

## ORIGINAL ARTICLE OPEN ACCESS

# Artificial Intelligence Use for Financial Advice and Financial Behaviors: The Role of Financial Knowledge

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## ABSTRACT

With the advent of Artificial Intelligence (AI)-driven tools in financial services and planning, there is concern about the role of AI-driven financial advice and openness to these in relation to individual financial behaviors, particularly regarding clients' interpretation of this advice and its applicability to their financial situations. Therefore, this study, using data from the 2024 National Financial Capability Study (NFCS), investigated the relationship between the willingness to use AI for financial advice and financial behaviors (short and long term). Furthermore, this study tested how financial knowledge (objective and self-assessed) may moderate the aforementioned relationship. Findings showed that willingness to use AI relates to short- and long-term financial behaviors differently, and that only self-assessed financial knowledge significantly moderated these associations. These findings have implications for individuals and financial professionals working with clients and highlight the importance of perceived financial knowledge in how individuals translate AI-based advice into financial behaviors. This study suggests that while AI tools in financial planning are beneficial, they cannot eliminate the role of human financial advisors.

**JEL Classification:** B4, D10, D14, G51, G53, J1, J2, J3

## 1 | Introduction

Artificial Intelligence (AI) is transforming the financial service industry, making financial services more efficient and seamless (Adegbite 2025). AI tools support daily financial tasks such as budgeting, expense tracking, and long-term retirement planning. By allowing the analysis of various data sets, these tools can provide personalized insights and optimized asset allocation. This process supports strategic decision-making, which, is frequently associated with higher financial skillsets and well-being (Fauzi 2024; Vaduka et al. 2024). Senteio and Hughes (2024) found that individuals trust AI advisory services offered by reputable firms such as Vanguard, but still prefer human advisors when facing complex and risky financial decisions. Their preference for human advisors may stem from the fact that these AI financial advisors do not replicate the empathic, deliberate, and contextual characteristics of human

financial advisors (Eichler and Schwab 2024). The concern with the use of AI-financial advice is that individuals using these systems need to understand how to translate the information provided and apply it to their specific situations, an area where financial knowledge is crucial.

Together, previous studies have shown the key drivers of the openness and adoption of AI financial advice, factors linked to trust, and how AI may optimize financial decision making; however, less is known about whether openness to emerging technologies translates into healthy financial management and behavior. Particularly, if individuals who are open to using AI-based financial advice exhibit differences in their short-term and long-term financial behaviors, and the role of financial knowledge in these differences. This study addresses this gap by examining how the willingness to use AI for financial advice is associated with both short-term and long-term financial

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behaviors and whether this relationship is moderated by their financial knowledge (objective and subjective) using the 2024 National Financial Capability Study.

Understanding these nuances can help financial professionals support clients as they navigate digital and AI tools. Additionally, understanding what specific financial behaviors are associated with AI use could help to effectively guide clients, especially since some studies have shown that financial digital tools and AI-driven platforms have the potential to either substitute or enhance personal financial skills (Bhattacharya et al. 2012; D'Acunto et al. 2019; Kaiser et al. 2020). Understanding how financial knowledge interacts with AI financial advice may help financial professionals tailor financial support to those who rely on AI.

## 2 | Literature Review

### 2.1 | Financial Advice, the Use of AI in Financial Advice, and Financial Behavior

Financial advice is a potentially valuable service provided by professionals to individuals and households, offering guidance associated with better financial decisions (Finke 2013). Financial advice has become increasingly important in today's complex financial marketplace. Agarwal and Chua (2020) show that financial advice is linked to better decisions about savings and investments and specifically suggest that fintech is associated with positive household outcomes, such as smoothing consumption over time. Other studies (de Jong and Wagenveld 2024; Zhang et al. 2021) further show that financial advice correlates with stronger financial decision-making behaviors and with sustainable financial outcomes.

AI-based financial advice, one of the digital tools used within the financial services industry, is an automated process that gives recommendations using algorithms with minimal human involvement (Phoon and Koh 2018). AI-based financial advice is easy to access, low-cost, and provides data-driven suggestions free of behavioral biases (Wexler and Oberlander 2021), making it more and more popular. However, a survey by the Financial Health Network (2024) in 2024 revealed that while individuals knew about AI, they hesitated to use it for financial decisions due to a lack of trust and familiarity.

A limited but emerging body of literature has investigated the adoption rate of AI-based financial advice and its subsequent relationship with financial behavior. Seeing that this is an emerging space in research, previous studies have often looked at digital tools like fintech and robo-advisors. Digital tools including AI financial advisors have the potential to help users process financial information and are linked to effective financial management. For instance, Gupta (2025) while studying the relationship between digital tools and long-term financial behavior, found that over time, adopters realized greater gains in diversification and turnover, with more modest improvements in risk-adjusted returns. Reher and Sokolinski (2024) also argue that robo-advisors predict systematic investing related to long-term financial behavior and wealth accumulation.

However, using these AI-based financial tools does not always associate with stronger financial behavior. These tools can co-occur with unfavorable outcomes for individuals who do not use them effectively or who lack the knowledge and skills to interpret the information. Mussa et al. (2022) found that being digitally literate was positively associated with long-term financial behavior but negatively associated with short-term financial behavior. Similarly, Sabir et al. (2023) found that while individuals who use digital tools are less likely to be financially vulnerable compared to non-users, they argue that being financially knowledgeable, together with being familiar with digital tools, is linked to a better capacity to track and control their expenses and correlates with lower financial vulnerability.

Together, these findings suggest that the relationship between the use of AI and financial management may not be uniformly positive, but could hold a dual relationship, reflecting the possibility of both positive and negative associations. The use of AI is linked to broader access to financial services, planning, and encouraging long-term investing, but is also associated with challenges for individuals who do not know how to use it effectively or who do not have the knowledge and skillset to interpret the information.

### 2.2 | Financial Knowledge and Financial Behavior

Financial knowledge refers to the understanding of financial concepts and skills and the confidence to apply these needed skills to make informed financial decisions and manage personal finances effectively. Research has demonstrated that financial knowledge encompasses multiple dimensions, extending beyond traditional knowledge-based assessments to include subjective elements, such as perception of one's financial knowledge.

Objective financial knowledge is often assessed by questions testing topics like inflation, interest rates, debt, and risk diversification (Lusardi 2008). Objective financial knowledge has been linked to various long- and short-term financial behaviors like increased savings habits, optimal debt management, retirement planning and savings, and wealth accumulation. For instance, using the 2021 NFCS data set, Lusardi and Streeter (2023) found that higher financial knowledge was associated with planning for retirement, preparedness for financial emergencies, and maintaining low debt levels, a similar result previously found by Lusardi and Mitchell (2014), in Germany, the Netherlands, Sweden, New Zealand, Italy, and Russia.

Perceived or subjective financial knowledge also matters for financial behavior. This aspect of financial knowledge speaks to an individual's assessment of their financial knowledge, and a large body of research has shown that both objective and self-assessed financial knowledge are positively associated with short- and long-term financial behavior (Lee et al. 2019; Mussa et al. 2022). With short-term financial behavior, Babiarczy and Robb (2014) found that ownership of emergency savings co-varies not only on measured financial knowledge but also on individuals' self-assessed financial knowledge,

with subjective financial knowledge sharing a stronger connection. In fact, Despard et al. (2020) found that only self-assessed financial knowledge, and not objective financial knowledge, in addition to money-management skills, consistently associated with the ownership of emergency funds. Korankye et al. (2024) take the studies on financial knowledge and short-term financial behavior a step further, showing that financial knowledge serves as a buffer in the relationship between student loan debt and emergency savings. With the use of overdraft, expensive credit cards, and other high-cost borrowing, Lusardi and de Bassa Scheresberg (2013) showed that financial knowledge was associated with a lower likelihood of reliance on these services.

Regarding long-term financial behaviors, financial knowledge also plays a significant role. For example, Henager and Cude (2016), while studying the role of financial knowledge on financial behaviors, found that both objective and perceived financial knowledge were linked to positive long-term actions like retirement planning, saving, and investing. Similar results were found by Lusardi and Mitchell (2011) and Zhuang and Yang (2025) in China. De Beckker et al. (2025) extend these studies on financial knowledge and long-term financial behavior by exploring the relationship between financial knowledge and wealth accumulation longitudinally. Their study confirms that financial knowledge strongly predicted wealth accumulation over time for the male sample alone. Given the findings of these previous studies on financial knowledge and financial behavior, this current study examines both objective and perceived financial knowledge, as well as both short- and long-term financial behaviors.

### 2.3 | Measures of Short-Term and Long-Term Financial Behavior

Previous studies have measured short- and long-term financial behaviors in different ways. For instance, a significant measure of short-term financial behavior widely studied in the literature is the ownership of emergency funds or sufficient liquid savings, since they highlight an individual or household's ability to meet unforeseen expenses without experiencing financial distress or turning to high-cost borrowing. One such study is that of Hamid et al. (2023). They measured short-term financial preparedness by examining whether households maintained a buffer of savings, met monthly expenses, and saved surplus income. Confirming Hamid et al.'s (2023) findings, Banuelos et al. (2024) showed that short-term financial resilience is depicted through positive financial behaviors such as having enough funds for emergencies, reducing spending, and maintaining low debt levels.

Turning to long-term financial behaviors, common indicators used in the literature include retirement planning, retirement savings, and investment behavior (Hauff et al. 2020; Lusardi and Mitchell 2011). Particularly through formal retirement planning, contributing consistently into retirement accounts (employer-sponsored and/or non-employer-sponsored), and wealth accumulation over time. Henager and Cude (2016) created an index for long-term behavior comprising all the aforementioned elements, which this current study adopts.

