Received: 7 July 2025 | Revised: 10 December 2025 | Accepted: 17 April 2026 | Published online: 29 May 2026

RESEARCH ARTICLE

FinTech and Sustainable Innovation
2026, Vol. 00(00) 1–9
DOI: 10.47852/bonviewFSI62026717

BON VIEW PUBLISHING

Empowering Long-Tail Investors Through Financial Technology: Evidence from Robo-Advisory Adoption in China

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Abstract: Financial technology (FinTech) has emerged as a catalyst for global sustainability projects as technology advances. Digital breakthroughs such as blockchain, artificial intelligence-powered analytics, and inclusive digital platforms are being used to democratize climate resilience investments and enhance environmental, social, and governance alignment across financial institutions. The purpose of this study is to perform an empirical inquiry of the potential of robo-advisors to see if they can make wealth management more accessible to individual investors by increasing affordability. The authors use longitudinal panel data from the China Household Finance Survey and the Digital Financial Inclusion Index to investigate the impact of FinTech infrastructure on automated investment advising service acceptance. The findings indicate that robo-advisors dramatically increase the number of retail investors. The inclusion of a larger number of people in the financial system can promote and encourage more logical investment decisions. Given these findings, it is clear that FinTech-driven solutions have the ability to close investment service gaps and promote equitable and sustainable financial inclusion in developing economies.

Keywords: robo-advisor, financial technology, digital financial inclusion, inclusive investment behavior, individual investors

1. Introduction

Recent advances in artificial intelligence and financial technology (FinTech) have reshaped personal wealth management, with robo-advisors emerging as one of the most influential innovations [1–4]. These algorithm-driven platforms leverage big data and machine learning to deliver low-cost and personalized investment services, expanding access to financial advice—particularly in rapidly digitalizing economies such as China. Despite growing evidence on their efficiency and cost advantages, the broader social and behavioral implications of robo-advisors, especially their role in promoting inclusive and sustainable investment participation, remain insufficiently explored [4, 5].

China's FinTech ecosystem, underpinned by widespread mobile payments and expanding digital financial services, provides a unique environment for examining robo-advisor usage (RA) among "long-tail investors"—individuals historically excluded from traditional financial advisory services due to high costs or limited financial knowledge [6, 7]. Robo-advisors have the potential to lower entry barriers, democratize access to investment products, and reduce behavioral biases such as overtrading or herding [3, 4], yet concerns remain about algorithmic opacity and user overreliance.

This study contributes to the literature on technology-enabled inclusive finance by analyzing how regional digital financial infrastructure influences robo-advisor adoption in China. Using nationally representative China Household Finance Survey (CHFS) microdata merged with the Digital Financial Inclusion Index (DFII), we empirically assess the relationship between digital finance development and individual investment behavior, proxied by mutual fund participation.

By integrating insights from behavioral finance, the technology adoption model, and financial inclusion theory, this study provides new evidence on how digital technologies can foster more inclusive, sustainable, and behaviorally informed investment decisions [8, 9]. The findings carry important implications for regulators, financial institutions, and FinTech developers seeking to leverage technology for equitable wealth management.

Figure 1 summarizes the study's core mechanism: digital financial inclusion (DFI) reduces access barriers to financial services, which in turn increases the likelihood of adopting robo-advisory tools. Individual characteristics (education, gender, age, debt) and enabling conditions (digital literacy, trust, regulation) shape how strongly DFI translates into RA. The diagram highlights that adoption is not driven solely by infrastructure but by the interaction between digital access, demographic factors, and institutional environments.

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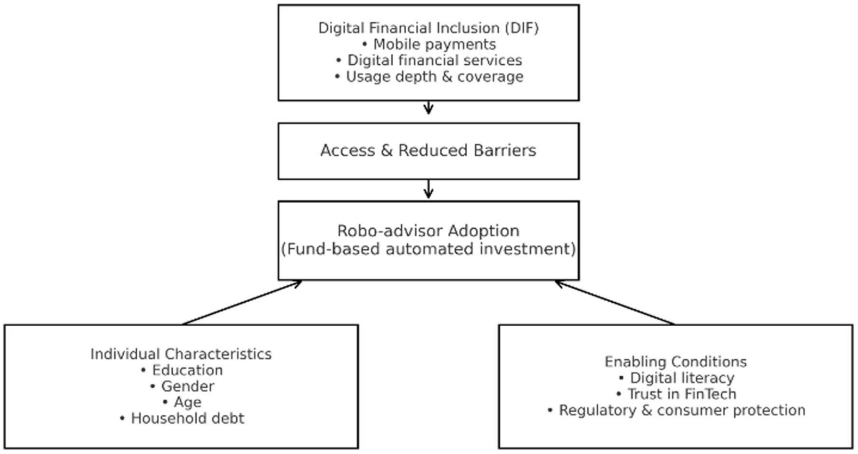
Figure 1
Conceptual framework of the determinants of robo-advisor adoption



