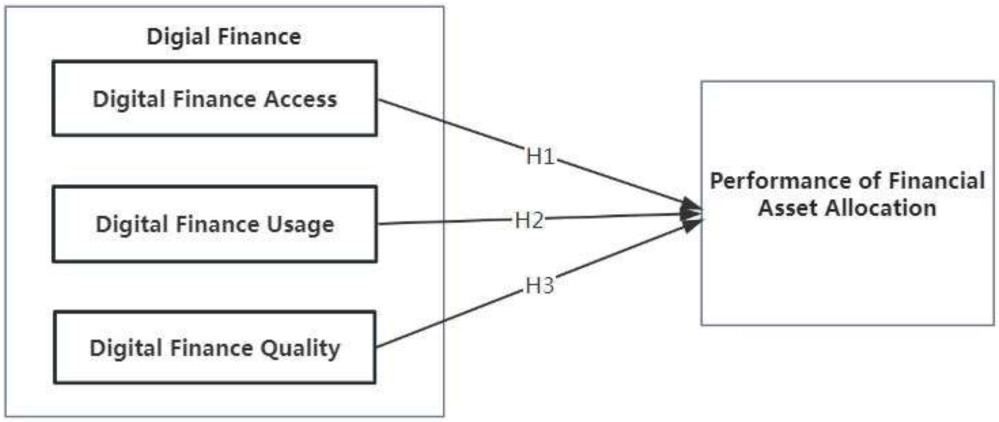

Figure 1. Research Framework

3. Methodology

3.1 Data Collection

This quantitative research was conducted on primary data collected through questionnaires. A field survey was conducted from July 2023 to September 2023 in 19 first-tier cities in China. The target respondents were the heads of households responsible for managing household finances. Statistical formulas are generally used to calculate the minimum sample size required for data analysis, precisely when estimating proportions in a large population. Mohanasundari and Sonia (2022) suggested that a 95% confidence level and 5% margin of error were sufficient to ensure sample validity. Correspondingly, researchers have used this formula to estimate the minimum sample size required for the overall population to be 384. The validity of a sample depends on the representativeness of its population. When many respondents did not respond, the sample was less likely to accurately represent the overall population. Taherdoost (2017) suggested that increasing the initial survey sample size by 50% is the most effective method for meeting the minimum sample size requirement. The total sample size was calculated to be 576.

The data quality was assured through the implementation of a rigorous sampling frame process. Given the considerable number of households within the designated target population spanning 19 first-tier cities, simple random sampling could lead to noteworthy sampling errors, potentially hindering the attainment of a truly representative sample. In alignment with the suggestion put forth by Elmardi et al. (2020), this study adopts a multi-stage stratified random sampling approach. Here, a probability proportional to the size of the sampling method was employed to ensure that the sampling design adhered to the principles of randomness and independence. The specific number of family households in each city can be obtained from the latest published data from China's seventh national census and the 2021 China Urban Statistical Yearbook. Accordingly, the multistage stratified random sampling process comprised three stages. The first stage of the sample size distribution is based on the proportion of households in each city to the total number of households. This means that cities with larger household sizes are more likely to be sampled. In the second stage, the administrative districts in each city are divided, and the number of sampled households in each district is calculated based on their size. In the third stage, simple random sampling was used to collect a valid sample size of 518 after excluding missing values and outliers.

3.2 Measurement of Variables

A structured questionnaire was prepared after a comprehensive review of the current literature. The questionnaire consisted of two parts and an introduction emphasizing the authors' research intent and strong commitment to research ethics. The questionnaire initiated with four screening questions to filter out respondents who were not the households heads. The initial section of the survey gathered categorical variables that delineated the demographic attributes of the respondents. The variables in question served as crucial sources of background and economic information for the participants involved in the survey. The second part collected data on the research variables concerning digital finance and financial asset allocation performance. These variables were assessed using a five-point Likert scale, where respondents' ratings ranged from 1 (strongly disagree) to 5 (strongly agree). The Likert scale allowed researchers to gather detailed information about respondents' viewpoints and attitudes, thus enhancing data collection and analysis depth.