### 2.4 | Other Demographic Characteristics, Financial Behavior and Outcomes

Socioeconomic and demographic factors such as age, gender, race/ethnicity, education, income, and asset ownership also explain the financial behavior and outcomes of individuals. Martinchek (2024) found that young adults who belonged to racial marginalized groups displayed negative financial behaviors compared to their white counterparts, such as a higher likelihood of credit constraints, higher debt burdens, and extended periods of income volatility in the face of economic shocks. Household income and asset holdings, particularly the housing wealth, also emerge as significant predictors of financial outcomes. In a scoping review, Jalili et al. (2025) provided evidence that low- and middle-income families face the greatest challenges in reducing expenses and managing debt. The higher-income groups can reach better financial resilience outcomes in part because they have more capacity to save for emergencies and utilize their financial knowledge with higher confidence to navigate their financial situations (Despard et al. 2020). In a longitudinal study, Lusardi (2019) found that the financial shock, in the form of sudden income loss, correlated with lower individuals' financial well-being while financial knowledge and asset ownership were associated with stronger financial well-being. Housing assets were found to function as an implicit commitment device that provided families with a coordination device for the savings behavior of individual family members (De Beckker et al. 2025). Pfeffer and Killewald (2018) estimated that education accounted for a large portion of the variation in financial well-being across different households using the multigenerational PSID dataset.

Finally, Henager and Cude (2016), while exploring financial literacy and financial behaviors in different age groups, found that being white, being married, earning higher incomes, and having at least some college experiences were each associated with positive financial behavior at the short or long-term. However, age and gender showed differing results, with people of all age groups and women showing optimal long-term financial behavior, and only older individuals (age 55 and older) and men showing better short-term financial behavior. To account for these established determinants of financial behavior, the present study includes these demographic variables as controls to assess their relationship with households' financial behaviors.

### 2.5 | Contributions

Previous studies have examined the adoption of digital tools such as fintech and robo-advisors. However, there is a gap in the literature on the association between individuals' openness to AI-based financial advice and their financial behavior, a gap our study hopes to fill. Specifically, using the 2024 National Financial Capability Study (NFCS), we explore individuals' willingness to use AI for financial advice as a predictor of financial behavior and how their level of financial knowledge and confidence in their knowledge may moderate this relationship.

### 3 | Theoretical Framework

Adopting AI-driven financial tools is inherently a technology acceptance process. To understand adoption, this study utilizes and integrates the Technology Acceptance Model (TAM/UTAUT) with Financial Capability Theory. This approach allows us to understand factors associated with the willingness to use AI (TAM/UTAUT) and then explain how internal capacities, such as financial knowledge, relate to the quality of financial behaviors (Financial Capability Theory).

The Technology Acceptance model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) posit that individuals are more willing to adopt technologies when they find them useful (performance expectancy) and easy to use (effort expectancy) (Davis 1989; Venkatesh et al. 2003). In the context of this study, if individuals perceive AI-driven tools as efficient for managing their finances and also easy to navigate, their willingness to use AI for financial advice increases. This willingness becomes a precursor to actual financial behaviors. Individuals open to using AI for financial advice will be more likely to engage with AI-driven tools to automate budgets and plan for long-term investment shifts, which co-occurs with distinct short-term and long-term financial behaviors. However, the acceptance of technology alone is not enough to explain behavioral changes; the overall relationship relies on financial capability.

While the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) explain the willingness to adopt AI-driven tools, the Financial Capability Theory describes the capacity and ability to turn that advice into action. Financial Capability is not limited to having access to tools (e.g., AI-driven technologies), it also involves the ability to appropriately apply financial knowledge, make sound financial behaviors, and leverage opportunities that help achieve financial well-being (Xiao and Huang 2021). Accordingly, the Financial Capability Theory is supported by three key elements: financial knowledge, financial perceptions, and financial behaviors (Friedline and West 2016; Xiao et al. 2014, 2015; Taylor et al. 2011). In this study, financial knowledge serves as an internal device to evaluate whether the willingness to use AI-driven tools is positively associated with positive financial behavior.

Based on the theoretical framework, we propose the following hypotheses:

**Hypothesis 1.** *Willingness to use AI for financial advice is positively associated with short-term and long-term financial behaviors.*

As individuals perceive AI-driven tools as useful and easy to use/navigate (TAM/UTAUT), they will be more likely to integrate AI tools into their financial decision-making. This willingness serves as a positive predictor, co-occurring with proactive financial management.

**Hypothesis 2.** *Subjective financial knowledge moderates the relationship between willingness to use AI for financial advice and financial behaviors (short and long-term).*

While openness to AI-based financial advice is linked to higher engagement with digital tools, subjective financial knowledge correlates with the confidence associated with putting that advice into action. When that confidence is lacking, an individual may report a willingness to use the tools but demonstrate hesitation in executing the recommendation.

**Hypothesis 3.** *Objective financial knowledge moderates the relationship between willingness to use AI for financial advice and financial behaviors (short and long-term).*

Finally, AI technological advancements are becoming more prevalent, such that individuals must first be able to evaluate them and find ways to use them optimally. Objective financial knowledge acts as an evaluative filter associated with how individuals interpret financial advice and verify if it aligns with their financial situations.

## 4 | Methods

### 4.1 | Data and Sample

The dataset used in this analysis comes from the 2024 National Financial Capability Study (NFCS). This survey is nationally representative, administered by the FINRA Investor Education Foundation, and collected through an online questionnaire. It sampled 500 respondents from 50 states in the United States, including Puerto Rico. The NFCS dataset consisted of 25,000 respondents aged 18 and older, and assessed these adults' financial behaviors, attitudes, and knowledge. To ensure that this dataset is nationally representative, this survey applied survey weights. Responses such as "I don't know" and "Prefer not to say" were list-wise deleted from the sample. After accounting for the aforementioned criteria, the sample used in this analysis consisted of 16,698 respondents.

### 4.2 | Measurement

#### 4.2.1 | Outcome Variable

There are two outcome variables in this analysis. The first is the Short-term Financial Behavior Index, and the second is the Long-term Financial Behavior Index. These variables were created based on guidance from Henager and Cude (2016). The short-term financial behavior index was created based on responses to three questions that evaluated whether they had set aside some emergency funds, whether they were spending more than their income, and whether they had overdrawn their checking accounts. Possible responses to the questions on emergency fund ownership and overdraft use were "Yes/No," and these were represented as a dichotomous variable, where 1 indicated positive behavior (having an emergency fund and not overdrawing their accounts each), and 0 indicated negative financial behavior (not owning emergency funds and overdrawing their accounts). For their spending relative to income, the possible responses were "spending less than income," "spending more than income," and "spending equal to income." This was converted into a dummy variable, where 0 represented spending more than income and 1 represented spending less than or

equal to income. The short-term financial behavior index was derived utilizing the Item Response Theory (IRT), to account for the relative weights of each individual behavior item, rather than a simple summation.

The long-term financial behavior index is the second outcome variable in this study. This measure was derived utilizing IRT to derive an index based on responses to questions on retirement needs calculation, retirement plan ownership, and non-retirement investment asset ownership. Responses to questions on the calculation of retirement savings and non-retirement investment asset ownership were dichotomous variables, each taking the value 1 if they had tried to calculate how much they would need to save for retirement or if they owned investment assets outside their retirement plans, and 0 if not. Retirement plan ownership was also a dichotomous variable taking the value 1 if they owned either employer-sponsored retirement plans or non-employer-sponsored retirement plans, and 0 if they owned neither. Results from the IRT model for both short and long-term financial behavior are in the Appendix A Tables A1–A3.

#### 4.2.2 | Explanatory Variables

The willingness to use artificial intelligence (AI) for financial advice is the main explanatory variable in this analysis. The NFCS asked a “Yes/No” question on the respondents’ willingness to seek financial advice from AI. This variable was measured as a dummy, taking the value of 1 if the respondents were open to AI and 0 otherwise.

The moderating variables in this analysis are objective financial knowledge and subjective financial knowledge. Objective financial knowledge is created based on responses to six questions that test the respondents’ knowledge of inflation, interest rates, portfolio diversification, and basic investing principles. Instead of summing correct responses, we estimated a one-parameter logistic Item Response Theory (IRT) model that accounted for the differences in the questions’ difficulty. Consequently, we generated individual objective financial knowledge scores as respondents’ latent trait estimates from the fitted IRT model. Results from the IRT model (see Appendix A Tables A1–A3) showed significant variation across the objective financial knowledge questions. Specifically, questions on mortgage concepts and basic investing were the easiest for respondents, while questions related to bonds and loans were the most difficult, further supporting the use of an IRT-based measurement approach. At the same time, subjective knowledge represented the respondents’ assessment of their financial knowledge on a scale of 1–7. Consequently, objective financial knowledge was measured as a continuous variable while subjective financial knowledge was measured as an ordered variable.

Other variables controlled for in this analysis include age, gender, race, marital status, income, homeownership, education, and employment status. Age was measured as a continuous variable, while marital status, income, education, and employment status are each categorical variables in this analysis. Specifically, marital status was grouped into married, single, separated, divorced, and widowed, with single as the reference category; income has

10 categories with “less than \$15,000” as the reference category; education was grouped into high school or less (reference), some college experience, and college degree or more; employment status was categorized into self-employed, working full-time, working part-time, homemaker, full-time student, permanently disabled, and unemployed (reference). Gender, race, and homeownership were measured as dichotomous variables, taking the value of 1 if the respondent was female, white, or a homeowner, and 0 if not.