2. Literature Review

Issues associated with financial inclusion, behavioral finance, and digital transformation have gained increasing attention in both developed and emerging economies [10]. Robo-advisors are defined as automated financial advisory platforms that use algorithms to provide investment recommendations, portfolio rebalancing, and risk profiling without human intervention [3, 4]. They are regarded as cost-effective alternatives to traditional financial advisory services and are rapidly changing the landscape of personal investment behavior globally.

Recent research has examined the influence of robo-advisory services on investor behavior, financial literacy, and market participation [11, 12]. The advent of robo-advisors is associated with increased efficiency, lowered entrance barriers for low-income investors, and improved financial decision-making discipline. Researchers highlighted that robo-advisors can facilitate inclusive finance by offering affordable and accessible investment services to marginalized people. Also, these platforms possess the capability to mitigate prevalent behavioral biases, including overconfidence, herding, and excessive trading [13, 14]. Additionally, researchers have examined the correlation between demographic variables and the adoption of robo-advisory services [15]. The adoption of these technologies by individuals is influenced by factors such as age, education level, income, and digital familiarity [16]. For example, younger, more digitally literate individuals are more inclined to exhibit an interest in automated advisory platforms, whereas older or risk-averse groups continue to harbor concerns regarding algorithmic transparency and trust.

Similarly, numerous studies have investigated the extent to which robo-advisors influence rational decision-making and portfolio diversification over the years [17, 18]. The results indicate that, despite the fact that robo-advisors can enhance risk-adjusted returns and reduce emotional decision-making, investors' comprehension of algorithm-based services is still limited, particularly among first-time users or less financially literate populations.

Nevertheless, prior research has primarily concentrated on the technological functionalities or investor sentiment in isolation, with minimal consideration given to the potential impact of digital financial infrastructure—such as regional variations in digital inclusion—on RA behavior [19–22]. Furthermore, the majority of empirical research is grounded in Western contexts, whereas data from rising economies such as China are rather limited.

This study enhances the existing literature by being one of the initial efforts to combine data from the CHFS with the DFII to empirically investigate the influence of FinTech advancement on individual investor behavior, specifically regarding the adoption of robo-advisory services. This research addresses a significant gap in the literature and offers novel insights into the inclusive capabilities of digital wealth management tools.

2.1. Theoretical framework

Individual investors often deviate from rational decision-making, especially in financial markets characterized by information asymmetry and emotional volatility. Accordingly, any examination of the influence of robo-advisors on investor behavior should be grounded in an integrated framework that draws from both behavioral finance theory and the technological advancements underpinning modern financial services.

2.1.1. Herding phenomenon

The behavior of investors is typically influenced by social cues, particularly in circumstances in which individuals do not possess sufficient self-assurance or information to make independent decisions. It is possible for this to lead to herd behavior, which is when individuals replicate behaviors based on the choices they believe others are making rather than on an objective evaluation of the circumstance. It has been stated by Singh et al. [23] that herding tendencies are most noticeable during times of market uncertainty. This indicates that these tendencies contribute to overreaction and market inefficiencies. As a response to behavioral distortions such as these, robo-advisors offer portfolio management that is driven by algorithms. The standardization of investment decisions and the reduction of the amount of reliance on the actions of peers are both outcomes of this management style. Tsai and Chen [24] state that the automation and transparency that are inherent in big data-enabled robo-advisors boost investor trust and eliminate emotional bias by delivering consistent and diversified asset allocation techniques. This is accomplished by delivering a wide range of asset allocation strategies. They [24] provided evidence to support this assertion. As a consequence of this, robo-advisors serve as a functional instrument for stabilization, guiding customers toward investment practices that are fairer and more sustainable.