Three drivers of digital finance, access, usage, and quality, were assessed using 12 items adapted from Thathsarani and Jianguo (2022). Digital finance access consists of four items. This construct is designed to examine respondents' access to digital financial services. The construct includes the following: availability of digital financial devices, availability of digital financial services at any time and place, availability of digital financial services without having to visit a financial institution, and whether each respondent is discriminated against regarding digital financial services. Digital finance also includes four measurement items focusing on household adaptability, familiarity, and convenience in daily payment, investment, and financing activities. Similarly, the four digital financial quality measures assess its functionality's reliability and safety and compare its quality with that of traditional financial services.

Owing to the lack of available scales in the existing literature to measure household financial asset allocation performance, our study compiled this construct comprehensively and objectively based on the available literature, as shown in Table 1. The initial questionnaire was revised based on feedback from two financial experts and two academic specialists, considering practical application scenarios and language clarity. Ultimately, a set of ten refined measurement items for PFAA was established. These items encompass scale, asset risk proportion, diversity, returns, liquidity, risk resistance, financial well-being, and long-term financial objectives.

Table 1

Measurement Construct of Performance of Financial Asset Allocation

Encoding	Scale Description	Source
PFAA1	The scale of financial asset allocation has been enhanced for my household.	Wang et al. (2023)
PFAA2	The proportion of risky financial assets has been enhanced for my household.	Shen et al. (2022)
PFAA3	The diversification of financial asset allocation has been enhanced for my household.	Lu et al. (2021)
PFAA4	The return on my household's financial asset allocation has been improved.	Li et al. (2022)
PFAA5	The return on financial asset allocation exceeds the interest rate of one-year deposits for my household.	Shen and Yang (2023)
PFAA6	Financial asset allocation can meet liquidity needs for my household.	Guido et al. (2020)
PFAA7	Financial asset allocation can withstand market risks for my household.	
PFAA8	Financial asset allocation maintains stable market value even during economic recessions for my household.	Gomes et al. (2021)
PFAA9	Financial asset allocation meets the financial needs of my household.	
PFAA10	Financial asset allocation achieves long-term financial goals for my household.	

3.3 Procedure of Data Analysis

This study's data analysis procedure was meticulously structured into four pivotal steps. Initially, the gathered data underwent systematic coding and were accurately entered into SPSS software version 27. In the second step, the reliability of the data was rigorously tested, and exploratory factor analysis (EFA) was conducted to discern the underlying patterns. In the third phase, confirmatory factor analysis (CFA) was performed using AMOS software version 24 to validate the identified factors. Finally, the fourth step involved the application of structural equation modeling (SEM). In this phase, SEM was employed to rigorously assess model fit and systematically test the research hypotheses, ensuring a comprehensive and robust study data analysis.

4. Main Findings

4.1 Demographic Analysis

Table 2 presents the distribution of demographic factors among the 518 participants. The data provided insight into the demographic composition of the study participants.

Table 2
Sample Distribution of Demographic Factors (N=518)

Demographic Variables	Groups	Frequency	Percentage
Gender	Male	223	43.1%
	Female	295	56.9%
Age	Below 25	41	7.9%
	25-40	245	47.3%
	41-55	158	30.5%
	56-70	64	12.4%
	Above 70	10	1.9%
Marriage	Married	434	83.7%
	Single	64	12.4%
	Others	20	3.9%
Education	Below diploma	70	13.5%
	Diploma	218	42.1%
	Bachelor	185	35.7%
	Master and above	45	8.7%

4.2 Reliability Test

The reliability of each latent variable was assessed using Cronbach's alpha. A reliable test requires Cronbach's alpha values above 0.7 and item-total corrected correlations greater than 0.4 (Purwanto, 2021). The reliability test results in Table 3 demonstrate that all observed variables show appropriate item-total corrected correlations (>0.4), indicating that the measurement items effectively measured the constructs. When the Cronbach's alpha coefficients for all latent variables exceeded 0.7, there was a high reliability level for each construct, meeting the reliability test requirements. Therefore, no items were excluded from this scale. After the reliability test, the study proceeded with exploratory factor analysis (EFA).