Following guidance from Pandey et al. (2025), our study accounted for “Don’t know” (DK) responses that is an option for all the objective financial knowledge questions. We first created a dichotomous variable to indicate whether a respondent selected a DK response and then created another variable for the total number of DK responses. Both variables were controlled for in this analysis.

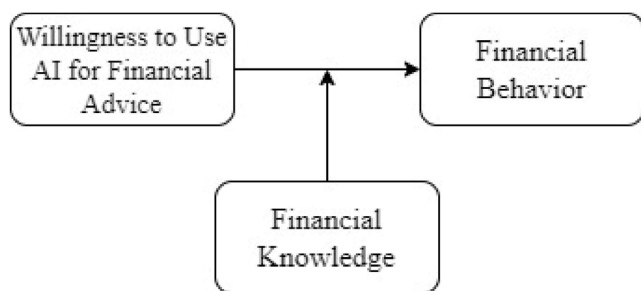
#### 4.3 | Data Analysis

First, we utilized Item Response Theory (IRT) to construct both short and long-term financial behavior measures to account for the relative weights of the different underlying behavior items. Consequently, short and long-term financial behaviors are evaluated as continuous latent measures, and six Ordinary Least Squares (OLS) regression models were estimated. Similarly, objective financial knowledge was measured using an IRT-based latent score to control for variations in the financial knowledge questions’ difficulty.

Model 1 assessed the direct relationship between willingness to use AI for financial advice, financial knowledge, and short-term financial behavior; Model 2 evaluated the moderating role of objective financial knowledge on the relationship between willingness to use AI for financial advice and short-term behavior, while Model 3 tested the moderating role of subjective financial knowledge.

The remaining three models (Models 4 to 6) examined the interrelationship between willingness to use AI for financial advice, financial knowledge (both objective and subjective), and long-term financial behaviors. Specifically, Model 4 assessed the direct relationship, while Models 5 and 6 evaluated the moderating roles of objective and subjective knowledge on this relationship between willingness to use AI’s financial advice and long-term financial behavior. Across all six models, age, gender, race, marital status, income, homeownership, education, and employment status were included as controls to account for variance in households’ financial behaviors. The model being tested is presented below in Figure 1.

A concern about estimating the relationship between willingness to use AI for financial advice and financial behavior is the possibility that the individuals who are willing to use AI for financial advice may differ from those who are not in ways associated with financial behavior. For instance, previous studies have shown that income, education, financial literacy, digital financial knowledge, and familiarity with financial technology may be associated with greater interest in or use of robo-advisors and AI financial services, although these



**FIGURE 1** | Estimated model. Financial behavior includes short-term and long-term. Financial knowledge includes objective and subjective.

relationships may vary across different populations (Aristei and Gallo 2025; Nourallah et al. 2025). These same characteristics may also be associated with short- and long-term financial behavior. Therefore, observed differences in financial behavior between respondents who were and were not open to using AI for financial advice may partly reflect preexisting demographic, socioeconomic, and financial knowledge differences.

Therefore, to evaluate robustness and to address this potential selection bias, we conducted a sensitivity analysis using Propensity Score Matching (PSM). Specifically, we used one-to-one matching with replacement. The treatment group consisted of respondents who were open to using AI for financial advice, while the comparison group consisted of respondents who were not open to using AI for financial advice. First, we estimated the propensity scores using a logistic treatment model, given the binary nature of the “willingness to use AI for financial advice” variable. The propensity scores are derived by estimating each respondent’s probability of being willing to use AI for financial advice based on observed characteristics like financial knowledge, age, gender, race, income, education, homeownership, marital status, and employment status. Then, we matched respondents who were open to using AI for financial advice with those who were not but had similar propensity scores. Given this matching procedure, the Average Treatment Effect on the Treated (ATET) was then calculated for both short-term and long-term financial behaviors to compare conditional means across groups.

Propensity score matching is based on a few assumptions. The first is the conditional independence assumption which assumes that all factors associated with both the treatment group status (openness to AI for financial advice) and the outcome (financial behavior) are observed and controlled for (Rosenbaum and Rubin 1983; Austin 2011). Although this assumption is harder to justify because there may be unobserved characteristics that are not captured in this analysis, we included a rich set of covariates in the propensity score model to address this. These covariates which may co-vary with both openness to AI for financial advice and financial behavior include financial knowledge (objective, subjective, and “don’t know”), age, gender, race, marital status, income, homeownership, education, and employment status.

Another assumption is that there is enough overlap between treatment and comparison groups (Caliendo and

Kopeinig 2008). This assumption means that for respondents who are willing to use AI for financial advice, there should be similar respondents who are not willing to use AI for financial advice. We address this by examining the propensity score distribution across both groups and present it in the result section.

The third diagnostic for evaluating the matching procedure is covariate balance. This means that after matching, the treatment and comparison group should have similar distributions of the observed covariates included in the propensity score model. We assessed this by estimating standardized mean differences, reported as percent bias, before and after matching (Garrido et al. 2014). We show the outcomes of these tests in the results section.

## 5 | Results

### 5.1 | Sample Descriptive Statistics

Table 1 presents the summary statistics of our analytic sample, which comprised 16,698 respondents. Observing the dependent variables and their means, we find that on average respondents showed below-average levels of both short and long-term financial behavior. Also, a large proportion of the analytical sample was not open to using AI for financial advice (69%).

Regarding financial knowledge, although objective financial knowledge of the respondents was below average, a large proportion rated their perceived financial knowledge to be 5 and above over 7, indicating a discrepancy in their observed and perceived financial knowledge, a finding that has been confirmed repeatedly in the literature (Xin et al. 2024). Also, about 66% of the sample responded “don’t know” to the objective financial knowledge questions, with an average of 1.7 “don’t know” responses.

Finally, we present the summary statistics of sociodemographic and economic factors, including gender, age, race, income, education, homeownership, and employment status. A larger proportion of the sample was white (56%), had earned a higher education than a high school degree (69%), and were homeowners (52%), while the gender distribution was almost evenly split between men and women. Also, the majority of the sample earned between \$50,000 and \$150,000 and were employed full-time by an employer. The average age of the sample was approximately 43 years.

### 5.2 | Overlap Test and Covariate Balance

Figure 2 shows the result of the overlap test, and Table 2 shows the result of the balance tests. Specifically, we present the distribution of the propensity scores for the treatment group (respondents who are open to using AI for financial advice) and the comparison group (respondents who are not open to using AI for financial advice). As shown in Figure 2, there was substantial overlap in estimated propensity scores between respondents who were open to using AI for financial advice and those who

**TABLE 1** | Descriptive statistics—Full sample ( $N = 16,698$ ).

| Variables                                            | Proportion/Mean     |
|------------------------------------------------------|---------------------|
| Openness to AI for Financial Advice                  |                     |
| Yes                                                  | 30.82%              |
| No                                                   | 69.18%              |
| Short-term Financial behavior (IRT)                  | −0.0934<br>(0.0077) |
| Long-term Financial behavior (IRT)                   | −0.0788<br>(0.0084) |
| Objective Financial Knowledge (IRT)                  | −0.1308<br>(0.0084) |
| Any Don't Know – Objective Financial Knowledge       |                     |
| Yes                                                  | 65.70%              |
| No                                                   | 34.30%              |
| Number of Don't Know – Objective Financial Knowledge | 1.6765              |
| Subjective Financial Knowledge                       |                     |
| 1 (Very low)                                         | 3.23%               |
| 2                                                    | 3.25%               |
| 3                                                    | 8.30%               |
| 4                                                    | 20.68%              |
| 5                                                    | 31.58%              |
| 6                                                    | 19.51%              |
| 7 (Very high)                                        | 13.45%              |
| Gender                                               |                     |
| Woman                                                | 48.49%              |
| Man                                                  | 51.51%              |
| Race                                                 |                     |
| White                                                | 55.66%              |
| Non-white                                            | 44.34%              |
| Education                                            |                     |
| High school degree or less                           | 30.54%              |
| Some college experience                              | 35.40%              |
| College graduate or more                             | 34.05%              |
| Marital Status                                       |                     |
| Single                                               | 41.83%              |
| Married                                              | 42.72%              |
| Separated                                            | 1.75%               |
| Divorced                                             | 11.17%              |
| Widowed                                              | 2.53%               |

(Continues)