2.1.2. Momentum and reversal effects

Investors have a tendency to follow current market trends, which include buying assets at inflated prices and selling them prematurely when prices fall. This tendency is frequently motivated by overconfidence or market sentiment [25]. The momentum effect is a term that describes this tendency. The reverse effect, on the other hand, makes the assumption that asset prices have a tendency to return to their long-term mean over the course of time, which is a reflection of underlying worth. It is possible for these behavioral biases to lead to timing that is less than optimal and asset misallocation [26]. Robo-advisors give systematic, emotion-free counsel that prioritizes long-term investment stability over reactive behavior. They do this by utilizing algorithmic rebalancing and diversified portfolio creation. Robo-advisors assist in counteracting these inclinations.

2.1.3. Heterogeneous expectations and market volatility

There is a tendency for investors to create heterogeneous expectations in the financial markets. This means that individuals perceive the same information in different ways due to cognitive biases, different risk preferences, or varied access to information. Divergences of this kind are a contributing factor to price volatility as well as departures from fundamental values [27]. Using standardized algorithms and data-driven models, robo-advisors assist in limiting the influence of individual biases and aligning decision-making with consistent investment principles [28]. Robo-advisors are becoming increasingly popular in the financial investing industry. The presence of this uniformity in interpretation helps to reduce the behavioral distortions that are normally brought about by the fragmentation of investor expectations.

2.1.4. FinTech, digital financial inclusion, and sustainable innovation

By eliminating entry barriers and streamlining investment processes, robo-advisors are able to improve access to financial services, particularly among underserved and long-tail investors [29]. This is made possible by the help of developing technologies. This democratization of financial tools is an essential component of DFI, which is responsible for playing a critical role in the formation of economic growth that is both sustainable and inclusive [30].

In addition, the rising convergence between sustainable innovation and FinTech is becoming an increasingly important factor in the landscape of digital banking. For example, Jiang et al. [31] revealed how carbon pricing and clean energy markets are interconnected through asymmetric causal dynamics that amplify during times of market volatility. This was proved by demonstrating how the two markets are interconnected. Based on these findings, it can be inferred that intelligent financial systems, such as robo-advisors, have the potential to be improved in order to add sustainability-focused characteristics. These factors may include carbon market signals or environmental asset trends, which would ultimately direct investors toward greener investment portfolios.

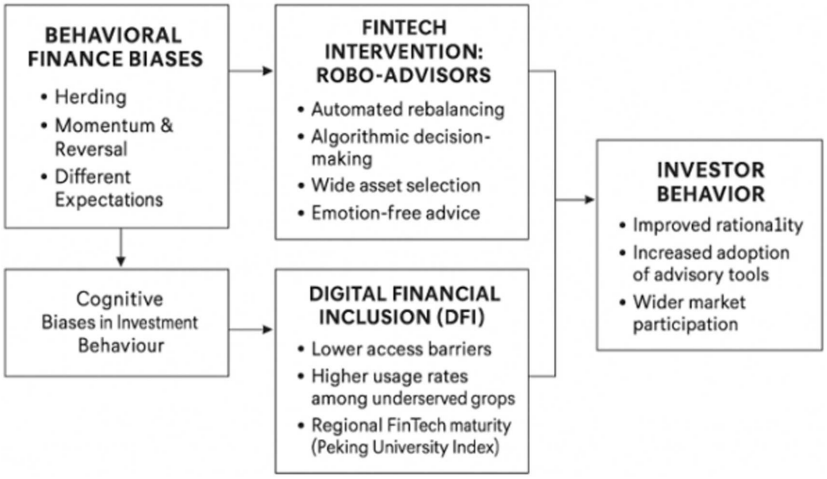
Not only may robo-advisors serve to increase portfolio efficiency, but they could also contribute to promoting green transition goals if they were to include such sustainability signals in algorithmic models. Personalized digital tools not only improve involvement but also direct capital toward climate-resilient assets, which underlines the potential of FinTech as a conduit for sustainable innovation. This highlights the nature of the promise that FinTech possesses. Because of this, the level of maturity of regional digital financial systems, which may be evaluated by indices such as the Peking University DFII, can have a substantial impact on the adoption of robo-advisory services as well as their ability to deliver sustainable investment outcomes.