Table 3
Reliability of Scale

Variables	Cronbach's Alpha	Items	Corrected Item-Total Correlation	Cronbach's Alpha if Items Deleted
Digital Finance Access (DFA)	0.845	DFA1	0.729	0.781
		DFA2	0.720	0.786
		DFA3	0.703	0.793
		DFA4	0.575	0.844

Digital Finance Usage (DFU)	0.832	DFU1	0.691	0.774
		DFU2	0.719	0.761
		DFU3	0.659	0.789
		DFU4	0.576	0.824
Digital Finance Quality (DFQ)	0.840	DFQ1	0.651	0.806
		DFQ2	0.667	0.800
		DFQ3	0.673	0.797
		DFQ4	0.700	0.785
Performance of Financial Asset Allocation (PFAA)	0.919	PFAA1	0.730	0.908
		PFAA2	0.707	0.910
		PFAA3	0.655	0.913
		PFAA4	0.705	0.910
		PFAA5	0.686	0.911
		PFAA6	0.702	0.910
		PFAA7	0.695	0.910
		PFAA8	0.684	0.911
		PFAA9	0.686	0.911
		PFAA10	0.699	0.910

4.3 Exploratory Factor Analysis for Three Drivers of Digital Finance

Exploratory factor analysis (EFA) is a dimensionality reduction technique used to identify common factors influencing the observed variables. The primary objective is to explore the intrinsic essential structure of multivariate complex variables by streamlining variables with complex relationships into a few essential factors (Schreiber, 2021). Considering that the research variables were not derived from mature measurement scales, conducting an EFA was necessary. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity are two crucial indicators used to assess the suitability of the dataset for EFA. Wen et al. (2020) suggested that a KMO value exceeding 0.7 indicates good sampling adequacy. As per the findings in Table 4, the KMO value for the independent variables was 0.907, which is above the 0.7 threshold, indicating that the sampling adequacy criteria were satisfied.

Table 4

KMO and Bartlett's Test Result for Three Drivers of Digital Finance

KMO Values		0.907
Bartlett's test of Sphericity	Approx. Chi-Square	2819.448
	df	66
	Sig.	0.000

Bartlett's test of sphericity, as indicated by the approximate chi-square value of 2819.448, demonstrated statistical significance with a p-value of less than 0.001. The findings presented in

Table 4 suggest that the correlation matrix is statistically different from the identity matrix. This further indicates the feasibility of conducting factor analysis on the sample data.

Table 5
Results of Exploratory Factor Analysis of Three Drivers of Digital Finance

	Factor		
Scale	1	2	3
DFA1	0.763		
DFA2	0.741		
DFA3	0.731		
DFA4	0.559		
DFU2		0.747	
DFU1		0.730	
DFU3		0.673	
DFU4		0.552	
DFQ4			0.722
DFQ2			0.693
DFQ3			0.680
DFQ1			0.662

Factors were extracted based on the maximum likelihood method, and digital finance (DF) items were loaded into three common factors with reporting eigenvalues greater than one, as shown in Table 5. All rotated factor loadings are above 0.5, indicating that the well-loaded items are relevant for measuring the three drivers of digital finance. Furthermore, the three-factor solution accounted for 57.24% of the total variance, demonstrating a substantial explanatory power. The outcomes of the EFA validated the identified factors. Hence, 12 items in three factors were considered for further analysis.

4.4 Exploratory Factor Analysis for Performance of Financial Asset Allocation

EFA was also conducted on PFAA. As Table 6 indicates, sample adequacy was confirmed with a KMO value of 0.959. Additionally, Bartlett's test yielded a highly significant result, with a chi-square value of 2633.35 ($p<0.001$). Given that all the requisite criteria have been met, it is appropriate to proceed with the EFA of the PFAA.

Table 6
KMO and Bartlett's Test Result for Performance of Financial Asset Allocation

KMO Values		0.959
Bartlett's test of Sphericity	Approx. Chi-Square	2633.35

	df	45
	Sig.	0.000

Similarly, maximum likelihood estimation was used to conduct EFA for the ten items of the PFAA. Only one factor had an eigenvalue greater than 1, with each factor loading of PFAA above 0.5. Hence, this common factor effectively summarized the information from the ten observed variables in the EFA. The total variance explained by this factor was 53.11%, which was more than 50%, indicating that this factor accounted for 53.11% of the variance among the ten observed variables. Matrix rotation could not be performed because only one factor was extracted. Therefore, the ten loaded items were considered for further analysis. After conducting the EFA, we proceeded with a confirmatory factor analysis (CFA), which is discussed next.