**TABLE 1** | (Continued)

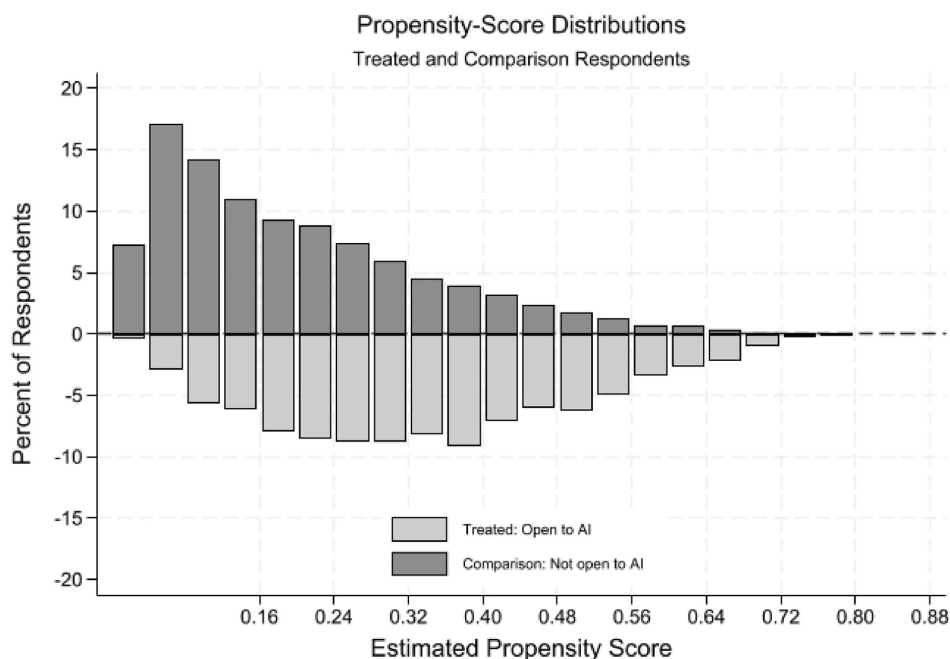
| Variables                      | Proportion/Mean         |
|--------------------------------|-------------------------|
| Age                            | 42.67 years<br>(0.1565) |
| Homeowner                      |                         |
| Yes                            | 52.10%                  |
| No                             | 48.90%                  |
| Income                         |                         |
| Less than \$15,000             | 11.42%                  |
| \$15,000–\$24,999              | 9.14%                   |
| \$25,000–\$34,999              | 9.85%                   |
| \$50,000–\$49,999              | 13.00%                  |
| \$50,000–\$74,999              | 18.14%                  |
| \$75,000–\$99,999              | 13.51%                  |
| \$100,000–\$144,999            | 13.73%                  |
| \$150,000 or more              | 11.21%                  |
| Employment Status              |                         |
| Self-employed                  | 10.00%                  |
| Work full-time for an employer | 52.57%                  |
| Work part-time for an employer | 11.96%                  |
| Homemaker                      | 6.59%                   |
| Full-time student              | 3.35%                   |
| Disabled                       | 6.26%                   |
| Unemployed                     | 9.36%                   |

Note: Data from the 2024 National Financial Capability Study State by State Survey. Standard errors in parenthesis.

were not, indicating that respondents in the treated group had comparable comparison respondents with similar propensity scores.

In Table 2, we depict the results from assessing covariate balance using standardized mean differences, reported as percent bias. Following guidance from Benedetto et al. (2018), we defined good covariate balance as standardized mean differences of less than 10% in our matched sample. After matching, these differences were reduced across all covariates to less than 10%, resulting in a decrease in mean standardized bias from 13.2% in the unmatched sample to 1.9% in the matched sample, and a decrease in median standardized bias from 6.5% to 1.3%. These results indicate adequate covariate balance.

Together, the results from assessing overlap and covariate balance indicate that respondents willing to use AI for financial advice are comparable to those unwilling to do so on the observed covariates in the propensity score model. These results allowed us to estimate the Average Treatment Effect on the Treated (ATET). However, due to the cross-sectional nature of the dataset, we do not interpret the ATET as a causal effect,



**FIGURE 2** | Distribution of estimated propensity for respondents open and not open to using AI for financial advice.

but rather as an adjusted conditional association between willingness to use AI for financial advice and financial behavior.

### 5.3 | Model Results

#### 5.3.1 | Willingness to Use AI for Financial Advice, Financial Knowledge and Short-Term Financial Behavior

Table 3 presents the results from Models 1 to 3 which assessed the interrelationship between willingness to use AI for financial advice, financial knowledge, and short-term financial behavior for non-retired respondents. Model 1 evaluated the direct association between openness to using AI for financial advice, financial knowledge (both objective and subjective), and short-term financial behavior, as depicted in Column 2 of Table 3. Results from Model 1 indicated that respondents who were open to using AI for financial advice were less likely to exhibit positive short-term financial behavior ( $\beta = -0.07$ ) compared to those who were not. Conversely, higher levels of both objective and subjective financial knowledge were also associated with exhibiting positive short-term financial behaviors.

The results of Model 2, which evaluated the moderating role of objective financial knowledge within the relationship between openness to using AI for financial advice and short-term financial behaviors, are displayed in Column 3 of Table 3 and Figure 3. Results indicate no statistically significant moderating role of objective financial knowledge. Similarly, in Column 4 of Table 3 and Figure 4, we test Model 3, examining the moderating role of subjective financial knowledge on the association between willingness to use AI for financial advice and short-term financial behavior. We found no statistical evidence for this moderation.

#### 5.3.2 | Willingness to Use AI for Financial Advice, Financial Knowledge and Long-Term Financial Behavior

In Table 4, the results from testing Models 4 to 6 are depicted, illustrating the interrelationship between willingness to use AI for financial advice, financial knowledge (both objective and subjective), and long-term financial behaviors. Recall that Model 4 tested the direct association of willingness to use AI for financial advice and financial knowledge (objective and subjective) on long-term financial behavior, while Models 5 and 6 test the moderating roles of objective and subjective financial knowledge.

Results on Column 2 of Table 4 show that respondents who are more open to using AI for financial advice are more likely to exhibiting positive long-term financial behaviors identified ( $\beta = 0.16$ ). Similarly, respondents with higher objective and subjective financial knowledge were also more likely to exhibit one or more of the positive long-term financial behaviors. Interestingly, respondents that have a higher “don't know” response were less likely to exhibit positive financial behaviors.

Turning to the moderating role of financial knowledge (objective and subjective) on Column 3 and 4 of Table 4 and Figures 5 and 6, mixed results are observed. While there is no statistical evidence for the moderating role of objective knowledge on the relationship between willingness to use AI for financial advice and long-term financial behavior, we found statistical evidence for the moderating role of subjective knowledge. Specifically, respondents who are both willing to use AI for financial advice and rated their financial knowledge as very high ( $\beta = 0.31$ ) are more likely to show positive long-term financial behaviors compared to respondents who

**TABLE 2** | Summary statistics of matched and unmatched samples—propensity score matching.

| Variable                                   | Unmatched sample                |                                     |                  | Propensity score logit coefficients | Matched sample                  |                                     |                  |
|--------------------------------------------|---------------------------------|-------------------------------------|------------------|-------------------------------------|---------------------------------|-------------------------------------|------------------|
|                                            | Open to AI for financial advice | Not open to AI for financial advice | Percent bias (%) |                                     | Open to AI for financial advice | Not open to AI for financial advice | Percent bias (%) |
| Objective financial knowledge              |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Objective financial knowledge, IRT score   | 0.0125                          | −0.0277                             | 5.1%             | −0.1358***                          | 0.0125                          | 0.0391                              | −3.4%            |
| Subjective financial knowledge             |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Very low (1)                               | 0.0254                          | 0.0241                              | 0.9              |                                     | 0.0254                          | 0.0291                              | −2.4             |
| 2                                          | 0.0346                          | 0.0241                              | 6.2              | 0.3541*                             | 0.0346                          | 0.0291                              | 3.3              |
| 3                                          | 0.0744                          | 0.0673                              | 2.8              | −0.0359                             | 0.0744                          | 0.0666                              | 3.1              |
| 4                                          | 0.1827                          | 0.1845                              | −0.5             | −0.1351                             | 0.1827                          | 0.1965                              | −3.6             |
| 5                                          | 0.3043                          | 0.3225                              | −3.9             | −0.1007                             | 0.3043                          | 0.3197                              | −3.3             |
| 6                                          | 0.2149                          | 0.2424                              | −6.5             | −0.0996                             | 0.2149                          | 0.2138                              | 0.2              |
| Very high (7)                              | 0.1638                          | 0.1351                              | 8.1              | 0.0304                              | 0.1638                          | 0.1452                              | 5.2              |
| Financial knowledge “don’t know” responses |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Number of “don’t know” responses           | 1.2117                          | 1.6585                              | −27.6            | −0.2046***                          | 1.2117                          | 1.2191                              | −0.5             |
| Any “don’t know” response (Yes = 1)        | 0.5414                          | 0.6663                              | −25.7            | −0.1803**                           | 0.5414                          | 0.5456                              | −0.9             |
| Age                                        |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Age, years                                 | 42.049                          | 53.207                              | −70.4            | −0.0329***                          | 42.049                          | 41.576                              | 3.0              |
| Woman (Yes = 1)                            | 0.3847                          | 0.5455                              | −32.7            | −0.5159***                          | 0.3847                          | 0.3863                              | −0.3             |
| White race (Yes = 1)                       | 0.5736                          | 0.7799                              | −45.2            | −0.6207***                          | 0.5736                          | 0.5770                              | −0.7             |
| Marital status                             |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Married                                    | 0.4303                          | 0.4856                              | −11.1            | 0.0007                              | 0.4303                          | 0.4282                              | 0.4              |
| Single                                     | 0.4295                          | 0.2843                              | 30.7             |                                     | 0.4295                          | 0.4374                              | −1.7             |
| Separated                                  | 0.0191                          | 0.0151                              | 3.1              | 0.3105*                             | 0.0191                          | 0.0181                              | 0.8              |
| Divorced                                   | 0.1025                          | 0.1428                              | −12.3            | 0.0997                              | 0.1025                          | 0.1019                              | 0.2              |
| Widowed                                    | 0.0186                          | 0.0723                              | −26.0            | −0.2809*                            | 0.0186                          | 0.0144                              | 2.0              |
| Household income                           |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Less than \$15,000                         | 0.0928                          | 0.0898                              | 1.0              |                                     | 0.0928                          | 0.0860                              | 2.4              |
| \$15,000–\$24,999                          | 0.0852                          | 0.0950                              | −3.4             | 0.2081*                             | 0.0852                          | 0.0846                              | 0.2              |
| \$25,000–\$34,999                          | 0.0894                          | 0.1032                              | −4.7             | 0.0760                              | 0.0894                          | 0.0998                              | −3.6             |
| \$35,000–\$49,999                          | 0.1268                          | 0.1372                              | −3.1             | 0.0893                              | 0.1268                          | 0.1224                              | 1.3              |
| \$50,000–\$74,999                          | 0.1819                          | 0.1877                              | −1.5             | 0.1129                              | 0.1819                          | 0.1924                              | −2.7             |
| \$75,000–\$99,999                          | 0.1344                          | 0.1420                              | −2.2             | 0.0894                              | 0.1344                          | 0.1271                              | 2.1              |
| \$100,000–\$149,999                        | 0.1625                          | 0.1393                              | 6.5              | 0.2433*                             | 0.1625                          | 0.1601                              | 0.7              |
| \$150,000 or more                          | 0.1271                          | 0.1058                              | 6.6              | 0.1601                              | 0.1271                          | 0.1276                              | −0.2             |