Figure 2 illustrates a conceptual framework depicting the interaction between behavioral finance biases, FinTech interventions—specifically robo-advisory services—and DFI in influencing individual investment behavior [32]. The framework is based on behavioral finance theories, emphasizing significant psychological distortions including herding behavior, momentum and reversal effects, and heterogeneous expectations, all of which lead to irrational investment decisions in situations of uncertainty and information asymmetry.

To alleviate these cognitive biases, robo-advisors function as a technology middleman by providing algorithm-driven asset allocation, automated portfolio rebalancing, and impartial investment advice. These attributes mitigate emotional interference and foster long-term investment discipline.

Moreover, the model integrates the aspect of DFI, highlighting its significance in broadening access to investment instruments and services, especially for marginalized and low-income groups. The advancement of digital infrastructure, as indicated by metrics like the DFII, reduces entry barriers and

Figure 2
Theoretical framework of robo-advisors and investor behavior



facilitates the proliferation of FinTech instruments such as robo-advisors.

The framework illustrates how FinTech, when combined with inclusive digital systems, can effectively mitigate behavioral anomalies and democratize investment participation, thus fostering more rational, efficient, and equitable financial decision-making among individual investors.

2.2. Research hypotheses

Informed by the aforementioned theoretical frameworks, this study posits the subsequent hypotheses:

H1: An elevated degree of digital financial inclusion enhances the probability of individual investors utilizing robo-advisors.

H2: Robo-advisors mitigate irrational investment behaviors.

H3: Financial technology is more likely to empower lower- and middle-income groups to engage in investment markets.

The assumptions will be empirically evaluated utilizing data from the CHFS and the DFII, facilitating a comprehensive examination of the behaviors and mechanisms underlying robo-advisor adoption.

3. Research Methodology

3.1. Research design and sampling

This study employs a quantitative empirical design using nationally representative micro-level data from the CHFS. The CHFS adopts a stratified, multistage probability sampling approach, covering 29 provinces with representation of urban and rural households. Sampling follows:

1) Province-level stratification,
2) Random selection of counties/districts,
3) Selection of communities/villages,
4) Random sampling of households, and
5) Random selection of individual respondents within households.

This sampling strategy ensures that the dataset reflects China's diverse demographic and financial characteristics, making it suitable for studying household investment behavior and FinTech adoption.

3.2. Data sources and period

This study utilizes micro-level data from the 2019 CHFS, a nationally representative dataset collected by the Southwestern University of Finance and Economics. The CHFS uses a stratified, multistage probability sampling design and contains detailed information on household financial behavior, asset allocation, demographic characteristics, and investment preferences.

To capture the regional level of FinTech development, this study incorporates provincial-level indicators from the DFII. It measures coverage breadth, usage depth, and the degree of digitalization of financial services. The index values used in this study correspond to 2018–2019, matching the years closest to the CHFS survey period to ensure temporal consistency.

By merging household-level CHFS data with regional DFI indicators, the study constructs a comprehensive dataset for analyzing the behavioral impact of robo-advisory services in a real-world setting.

3.2.1. Variable design

1) **Explained variable (dependent variable)**

Robo-advisor adoption behavior is proxied by whether an individual **holds mutual funds** (Fund_Holding), as robo-advisory services are most commonly used for fund portfolio management. This binary variable takes the value 1 if the respondent holds any mutual funds, and 0 otherwise.

2) **Core explanatory variable**

Digital Financial Inclusion Index (DFII): This continuous variable reflects the degree of digital financial infrastructure development in each province. A higher index value indicates stronger digital finance capability, which potentially promotes the adoption of technology-enabled investment tools.

3) **Control variables**

To mitigate omitted variable bias, the model controls for various individual and household characteristics:

a. Age, gender, education level, income
b. Employment status, risk preference
c. Financial literacy, urban/rural residence
d. Household asset and debt level

3.2.2. Empirical model

To examine the relationship between digital financial development and robo-advisor adoption (RA), we adopt a probit model, given the binary nature of the dependent variable:

$$P(Y_i = 1) = \Phi(\beta_0 + \beta_1 DFI_i + \beta_2 X_i + \epsilon_i) \quad (1)$$

Where:

Y_i is the likelihood that individual i uses robo-advisory services (proxied by fund holding).

DFI_i is the Digital Financial Inclusion Index.