4.5 Measurement Model Evaluation

Confirmatory factor analysis (CFA) is a statistical method widely used in contemporary studies to estimate the validity and reliability of constructs in empirical analyses (Sujati & Akhyar, 2020). After conducting the EFA, further validation of the digital finance and PFAA constructs is required. This rigorous statistical approach ensured the robustness of the measurement instrument, thereby increasing the overall rigor and credibility of the research findings.

Table 7 displays the outcomes of Confirmatory Factor Analysis (CFA) performed on variables related to digital finance access (DFA), digital finance usage (DFU), digital finance quality (DFQ), and the performance of financial asset allocation (PFAA). First, convergent validity can be met if the loading factors exceed 0.7 (Purwanto, 2021). Based on this principle, DFA4, DFU4, and PFAA3 were excluded because their indicators were < 0.7. After eliminating these three items, the data for the measurement models were recalculated. The composite reliability values of all variables range from 0.82 to 0.91, exceeding the threshold value of 0.7 suggested by Daud et al. (2022). This indicated that the constructs had a good level of reliability. Furthermore, the discriminant validity of a construct can be demonstrated by comparing the correlation between the average variance extracted (AVE) value and the other constructs in the model. Discriminant validity can be achieved if the AVE value exceeds 0.5 (Purwanto, 2021). Moreover, the validation of discriminant validity is affirmed by the square root of AVE (√AVE) values surpassing 0.7, indicating distinctiveness among the constructs (Purwanto, 2021). All constructs met the required AVE and AVE threshold values, as shown in Table 7. Additionally, there is no evidence of multicollinearity among the independent constructs representing various facets of digital finance. The conclusion is substantiated by the variance inflation factor (VIF) values, which are much below the recommended upper threshold of five, as proposed by Attiany et al. (2023). The findings from the CFA demonstrate a strong confirmation of the measurement model's reliability and validity, which serves as a solid basis for further studies inside the structural model.

Table 7

Results of Confirmatory Factor Analysis

Variables	Items	Std. Loadings	AVE	C.R.	√AVE	VIF
Digital Finance Access (DFA)	DFA1	0.811	0.64	0.84	0.80	1.44
	DFA2	0.814				
	DFA3	0.782				
	DFA4	0.631				
Digital Finance Usage (DFU)	DFU1	0.766	0.61	0.82	0.78	1.48
	DFU2	0.824				
	DFU3	0.746				
	DFU4	0.646				
Digital Finance Quality (DFQ)	DFQ1	0.721	0.57	0.84	0.75	1.51
	DFQ2	0.731				
	DFQ3	0.766				
	DFQ4	0.792				
Performance of Financial Asset Allocation (PFAA)	PFAA1	0.766	0.54	0.91	0.73	---
	PFAA2	0.743				
	PFAA3	0.686				
	PFAA4	0.741				
	PFAA5	0.719				
	PFAA6	0.735				
	PFAA7	0.728				
	PFAA8	0.718				
	PFAA9	0.717				
	PFAA10	0.732				

4.6 Structural Model Evaluation

Structural equation Modeling (SEM) is a statistical approach employed to analyze the relationships between observed and latent variables as defined by a theoretical framework (Hair Jr et al., 2021). SEM enables the exploration of intricate relationships by assessing both the direct and indirect effects among variables (Al-Rwaidan et al., 2023). Hence, the SEM approach was applied to comprehensively evaluate the structural relationships in this study.

Table 8 presents the model fit indices used to evaluate the structural model. The χ^2/df ratio stands at 0.904, well below the recommended threshold of 5, indicating strong compatibility between the proposed model and data in terms of degrees of freedom considered. The overall model fit test displayed a probability value exceeding 0.05, suggesting a desirable absolute fit. The root mean square error of approximation (RMSEA) assesses the disparity between observed data and the model. A value below 0.08 was deemed satisfactory. Accordingly, the structural model's RMSEA value of 0.000 indicates an excellent fit. The goodness-of-fit index (GFI), normed fit index (NFI), and adjusted goodness-of-fit index (AGFI) are 0.974, 0.974, and 0.967, respectively. These indices surpassed the recommended threshold of 0.9, confirming an excellent structural model fit. Given the adherence of the structural fit indices to the recommended standards, the overall fit of the SEM was deemed highly satisfactory. Figure 2 illustrates the structural model used in this study and presents the relationships and pathways through which digital finance influences PFAA. This graphical representation demonstrates interactions among the latent constructs, providing a comprehensive and visual understanding of the model.