(Continues)

TABLE 2 | (Continued)

| Variable                       | Unmatched sample                |                                     |                  | Propensity score logit coefficients | Matched sample                  |                                     |                  |
|--------------------------------|---------------------------------|-------------------------------------|------------------|-------------------------------------|---------------------------------|-------------------------------------|------------------|
|                                | Open to AI for financial advice | Not open to AI for financial advice | Percent bias (%) |                                     | Open to AI for financial advice | Not open to AI for financial advice | Percent bias (%) |
| Homeowner (Yes = 1)            | 0.5482                          | 0.6269                              | −16.0            | 0.0275                              | 0.5482                          | 0.5472                              | 0.2              |
| Education                      |                                 |                                     |                  |                                     |                                 |                                     |                  |
| High school degree or less     | 0.2576                          | 0.2507                              | 1.6              |                                     | 0.2576                          | 0.2563                              | 0.3              |
| Some college experience        | 0.3265                          | 0.3576                              | −6.6             | 0.1089*                             | 0.3265                          | 0.3223                              | 0.9              |
| College degree or more         | 0.4159                          | 0.3916                              | 4.9              | 0.2096***                           | 0.4159                          | 0.4214                              | −1.1             |
| Employment status              |                                 |                                     |                  |                                     |                                 |                                     |                  |
| Self-employed                  | 0.0980                          | 0.0702                              | 10.0             | 0.2095*                             | 0.0980                          | 0.0810                              | 6.1              |
| Work full-time for an employer | 0.5461                          | 0.3506                              | 40.1             | 0.1901*                             | 0.5461                          | 0.5624                              | −3.3             |
| Work part-time for an employer | 0.0930                          | 0.0842                              | 3.1              | 0.0456                              | 0.0930                          | 0.0833                              | 3.4              |
| Homemaker                      | 0.0364                          | 0.0509                              | −7.1             | −0.1136                             | 0.0364                          | 0.0417                              | −2.6             |
| Full-time student              | 0.0315                          | 0.0177                              | 8.9              | −0.0634                             | 0.0315                          | 0.0359                              | −2.9             |
| Permanently disabled           | 0.0335                          | 0.0514                              | −8.9             | −0.1114                             | 0.0335                          | 0.0315                              | 1.0              |
| Unemployed                     | 0.0744                          | 0.0599                              | 5.8              |                                     | 0.0744                          | 0.0747                              | −0.1             |
| Mean Standardized Bias         |                                 |                                     | 13.2             |                                     |                                 | 6.6                                 |                  |
| Median Standardized Bias       |                                 |                                     | 6.5              |                                     |                                 | 1.3                                 |                  |
| N                              | 3816                            | 12,882                              |                  | 16,698                              |                                 | 3816                                | 12,882           |

Note: Data from the 2024 National Financial Capability Study State by State Survey. Standard errors in parentheses Full sample size = 16,698.

\*\*\* $p < 0.001$ .

\*\* $p < 0.01$ .

\* $p < 0.05$ .

are not willing to use AI for financial advice and rated their financial knowledge as very low.

### 5.4 | Robustness Check Using Propensity Score Matching (PSM)

To assess the robustness of the main findings to the differences observed between respondents who were and were not willing to use AI for financial advice, we estimated treatment effects models using one-to-one propensity score matching with replacement and present the results in Table 5. Results showed statistically significant ATTs for both short and long-term financial behavior. While openness to AI use was associated with a 0.13 increase in long-term financial behaviors, it was associated with a 0.08 decrease in short-term financial behaviors.

## 6 | Discussion

The study explores how the willingness to use AI for financial advice is associated with short-term and long-term financial behaviors and whether this relationship is moderated by financial knowledge (objective and subjective). Based on the Financial Capability Theory and the TAM/UTAUT, we hypothesized that willingness to use AI for financial advice would be positively associated with both short-term and long-term financial behaviors; this hypothesis is partially supported. Openness to AI financial advice was positively associated with long-term financial behavior and negatively associated with short-term financial behavior, suggesting that AI openness may facilitate future financial planning but not necessarily translate into immediate or short-term financial behaviors. The result that openness to AI financial advice was positively associated with long-term

**TABLE 3** | OLS regression of short-term financial behavior, openness to AI financial advice, objective financial knowledge, and subjective financial knowledge.

| Variables                                                                                                                       | Model 1 coefficients (SE) | Model 2 coefficients (SE) | Model 3 coefficients (SE) |
|---------------------------------------------------------------------------------------------------------------------------------|---------------------------|---------------------------|---------------------------|
| Openness to AI for Financial Advice (Ref: No)                                                                                   | −0.0702***<br>(0.0155)    | −0.0701***<br>(0.0154)    | −0.1641*<br>(0.0792)      |
| Objective Financial Knowledge                                                                                                   | 0.0702***<br>(0.0118)     | 0.0689***<br>(0.0124)     | 0.0708***<br>(0.0118)     |
| Subjective Financial Knowledge<br>(Ref: 1 = Very low)                                                                           |                           |                           |                           |
| 2                                                                                                                               | −0.0125<br>(0.0494)       | −0.0125<br>(0.0494)       |                           |
| 3                                                                                                                               | 0.1121*<br>(0.0433)       | 0.1121*<br>(0.0433)       |                           |
| 4                                                                                                                               | 0.2454***<br>(0.0389)     | 0.2454***<br>(0.0389)     |                           |
| 5                                                                                                                               | 0.3966***<br>(0.0384)     | 0.3966***<br>(0.0384)     |                           |
| 6                                                                                                                               | 0.4842***<br>(0.0395)     | 0.4843***<br>(0.0395)     |                           |
| 7 (Very high)                                                                                                                   | 0.4725***<br>(0.0406)     | 0.4726***<br>(0.0406)     |                           |
| Group (Openness to AI ×<br>Objective Financial Knowledge)                                                                       |                           | 0.0043<br>(0.0181)        |                           |
| Group (Openness to AI ×<br>Subjective Financial Knowledge)<br>(Ref: Not open to AI, Very Low<br>Subjective Financial Knowledge) |                           |                           |                           |
| 2 × Open to AI                                                                                                                  |                           |                           | −0.0949<br>(0.1292)       |
| 3 × Open to AI                                                                                                                  |                           |                           | −0.1021<br>(0.1122)       |
| 4 × Open to AI                                                                                                                  |                           |                           | 0.0457<br>(0.1024)        |
| 5 × Open to AI                                                                                                                  |                           |                           | 0.0667<br>(0.1003)        |
| 6 × Open to AI                                                                                                                  |                           |                           | 0.0330<br>(0.1021)        |
| 7 × Open to AI                                                                                                                  |                           |                           | 0.1169<br>(0.0873)        |
| Woman (Ref: Man)                                                                                                                | −0.0320**<br>(0.0123)     | −0.0321**<br>(0.0123)     | −0.0319*<br>(0.0123)      |
| White (Ref: Non-white)                                                                                                          | 0.0060<br>(0.0137)        | 0.0060<br>(0.0137)        | 0.0066<br>(0.0136)        |
| Education (Ref: High school degree or less)                                                                                     |                           |                           |                           |
| Some college experience                                                                                                         | −0.0134<br>(0.0157)       | −0.0134<br>(0.0157)       | −0.0121<br>(0.0157)       |

(Continues)

TABLE 3 | (Continued)

| Variables                        | Model 1 coefficients (SE) | Model 2 coefficients (SE) | Model 3 coefficients (SE) |
|----------------------------------|---------------------------|---------------------------|---------------------------|
| College graduate or more         | 0.0942***<br>(0.0174)     | 0.0942***<br>(0.0174)     | 0.0944***<br>(0.0174)     |
| Marital Status (Ref: Single)     |                           |                           |                           |
| Married                          | −0.0884***<br>(0.0170)    | −0.0885***<br>(0.0170)    | −0.0881***<br>(0.0169)    |
| Separated                        | −0.2123***<br>(0.0511)    | −0.2124***<br>(0.0511)    | −0.2102***<br>(0.0509)    |
| Divorced                         | −0.1197***<br>(0.0201)    | −0.1199***<br>(0.0201)    | −0.1197***<br>(0.0201)    |
| Widowed                          | −0.1127***<br>(0.0265)    | −0.1128***<br>(0.0265)    | −0.1125***<br>(0.0264)    |
| Age                              | 0.0065***<br>(0.0005)     | 0.0065***<br>(0.0005)     | 0.0065***<br>(0.0005)     |
| Homeowner (Ref: No)              | 0.1859***<br>(0.0148)     | 0.1860***<br>(0.0148)     | 0.1854***<br>(0.0148)     |
| Income (Ref: Less than \$15,000) |                           |                           |                           |
| \$15,000–\$24,999                | −0.0489<br>(0.0273)       | −0.0489<br>(0.0273)       | −0.0472<br>(0.0273)       |
| \$25,000–\$34,999                | −0.0098<br>(0.0275)       | −0.0097<br>(0.0275)       | −0.0068<br>(0.0275)       |
| \$50,000–\$49,999                | 0.0425<br>(0.0265)        | 0.0426<br>(0.0265)        | 0.0453<br>(0.0265)        |
| \$50,000–\$74,999                | 0.1196***<br>(0.0266)     | 0.1197***<br>(0.0266)     | 0.1224***<br>(0.0267)     |
| \$75,000–\$99,999                | 0.2000***<br>(0.0292)     | 0.2002***<br>(0.0292)     | 0.2022***<br>(0.0293)     |
| \$100,000–\$144,999              | 0.2575***<br>(0.0295)     | 0.2577***<br>(0.0295)     | 0.2598***<br>(0.0295)     |
| \$150,000 or more                | 0.3514***<br>(0.0320)     | 0.3515***<br>(0.0320)     | 0.3548***<br>(0.0321)     |
| Employment status                |                           |                           |                           |
| Self-employed                    | −0.0477*<br>(0.0240)      | −0.0477*<br>(0.0240)      | −0.0481*<br>(0.0240)      |
| Work full-time for an employer   | −0.0840***<br>(0.0171)    | −0.0841***<br>(0.0171)    | −0.0856***<br>(0.0171)    |
| Work part-time for an employer   | −0.0228<br>(0.0231)       | −0.0227<br>(0.0231)       | −0.0234<br>(0.0231)       |
| Homemaker                        | −0.0421<br>(0.0295)       | −0.0422<br>(0.0295)       | −0.0430<br>(0.0295)       |
| Full-time student                | 0.1332**<br>(0.0467)      | 0.1333**<br>(0.0467)      | 0.1328**<br>(0.0467)      |
| Disabled                         | −0.2183***<br>(0.0288)    | −0.2184***<br>(0.0289)    | −0.2211***<br>(0.0288)    |