X_i represents the vector of control variables.

ϵ_i is the error term.

3.3. Model assumptions and controls

Given the binary nature of robo-advisor adoption (proxied by mutual fund holding), the study applies a probit model, assuming:

1) Normal distribution of the latent propensity score,
2) Independence and identical distribution of error terms,
3) Linearity in parameters between covariates and latent adoption tendency, and
4) Exogeneity of control variables, that is, demographic and socioeconomic controls are not jointly determined with the dependent variable.

To address omitted variable bias, the model includes a comprehensive set of individual-, household-, and region-level controls, including:

1) Age, gender, education, income,
2) Employment status, risk preference,
3) Financial literacy,
4) Urban vs. rural residence, and
5) Household assets and liabilities.

These controls capture key determinants of financial decision-making and mitigate confounding in the relationship between FinTech infrastructure and robo-advisor adoption.

3.4. Statistical model and causality statement

Because the study uses observational cross-sectional data, the results identify associations (correlations) rather than strict causal effects. No causal identification strategy (e.g., instrumental variables (IVs), difference-in-differences (DID), regression discontinuity design (RDD)) is applied, so estimates reflect correlational relationships between regional FinTech development and RA.

1) **Baseline model**

A probit regression is estimated as:

$$Pr(RA_i = 1) = \Phi(\alpha + \beta DFIIC_{r(i)} + \gamma X_i + \epsilon_i) \quad (2)$$

Where:

a. RA_i: binary indicator of robo-advisor usage.
b. Φ: cumulative normal distribution function.
c. $DFIIC_{r(i)}$: FinTech development level in region r.
d. X_i: vector of demographic and financial controls.

2) **Marginal effects**

To aid interpretation and replicability, marginal effects at the mean are reported, showing percentage-point changes in adoption probability due to one-unit changes in explanatory variables.

3.5. Replicability notes

To ensure methodological transparency:

1) All variable definitions follow CHFS 2019 codebook conventions.
2) DFI measures use the official DFII dataset.
3) The probit model is estimated in Stata 17 using the probit and margins commands.
4) Robust standard errors are clustered at the **province level** to account for regional correlation in FinTech indicators.

These details allow other researchers to independently reproduce the empirical results.

4. Results

4.1. Descriptive statistics

Table 1 presents descriptive statistics for the main variables in the sample. Robo-advisor adoption, proxied by mutual fund holdings, remains low at 3%, highlighting early-stage penetration of automated advisory tools in China. The DFII shows substantial variation across provinces (mean = 2.76, SD = 0.51), suggesting heterogeneous FinTech infrastructure.

Table 1 summarizes the descriptive statistics of the key variables. RA has a mean value of 0.03, indicating that only 3% of sampled individuals hold fund-type robo-advisory products. This highlights the early-stage penetration of automated advisory services in China. The DFII has a mean of 2.76 (SD = 0.51) and ranges from 1.93 to 4.10, reflecting substantial regional differences in digital finance development.

Compared with the relatively moderate dispersion of DFI, the large variation in RA suggests that individual-level factors (e.g., education, digital literacy, investment experience) contribute more strongly to robo-advisor adoption than regional FinTech infrastructure alone. These descriptive patterns provide important foundational insights for the subsequent regression analysis.

4.2. Correlation matrix

Table 2 displays Pearson correlations among key variables. DFI is positively correlated with RA (r = 0.037, p < 0.01), suggesting that regions with stronger digital financial ecosystems experience slightly higher RA. Education shows the strongest positive correlation with RA (r = 0.195).

Table 2 presents the Pearson correlation matrix of the main variables. The DFII shows a small but statistically significant positive correlation with RA (r = 0.037, p < 0.01), indicating that

Table 1
Descriptive statistics

Variable	Mean	SD	Median	Min	Max
RA (robo-advisor usage)	0.030	0.160	0	0	1
Digital financial inclusion (DFI)	2.760	0.510	2.720	1.930	4.100
Age	54.44	12.88	54	3	99
Gender (1 = male)	0.790	0.400	1	0	1
Education	3.300	1.510	3	1	9
Household debt (×10k RMB)	3.460	5.070	0	0	16.13

Note: Visual aids can be added as a figure, such as a histogram of DFI distribution or a heatmap of adoption across provinces.