Table 8
Model Fit Indices

Model Fit Indices	Fit Indices	Suggested Value	Acceptance
χ2/df	0.904	Below 5	Acceptable
RMSEA	0.000	Below 0.08	Acceptable
P	0.790	Above 0.05	Acceptable
GFI	0.974	Above 0.9	Acceptable
NFI	0.974	Above 0.9	Acceptable
AGFI	0.967	Above 0.9	Acceptable

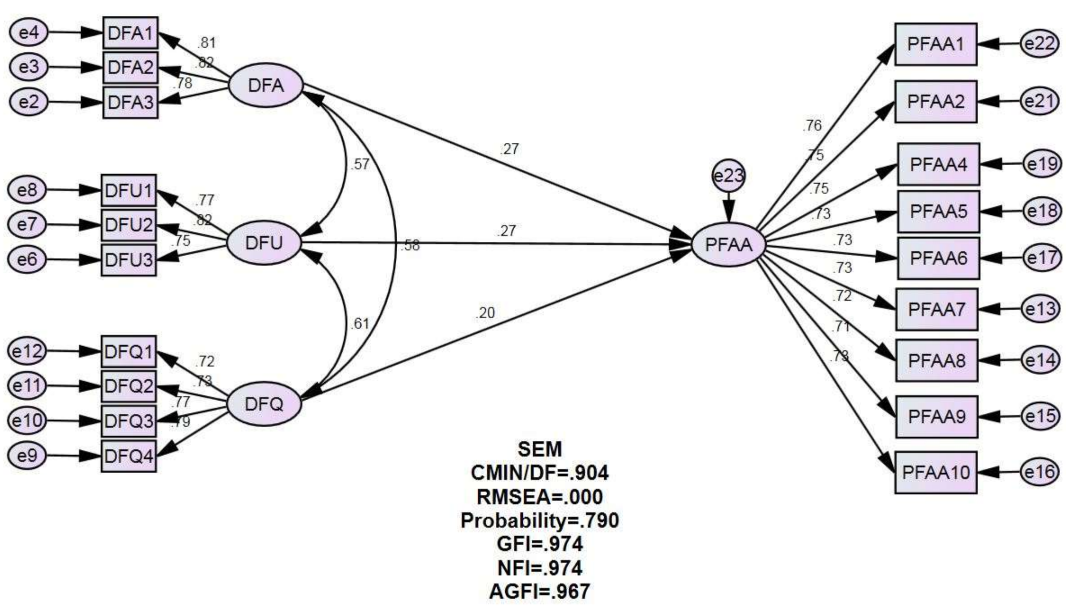

Figure 2. Structural Model Used Evaluated Research Hypotheses

Table 9 provides the maximum likelihood estimates for the structural model, which examines the relationships among the three drivers of digital finance–digital finance access (DFA), digital finance usage (DFU), and digital finance quality (DFQ)–and their impact on the performance of financial asset allocation (PFAA). In this analysis, the critical ratio (C.R.) and p-value (P) served as vital indicators for evaluating the significance levels of path relationships. The standardized path estimates of the regression weights in Table 10 indicate the strength and direction of the relationships between the latent variables.

Table 9

Structural Model Estimation

Path	Estimate	S.E.	C.R.	P
DFA→PFAA	0.261	0.058	4.51	0.000
DFU→PFAA	0.268	0.062	4.33	0.000
DFQ→PFAA	0.200	0.062	3.21	0.001

According to the data presented in Tables 9 and 10, the calculated standard path coefficient of 0.269 suggests a moderately positive relationship between DFA and PFAA. The CR value of 4.51 affirms the significance of this path relationship ($p<0.001$), providing substantial support for Hypothesis H1. This indicates a significant positive impact of DFA on PFAA. Similarly, the standard path estimate of 0.273 revealed a moderately positive relationship between DFU and PFAA. With a CR value of 4.33 ($p<0.001$), H2 was supported, indicating a noteworthy positive effect of DFU on PFAA. Finally, H3, which posits that digital finance quality positively influences PFAA, is also confirmed. This evidence was supported by a CR value of 3.21 ($p<0.01$). However, the standard path coefficient for digital financial quality on PFAA was 0.2, indicating a weak relationship. Table 11 summarizes the test results for the three research hypotheses. The findings from the SEM model analysis present compelling evidence that PFAA is substantially impacted by three key factors: access, usage, and quality of digital finance..