(Continues)

TABLE 3 | (Continued)

| Variables                                            | Model 1 coefficients (SE) | Model 2 coefficients (SE) | Model 3 coefficients (SE) |
|------------------------------------------------------|---------------------------|---------------------------|---------------------------|
| Any Don't Know – Objective Financial Knowledge       | −0.0382*<br>(0.0174)      | −0.0381*<br>(0.0174)      | −0.0365*<br>(0.0174)      |
| Number of Don't Know – Objective Financial Knowledge | 0.0225***<br>(0.0062)     | 0.0223***<br>(0.0062)     | 0.0221***<br>(0.0062)     |

Note: Data from the 2024 National Financial Capability Study State by State Survey. Full sample size = 16,698.

\*\*\* $p < 0.001$ .

\*\* $p < 0.01$ .

\* $p < 0.05$ .

financial behavior is supported by theory, as the Financial Capability theory suggests that individuals who combine financial knowledge, confidence, and access to tools are more likely to achieve financial well-being (Xiao and O'Neill 2016; Friedline and West 2016). In this case, individuals who are willing to use AI tools appear to utilize them for long-term financial behaviors, further supporting the idea that financial capability should integrate digital tools and platforms (Xiao and Huang 2021; Zhu et al. 2024). The TAM/UTAUT model also supports this result, as many AI-based tools (e.g., robo-advisors, retirement planners) are designed for long-term planning rather than short-term planning, which would likely lead to a higher perceived usefulness for future-oriented financial behaviors (Belanche et al. 2019).

We also hypothesized that objective financial knowledge would moderate the relationship between willingness to use AI for financial advice and financial behaviors. This hypothesis was not supported by the results as the estimates showed no statistically significant moderating interaction for objective financial knowledge across either short- or long-term financial behaviors. The TAM/UTAUT models can explain this result. Based on the theory, higher levels of objective knowledge typically relate to greater perceived ease of use. However, for highly knowledgeable individuals, the relative advantage of AI-based advice may be diminished if they perceive their own human expertise as superior or a substitute for technology (Rogers 2003). In this case, the perceived usefulness of technology may plateau regardless of the ease of use. Conversely, for those with lower levels of objective financial knowledge, the perceived effort required to interpret AI-driven financial decisions may create a barrier to the willingness to adopt such advice, limiting the conditional association between AI openness and optimal financial behaviors.

The third hypothesis posited that subjective financial knowledge moderates the relationship between willingness to use AI for financial advice and financial behaviors (both short-term and long-term). The results provided partial support for this hypothesis, demonstrating that subjective financial knowledge moderates the relationship for long-term financial behaviors and AI openness, but not for short-term financial behaviors. Individuals who reported openness to AI and rated their financial knowledge as high were more likely to showcase long-term financial behaviors than those who weren't open to AI-based advice and rated themselves low on financial knowledge. This finding aligns with the Financial Capability theory, which explains that translation of financial knowledge into action often depends on personal confidence and perceived competence, in

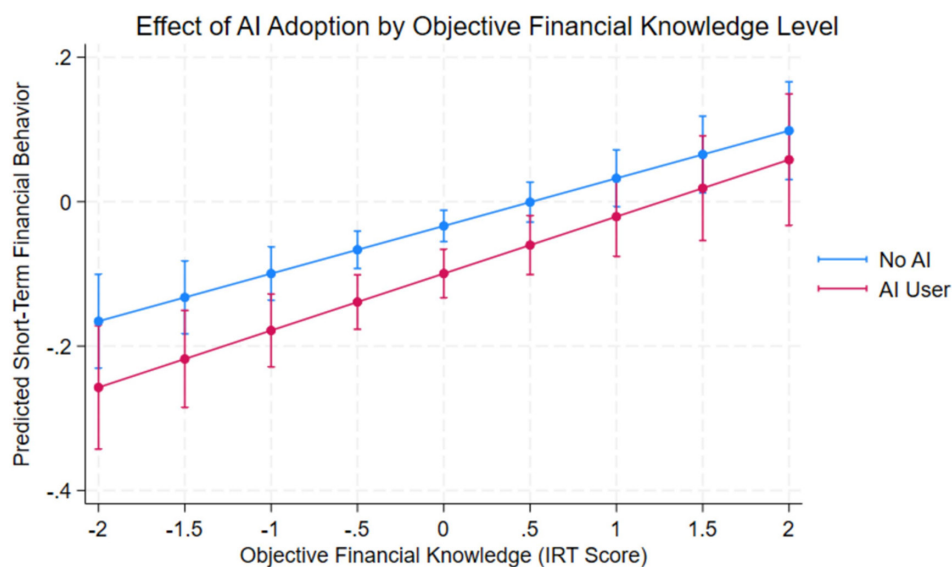
addition to access to tools (Xiao and O'Neill 2016; Friedline and West 2016). The TAM/UTAUT models also align with this, as individuals who perceive themselves to be knowledgeable may evaluate AI-based advice as requiring less effort to utilize and offering greater utility, thereby increasing the openness to AI-based financial advice. This suggests that individuals who perceive themselves as financially knowledgeable may feel more capable and motivated to leverage AI-based advice for longer-term planning. Conversely, this finding highlights a potential vulnerability, as subjective knowledge may not always reflect one's actual financial capability. Overconfident individuals risk misinterpreting AI-generated outputs and overlooking contextual nuances that allow for optimal financial planning (Lee and Hanna 2020).

An interesting finding of our study is that the majority of the sample is not open to using AI for financial advice. This aversion may be attributed to several systemic factors, including a fundamental lack of trust in AI technologies, the inherent risk of inaccurate guidance, an absence of regulatory accountability, and limited consumer awareness. A huge part of financial planning and advice is the human touch; individuals may be worried that the emotional and contextual factors that financial planners offer are often missing with AI, making it hard to trust the advice. This concern is compounded by the technical limitations of AI, which occasionally generate erroneous inferences based on simulated or fabricated data. Furthermore, while traditional financial professionals are legally bound by fiduciary duties, such ethical and legal responsibilities are currently absent in automated AI financial advisors. Finally, a general deficit in public understanding regarding the underlying mechanisms of AI tools further inhibits consumer trust (Jackson and Cepa 2025; Rapanos 2024; Rosenberg 2023).

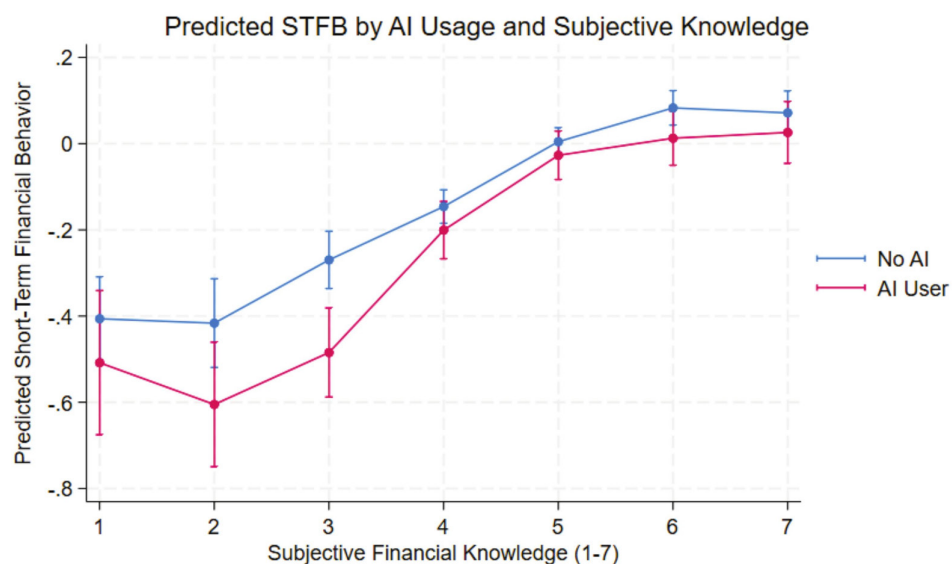
A limitation to our study is the cross-sectional nature of the 2024 NFCS, which limits our ability to examine changes in AI use for financial advice and financial decision-making over time. Another limitation is the grouping of respondents' race and ethnicity into only two categories (White and Other), which may mask important differences across diverse populations. Future research should use longitudinal data to examine patterns of AI use for financial advice and associated financial behaviors over time.