Table 2
Correlation matrix of key variables

Variable	RA	DFI	AGE	GEN	DEG	DEB
RA	1	0.037***	–0.020***	–0.058***	0.195***	–0.004
DFI	0.037***	1	0.139***	–0.059***	0.087***	–0.065***
AGE	–0.020***	0.139***	1	–0.039***	–0.278***	–0.282***
GEN	–0.058***	–0.059***	–0.039***	1	–0.027***	0.047***
DEG	0.195***	0.087***	–0.278***	–0.027***	1	0.053***
DEB	–0.004	–0.065***	–0.282***	0.047***	0.053***	1

Note: p < 0.1, p < 0.05, p < 0.01. Significance levels are denoted as * p < 0.10, ** p < 0.05, and *** p < 0.01

Table 3
Baseline probit regression results and marginal effects

Variables	Probit coefficient	Std. error	*z*-value	*p*-value	95% CI	Marginal effect
Digital financial inclusion (DFI)	0.083	0.034	2.41	0.016	[0.016, 0.150]	0.005*
Age	0.006	0.001	4.51	0.000	[0.003, 0.009]	0.000***
Gender (1 = male)	–0.277	0.038	–7.30	0.000	[–0.351, –0.202]	–0.015***
Education	0.290	0.010	30.30	0.000	[0.270, 0.310]	0.016***
Household debt	–0.004	0.004	0.98	0.327	[–0.013, 0.004]	≈ 0

Note: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Marginal effects reported at sample means. "≈ 0" indicates a marginal effect extremely close to zero after rounding.

regions with higher levels of digital financial development tend to have slightly higher adoption of robo-advisory products. However, the magnitude of this correlation is modest, suggesting that digital financial infrastructure alone does not strongly predict RA.

Among individual-level characteristics, education level (DEG) shows the strongest positive correlation with RA ($r = 0.195$, $p < 0.01$), while gender and age exhibit weak negative correlations. These patterns imply that demographic factors—particularly education—may have a more direct influence on robo-advisor adoption than regional FinTech development. Overall, the correlation structure provides preliminary insights but does not indicate strong linear relationships, which justifies the need for multivariate regression analysis.

4.3. Multicollinearity diagnostics

Before estimating the baseline model, multicollinearity was assessed using the variance inflation factor (VIF). All predictors have VIF values below 2 (mean $VIF = 1.09$), indicating no multicollinearity concerns and ensuring the stability of coefficient estimates.

Table 3 presents the results of the baseline probit regression examining the relationship between DFI and robo-advisor adoption. The coefficient of the DFII is positive and statistically significant ($\beta = 0.083$, $p = 0.016$), suggesting that individuals living in regions with more developed digital financial infrastructure are more likely to adopt robo-advisory products. The marginal effect (0.005) further indicates that a one-unit increase in DFI raises the probability of adoption by approximately 0.5 percentage points, holding other factors constant.

Among the control variables, education level exhibits the strongest positive association with RA (marginal effect = 0.016, $p < 0.01$), highlighting the role of financial and digital literacy in facilitating FinTech adoption. Gender shows a negative and highly significant effect, suggesting that males are less likely to adopt robo-advisory services compared with females. Age has a positive but modest marginal effect, while household debt shows no statistically significant relationship with adoption.

Overall, the baseline regression results support Hypothesis H1, demonstrating that DFI plays an enabling role in promoting the uptake of automated investment advisory tools among Chinese individual investors.

4.4. Robustness checks

To verify the stability of the baseline findings, robustness checks were conducted by replacing the overall DFII with its two subdimensions: coverage breadth (Wid) and usage depth (Dep). The probit estimates remain positive and statistically significant across both alternative specifications, indicating that regions with wider financial service availability or higher levels of digital financial activity show greater robo-advisor adoption.

These results demonstrate that the core conclusion is not sensitive to indicator definitions. Whether focusing on the spatial expansion of digital finance or its intensity of use, DFI consistently exerts a positive effect on RA. This reinforces the robustness and reliability of the baseline regression results.

The robustness results in Table 4 confirm the stability of the baseline findings. When replacing the overall DFII with its two subdimensions—coverage breadth (Wid) and usage depth (Dep)—the coefficients remain positive and statistically significant at the 5% level. This indicates that both the geographic expansion of digital financial services and the intensity of their usage are associated with higher robo-advisor adoption. The signs and significance levels of all control variables remain consistent with the baseline model, further reinforcing the reliability of the core results.