Table 10

Standardized Regression Weights

Path	Estimate (Std)
DFA→PFAA	0.269
DFU→PFAA	0.273
DFQ→PFAA	0.200

Table 11

Summary Results of Hypotheses Testing

No	Hypotheses	Sig.	Relation	Finding
H1	The access to digital finance positively influences PFAA.	Significant	Moderate, Positive	Supported

H2	The usage of digital finance positively influences PFAA.	Significant	Moderate, Positive	Supported
H3	The quality of digital finance positively influences PFAA.	Significant	Very Weak, Positive	Supported

5. Discussion and Conclusion

The primary objective of this study is to investigate the influence of three key drivers of digital finance on PFAA in urban households in China. The findings reveal a positive correlation between digital finance access, usage, quality, and PFAA. However, the impact of digital financial quality on PFAA is relatively weak. These fundamental findings confirm that digital finance consistently bolsters households' willingness to engage in financial markets (Wang et al., 2023). Moreover, this result agrees with previous studies on digital inclusive finance that have increased the share of holdings and returns on financial assets (Shen et al., 2022; Li et al., 2022). These findings enrich the argument for the validity of modern portfolio theory, which emphasizes that an ideal investment portfolio should maximize the expected return for a given level of risk. This discovery offers crucial insights into the puzzle of limited participation in financial markets (Gabaix & Koijen, 2021). Notably, our study adds depth to the exploration within the micro realm of digital finance. Unlike many prior studies that predominantly rely on macro-level digital financial index assessments, our research delves into individual households. The primary data obtained through our questionnaire survey provides detailed micro-level evaluations, capturing the complexity and diversity of households' experiences with digital finance. Furthermore, the relatively weak impact of digital finance quality on PFAA emphasizes the need for a robust customer protection framework. Mitigating the risk of cyberattacks on customer data is imperative, potentially eroding trust in digital financial channels. Thus, ensuring the security and integrity of digital financial platforms is vital to fostering trust among users.

Although this study unveiled crucial insights, it is not exempt from its limitations. One significant constraint is the limited scope of our study, which was restricted to urban households in China. Given the widespread adoption of digital finance nationwide, it is imperative to explore whether its positive impact on PFAA extends to rural households in remote areas. Additionally, the relentless advancement of technology has continually propelled the innovation and transformation of the digital finance landscape. Consequently, as explored in this study, the benefits of digital finance may undergo significant changes. These shifts could affect the relevance and applicability of our research findings. Future iterations of digital finance may exhibit even greater efficacy. Therefore, to thoroughly assess digital finance's impact on financial well-being, future research should consider individual countries and specific regions. Furthermore, a global perspective is essential to comprehensively compare the effects of digital finance across diverse socioeconomic contexts. This approach ensures a more nuanced understanding of the evolving dynamics of digital finance and its implications for global financial asset allocation strategies.

6. Implications

These empirical findings provide crucial insights for governmental authorities, financial institutions, and households. First, governments should formulate policies to encourage digital finance's development and widespread adoption. Special attention should be paid to the accessibility of digital financial products to ensure convenience and security. Government can encourage the advancement of financial services by implementing laws and regulations, bolstering regulatory initiatives, and promoting financial literacy. This will increase the opportunities and benefits for households to allocate financial assets. Second, financial institutions should ensure the quality of digital financial products and foster technological innovation. These include improving the convenience of digital financial services, reducing transaction costs, diversifying product options, and reinforcing information security and risk management. Financial institutions can achieve this by employing techniques, such as technological innovation, data analysis, and customer demand surveys. They offer superior digital financial products/services by meeting the needs of different household groups. Finally, households engaged in asset allocation using digital financial tools should enhance their financial literacy. They should gain in-depth knowledge of various digital financial products' characteristics, risks, and returns. Families can accomplish this by participating in financial training, consulting financial experts, or seeking advice from financial advisors, strengthening their financial knowledge and risk-identification abilities. Households should prudently select digital financial product providers and opt for reputable financial institutions with excellent services to mitigate financial risk and ensure asset security.

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