## 7 | Conclusions and Implications

This study aimed to investigate the interrelationship between openness to utilizing AI for financial planning, financial



**FIGURE 3** | Predicted short-term financial behavior by openness to AI use and objective financial knowledge.



**FIGURE 4** | Predicted short-term financial behavior by openness to AI use and subjective financial knowledge.

knowledge, and financial behaviors. To address these questions, the 2024 National Financial Capability State-by-State survey data set was utilized and analyzed through a series of regression models. Findings from this study reveal a significant relationship between AI financial advice and financial decision-making, as well as the role of financial knowledge in this relationship, and have implications for financial planners, clients, and researchers in this field.

A very interesting result this study found is that while openness to utilizing AI was associated with worse short-term financial behaviors. Conversely, it was associated with better long-term financial behavior. These short-term financial behaviors, such as maintaining emergency funds, avoiding overspending, and avoiding overdrafts, are foundational to an individual's holistic financial health, and addressing them is important for overall well-being. Therefore, the fact that individuals who are open to

utilizing AI for financial advice showed a lower tendency to exhibit these short-term financial behaviors may suggest that, to improve short-term financial behaviors and maintain healthy financial habits, human financial planners are very essential, and AI should be used as a complement and not a replacement. While AI tools can be useful for tracking investments, scenario simulations, and investment tracking, human guidance remains highly beneficial to these clients.

Furthermore, AI can offer information and strategies that work for the average person; however, it does not understand situational factors that apply to specific clients. This finding is beneficial to financial planners who are concerned about the possibility of AI replacing their jobs. According to a report by Burgess (2025), 40% of advisors surveyed are concerned about AI taking their jobs. Regardless, financial professionals need to understand that AI will not be able to replace them because of

**TABLE 4** | OLS regression of long-term financial behavior, openness to AI financial advice, objective financial knowledge, and subjective financial knowledge.

| Variables                                                                                                                 | Model 4 coefficients (SE) | Model 5 coefficients (SE) | Model 6 coefficients (SE) |
|---------------------------------------------------------------------------------------------------------------------------|---------------------------|---------------------------|---------------------------|
| Openness to AI for Financial Advice (Ref: No)                                                                             | 0.1540***<br>(0.0139)     | 0.1535***<br>(0.0139)     | −0.0301<br>(0.0691)       |
| Objective Financial Knowledge (IRT)                                                                                       | 0.0629***<br>(0.0117)     | 0.0688***<br>(0.0124)     | 0.0654***<br>(0.0118)     |
| Subjective Financial Knowledge (Ref: 1 = Very low)                                                                        |                           |                           |                           |
| 2                                                                                                                         | 0.0423<br>(0.0405)        | 0.0423<br>(0.0405)        | −0.0029<br>(0.0447)       |
| 3                                                                                                                         | 0.0569<br>(0.0346)        | 0.0570<br>(0.0346)        | 0.0548<br>(0.0375)        |
| 4                                                                                                                         | 0.0870**<br>(0.0316)      | 0.0871**<br>(0.0316)      | 0.0517<br>(0.0347)        |
| 5                                                                                                                         | 0.2193***<br>(0.0315)     | 0.2190***<br>(0.0315)     | 0.1732***<br>(0.0346)     |
| 6                                                                                                                         | 0.3041***<br>(0.0326)     | 0.3037***<br>(0.0326)     | 0.2620***<br>(0.0357)     |
| 7 (Very high)                                                                                                             | 0.3241***<br>(0.0338)     | 0.3236***<br>(0.0338)     | 0.2526***<br>(0.0374)     |
| Group (Openness to AI × Objective Financial Knowledge)                                                                    |                           | −0.0202<br>(0.0157)       |                           |
| Group (Openness to AI × Subjective Financial Knowledge)<br>(Ref: Not open to AI, Very Low Subjective Financial Knowledge) |                           |                           |                           |
| 2 × Open to AI                                                                                                            |                           |                           | 0.1969*<br>(0.0961)       |
| 3 × Open to AI                                                                                                            |                           |                           | 0.0420<br>(0.0846)        |
| 4 × Open to AI                                                                                                            |                           |                           | 0.1588*<br>(0.0754)       |
| 5 × Open to AI                                                                                                            |                           |                           | 0.2002**<br>(0.0732)      |
| 6 × Open to AI                                                                                                            |                           |                           | 0.1831*<br>(0.0743)       |
| 7 × Open to AI                                                                                                            |                           |                           | 0.2889***<br>(0.0762)     |
| Woman (Ref: Man)                                                                                                          | −0.0094<br>(0.0113)       | −0.0090<br>(0.0113)       | −0.0094<br>(0.0113)       |
| White (Ref: Non-white)                                                                                                    | 0.0093<br>(0.0126)        | 0.0094<br>(0.0126)        | 0.0089<br>(0.0126)        |
| Education (Ref: High school degree or less)                                                                               |                           |                           |                           |
| Some college experience                                                                                                   | 0.0472**<br>(0.0146)      | 0.0470**<br>(0.0146)      | 0.0488**<br>(0.0146)      |
| College graduate or more                                                                                                  | 0.1910***<br>(0.0162)     | 0.1908***<br>(0.0162)     | 0.1901***<br>(0.0162)     |

(Continues)

TABLE 4 | (Continued)

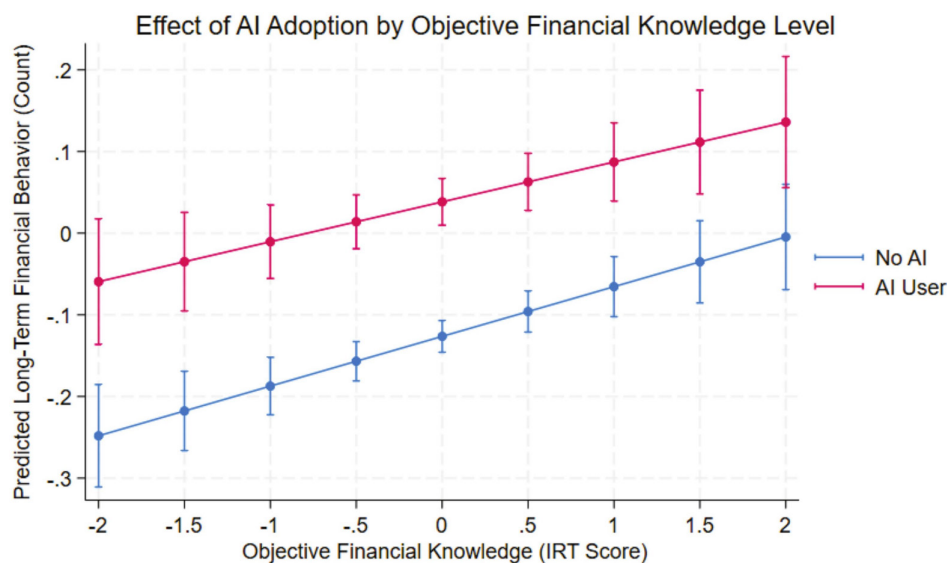
| Variables                                            | Model 4 coefficients (SE) | Model 5 coefficients (SE) | Model 6 coefficients (SE) |
|------------------------------------------------------|---------------------------|---------------------------|---------------------------|
| Marital status (Ref: Single)                         |                           |                           |                           |
| Married                                              | 0.0298<br>(0.0156)        | 0.0303<br>(0.0156)        | 0.0296<br>(0.0156)        |
| Separate                                             | −0.0569<br>(0.0432)       | −0.0564<br>(0.0433)       | −0.0597<br>(0.0429)       |
| Divorced                                             | −0.0439*<br>(0.0189)      | −0.0432*<br>(0.0189)      | −0.0434*<br>(0.0189)      |
| Widowed                                              | −0.0624*<br>(0.0259)      | −0.0620*<br>(0.0259)      | −0.0622*<br>(0.0259)      |
| Age                                                  | 0.0031***<br>(0.0005)     | 0.0031***<br>(0.0005)     | 0.0031***<br>(0.0005)     |
| Homeowner (Ref: No)                                  | 0.1836***<br>(0.0141)     | 0.1831***<br>(0.0141)     | 0.1824***<br>(0.0140)     |
| Income (Ref: Less than \$15,000)                     |                           |                           |                           |
| \$15,000–\$24,999                                    | 0.0203<br>(0.0225)        | 0.0200<br>(0.0225)        | 0.0232<br>(0.0225)        |
| \$25,000–\$34,999                                    | 0.1710***<br>(0.0256)     | 0.1705***<br>(0.0256)     | 0.1738***<br>(0.0255)     |
| \$50,000–\$49,999                                    | 0.3183***<br>(0.0241)     | 0.3179***<br>(0.0241)     | 0.3221***<br>(0.0240)     |
| \$50,000–\$74,999                                    | 0.4753***<br>(0.0236)     | 0.4747***<br>(0.0236)     | 0.4790***<br>(0.0235)     |
| \$75,000–\$99,999                                    | 0.6105***<br>(0.0256)     | 0.6098***<br>(0.0256)     | 0.6133***<br>(0.0255)     |
| \$100,000–\$144,999                                  | 0.6801***<br>(0.0262)     | 0.6791***<br>(0.0262)     | 0.6843***<br>(0.0261)     |
| \$150,000 or more                                    | 0.7532***<br>(0.0284)     | 0.7529***<br>(0.0284)     | 0.7585***<br>(0.0283)     |
| Employment status                                    |                           |                           |                           |
| Self-employed                                        | −0.0175<br>(0.0242)       | −0.0174<br>(0.0242)       | −0.0182<br>(0.0242)       |
| Work full-time for an employer                       | 0.1224***<br>(0.0160)     | 0.1231***<br>(0.0161)     | 0.1182***<br>(0.0161)     |
| Work part-time for an employer                       | 0.0540*<br>(0.0225)       | 0.0537*<br>(0.0225)       | 0.0545*<br>(0.0225)       |
| Homemaker                                            | −0.0363<br>(0.0287)       | −0.0359<br>(0.0287)       | −0.0377<br>(0.0286)       |
| Full-time student                                    | −0.0580<br>(0.0423)       | −0.0584<br>(0.0423)       | −0.0594<br>(0.0422)       |
| Disabled                                             | −0.1831***<br>(0.0226)    | −0.1826***<br>(0.0226)    | −0.1867***<br>(0.0225)    |
| Any Don't Know – Objective Financial Knowledge       | −0.0703***<br>(0.0160)    | −0.0712***<br>(0.0160)    | −0.0674***<br>(0.0160)    |
| Number of Don't Know – Objective Financial Knowledge | −0.0374***<br>(0.0057)    | −0.0366***<br>(0.0057)    | −0.0374***<br>(0.0057)    |