Table 4
Robustness checks using DFI subdimensions

Variables	(1) RA (Wid)	(2) RA (Dep)
Coverage breadth (Wid)	0.074 (0.032)**	–
	(2.315)	
Usage depth (Dep)	–	0.057 (0.024)**
		(2.319)
Age	0.006*** (0.001)	0.006*** (0.001)
	(4.537)	*(4.532)*
Gender (1 = male)	–0.277*** (0.038)	–0.279*** (0.038)
	(–7.303)	*(–7.366)*
Education	0.290*** (0.010)	0.290*** (0.010)
	(30.314)	*(30.397)*
Household debt	–0.004 (0.004)	–0.004 (0.004)
	(–0.975)	*(–1.006)*
N	26,892	26,892

Notes: Standard errors in parentheses; t-statistics in italics. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wid = digital financial inclusion coverage breadth; Dep = digital usage depth.

4.5. Interpretation of findings

The empirical results provide consistent evidence that DFI plays a meaningful role in facilitating robo-advisor adoption among Chinese individual investors. The positive and statistically significant coefficient of the DFII indicates that individuals residing in regions with more advanced digital financial ecosystems are more likely to use automated investment services. This suggests that improved digital infrastructure—such as mobile payment penetration, online financial service availability, and digital account coverage—lowers access barriers and enables broader participation in FinTech-enabled investment tools.

In addition to regional financial development, individual characteristics contribute significantly to adoption patterns. Education exhibits the strongest positive association with RA, implying that individuals with higher educational attainment may possess greater financial literacy, digital familiarity, and trust in algorithm-based financial innovations. Gender shows a negative relationship, with males being less likely to adopt robo-advisory products compared with females, potentially reflecting differences in risk preferences or FinTech acceptance. Age demonstrates a modest positive effect, indicating that older individuals may also benefit from enhanced digital financial environments, although the magnitude of influence remains relatively small. Household debt, by contrast, displays no significant association with adoption, suggesting that indebted households may prioritize repayment or exhibit limited capacity to engage in investment activities.

These findings highlight a dual mechanism behind robo-advisor adoption: regional digital financial infrastructure enables access, while individual demographic and socioeconomic characteristics shape actual uptake. The results underscore the importance of both external enabling conditions and internal personal attributes in driving the diffusion of digital investment advisory services. This aligns with theoretical perspectives suggesting that FinTech adoption is jointly influenced by technology readiness, financial literacy, and contextual digital environments.

4.6. Discussion

The findings of this study closely align with and extend prior research in several important ways. First, the positive association between DFI and robo-advisor adoption corroborates earlier evidence that improvements in digital infrastructure reduce participation frictions and broaden access to financial services [33]. Our results provide empirical confirmation that digital financial ecosystems not only support basic financial transactions but also facilitate higher-order investment behaviors, thereby extending existing financial inclusion theories into the domain of automated investment advisory services.

Second, the strong influence of education on adoption is consistent with technology acceptance and financial literacy frameworks [34], which emphasize cognitive ability, trust, and digital competency as prerequisites for engaging with innovative FinTech tools. In this respect, our study enriches the literature by demonstrating that these mechanisms remain central even in advanced digital advisory contexts.

Third, our results reveal a gender gap in robo-advisor adoption, which partially challenges some earlier studies that suggest digital finance reduces traditional gender disparities in financial participation. Instead, our findings indicate that even within inclusive digital environments, gendered preferences or behavioral biases may persist—highlighting the need for more targeted inclusion strategies.

While the study focuses on China, the mechanisms identified are relevant to a broader set of emerging markets undergoing rapid digitalization. Many economies in Southeast Asia, South Asia, Latin America, and Africa face similar structural constraints—such as limited traditional banking access, uneven financial literacy, and rapid mobile penetration—which create favorable conditions for FinTech-driven financial inclusion. In these contexts, improvements in digital financial infrastructure are also likely to reduce participation barriers and facilitate the adoption of automated investment tools, consistent with China's experience. However, the scalability of these findings may depend on country-specific institutional factors, including regulatory quality, consumer protection frameworks, and the maturity of digital identification systems. For instance, countries with weaker data governance or lower digital trust may experience slower diffusion of robo-advisory services despite improved mobile connectivity [33, 35]. Thus, while the underlying relationships appear theoretically transferable, the magnitude of the effects may vary across emerging markets. Future comparative research could examine how different regulatory environments and cultural factors shape the adoption of digital investment platforms in diverse developing economies.

These contributions show that this study both confirms foundational insights from the financial inclusion and FinTech adoption literature and extends theoretical understanding to a new segment of digital financial behavior: automated investment advisory services.

5. Conclusion

As a key manifestation of FinTech development, whether robo-advisory services can play a substantive role in guiding investors' asset allocation behavior still requires empirical analysis and interpretation. The findings of this study indicate that improved accessibility to robo-advisory services has, to some extent, lowered the barriers to wealth management and expanded investment participation channels for low- and middle-income groups, as well as financially underserved populations. Compared to traditional investment advisory services, robo-advisors—characterized by low cost, scalability, and automation—are better positioned to stimulate demand for investment advice among potential users. This is especially true for individuals who previously lacked access to professional financial guidance due to information asymmetry or high transaction costs, for whom the marginal impact is particularly significant. Furthermore, the study reveals that the development of DFI exerts heterogeneous effects on RA across different income groups. Investors in regions with higher levels of digital finance are more likely to access and adopt robo-advisory products, thereby enhancing their financial management efficiency and investment decision-making capabilities. At the same time, the widespread adoption of robo-advisors significantly increases investors' awareness of portfolio management, effectively guiding them to make rational choices in balancing returns and risks. The underlying mechanism lies in the algorithm-driven asset allocation recommendations, which help investors achieve the dual goals of return enhancement and risk control.

Recommendations

The findings revealed that the level of digital financial infrastructure and financial literacy were key factors influencing whether individual investors adopted robo-advisory services. Therefore, it is recommended that both financial service providers and policymakers invest in strengthening digital

financial infrastructure and enhancing financial literacy, particularly in underserved regions. Since robo-advisors offer algorithm-driven investment support, which can reduce behavioral biases and lower entry barriers, it is further recommended that financial institutions provide user-friendly training materials to guide first-time investors. These materials should include explanations of how robo-advisors work, their advantages, limitations, and associated risks. Additionally, as the adoption of robo-advisors generated positive experiences among early users, participants suggested encouraging their peers—especially those from low-income or rural backgrounds—to engage with these digital tools. Robo-advisory systems integrated into financial platforms can be further adapted and promoted by community-level financial educators and rural banks. Therefore, local governments and financial educators are recommended to introduce targeted awareness campaigns to promote the responsible and informed use of robo-advisory services for personal investment planning.

Funding Support

This work was supported by the Undergraduate Innovation and Entrepreneurship Training Program of Qingdao University (Project No. X2024110650736).

Ethical Statement

This study uses a publicly available dataset for which access requires formal permission. We obtained the necessary permission/authorization from the dataset provider prior to conducting any analysis, in accordance with the dataset's access policy. The dataset was originally collected under its own ethical approval and released in a de-identified form. As stated in the dataset documentation, secondary analyses conducted under an approved access agreement are exempt from additional ethical approval. No identifiable personal information or new human-subject data were collected in this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support this work are available upon reasonable request to the corresponding author.

Author Contribution Statement

Fei Wei: Formal analysis, Data curation, Writing – original draft, Funding acquisition. **Jianting Zhao:** Formal analysis, Investigation, Data curation, Visualization. **Yuting Zheng:** Formal analysis, Investigation, Data curation, Visualization. **Fangyuan Zhu:** Formal analysis, Investigation, Data curation, Visualization. **Yu Zhu:** Formal analysis, Investigation, Data curation, Visualization. **Ruyi Ding:** Formal analysis, Investigation, Data curation, Visualization. **Anna Xing Chen:** Methodology, Software, Writing – original draft. **Sonia Chien-I Chen:** Conceptualization, Validation, Formal analysis, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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How to Cite: Wei, F., Zhao, J., Zheng, Y., Zhu, F., Zhu, Y., Ding, R., …, & Chen, S. C.-I. (2026). Empowering Long-Tail Investors Through Financial Technology: Evidence from Robo-Advisory Adoption in China. *FinTech and Sustainable Innovation*. https://doi.org/10.47852/bonviewFSI62026717