Note: Data from the 2024 National Financial Capability Study State by State Survey. Full sample size = 16,698.

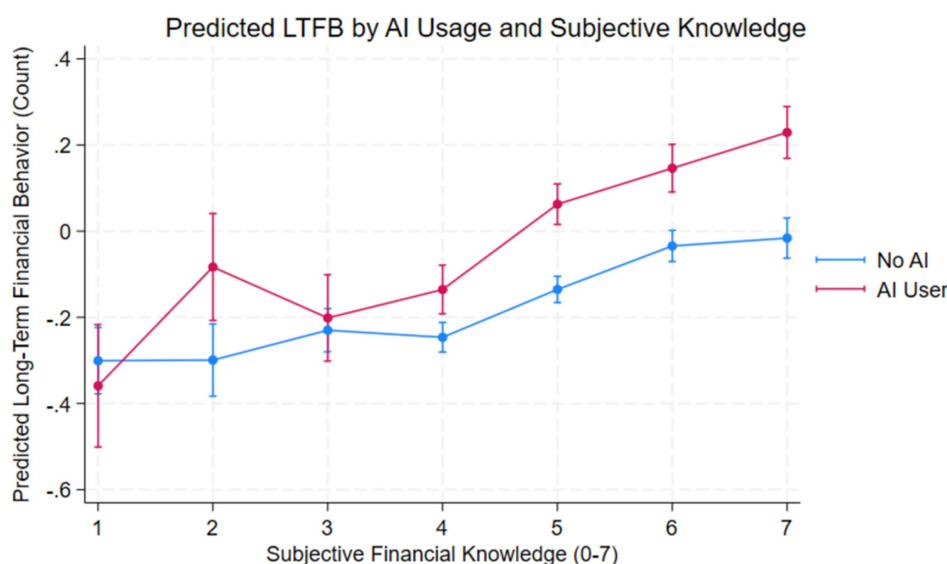
\*\*\* $p < 0.001$ .

\*\* $p < 0.01$ .

\* $p < 0.05$ .



**FIGURE 5** | Predicted long-term financial behavior by openness to AI use and objective financial knowledge.



**FIGURE 6** | Predicted long-term financial behavior by openness to AI use and subjective financial knowledge.

**TABLE 5** | Propensity score matching (PSM) estimates of the effect of openness to AI for financial advice on financial behaviors (ATET).

| Outcome variable              | Treatment average effects (ATTs) |
|-------------------------------|----------------------------------|
| Short-term Financial Behavior | -0.0811***<br>(0.0197)           |
| Long-term Financial Behavior  | 0.1341***<br>(0.0209)            |

Note: Data from the 2024 National Financial Capability Study State by State Survey. Standard errors in parentheses Full sample size = 16,698. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

several distinct factors. One, clients still desire the human touch. They require someone who can be held responsible and provide reassurance when their portfolio is underperforming, an assurance that AI financial advice may not be able to provide, but

human financial planners can. This is particularly true because financial planners have fiduciary responsibilities to act in the best interest of their clients. Second, the technology is evolving; specialized AI-native financial planning platforms such as Wavvest and Quinn Advisor now offer automated, high-level financial planning. These tools mark the shift from general AI to systems specifically built for professional financial advice (CFP Board 2025). Despite these advances in technology, AI remains limited in its reliance on data patterns as it cannot replicate subjective factors such as cultural values, unique family and life circumstances, or a clients' emotional view of money, an area in which financial planners are highly valuable.

Another finding worthy of note is that subjective financial knowledge moderated a positive association between willingness to utilize AI for financial advice and long-term financial behavior. Specifically, individuals who were open to utilizing AI for financial advice and perceived their financial knowledge to be high

were more likely to exhibit one or more of the long-term financial behaviors examined. This finding suggests that an individual's assessment of their financial knowledge influences how effectively they leverage AI tools to improve their financial behavior. This finding highlights an area where financial planners can help their clients: the identification of overconfidence, defined as rating one's knowledge higher than objective measures indicate (Lee and Hanna 2020). The concern is that clients may misinterpret or misuse recommendations provided by these AI tools while overlooking their unique circumstances, thereby leading to suboptimal financial decisions. As earlier stated, AI advice is usually generalized, and these clients have unique circumstances like risk tolerance, cultural, and emotional circumstances that these tools may not consider in their projections. Also, these overconfident clients may misinterpret a recommendation such as "your portfolio has an expected return of 8%" to mean that they will have a guaranteed annual return of 8% from their portfolios, ignoring the fact that expected returns are statistical averages, and annual returns fluctuate from gains to losses. If these individuals then proceed to adopt aggressive portfolios closer to retirement, this could be harmful to their long-term security.

Financial planners would benefit from assessments of their clients' objective and subjective financial knowledge to understand where their clients stand. Also, they should remain open to discussing whether and how their clients have utilized AI in decision-making. This creates a learning opportunity for clients and an educational opportunity for financial professionals. Through this process, financial professionals are able to clarify misconceptions about recommendations that AI tools may provide, explain the rationale behind the AI advice, and differentiate between AI-generated generic advice and client-tailored, client-specific advice based on their unique and contextual circumstances. Clients are therefore advised to utilize advice from AI as a starting point and consult with their human financial planner before making financial decisions.

This current study opens up opportunities for research regarding the use of AI and its role in financial knowledge, financial decision-making, and behaviors. Therefore, future research can benefit from gathering data from AI-native financial planning platforms, automated financial advisors, robo-advisors, and human financial planners to test how the adoption of AI advice influences clients' financial behavior over time compared to human-based financial advice. Also, longitudinal analyses testing how generational and cultural differences influence the relationship between the use of AI and financial behaviors would be beneficial to possibly explain the opposite relationships observed with short-term and long-term financial behaviors.

## Disclosure

AI (Grammarly) was used to facilitate general copy editing of original author written material, including some of the formatting of the reference list.

## Ethics Statement

We used de-identified secondary data from the 2024 National Financial Capability Study (NFCS). As a result, institutional review board approval was not required.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

The data that support the findings of this study are available in 2024 National Financial Capability Study (NFCS) at <https://www.finrafoundation.org/nfcs-data-and-downloads>. These data were derived from the following resources available in the public domain: 2024 National Financial Capability Study (NFCS), <https://www.finrafoundation.org/nfcs-data-and-downloads>.

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## Appendix A

**TABLE A1** | Item response theory (IRT) estimates for short-term financial behavior.

| Item                        | Discrimination | Difficulty |
|-----------------------------|----------------|------------|
| Spending relative to income | 1.3283***      | −1.0147*** |
| Use of overdraft            | 1.8306***      | −0.9918*** |
| Ownership of emergency fund | 1.8476***      | −0.0187    |

Note: Estimates are based on a two-parameter logistic model. Difficulty parameters indicate the relative difficulty of each item, with higher values representing more difficult questions. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**TABLE A2** | Item response theory (IRT) estimates for long-term financial behavior.

| Item                                    | Discrimination | Difficulty |
|-----------------------------------------|----------------|------------|
| Retirement plan ownership               | 2.7325***      | −0.4922*** |
| Retirement needs calculation            | 1.7493***      | −0.1459*** |
| Ownership of non-retirement investments | 1.6591***      | 0.2831***  |

Note: Estimates are based on a two-parameter logistic model. Difficulty parameters indicate the relative difficulty of each item, with higher values representing more difficult questions. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

**TABLE A3** | Item response theory (IRT) estimates for objective financial knowledge question.

| Item                                                                                                                                                                                                                                                                            | Difficulty |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|
| A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less. (Mortgage)                                                                                                           | −1.1111*** |
| Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? (Interest rate compounding – Asset)                                                         | −1.0797*** |
| Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? (Inflation)                                                                               | −0.6098*** |
| Buying a single company's stock usually provides a safer return than a stock mutual fund. (Understanding diversification)                                                                                                                                                       | 0.1352***  |
| Suppose you owe \$1000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you did not pay anything off, at this interest rate, how many years would it take for the amount you owe to double? (Loan repayment/ Interest rates compounding) | 0.8078***  |
| If interest rates rise, what will typically happen to bond prices? (Bond)                                                                                                                                                                                                       | 0.9232***  |

Note: Estimates are based on a one-parameter logistic model. Difficulty parameters indicate the relative difficulty of each item, with higher values representing more difficult questions. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .