Technology-Enabled Financial Help-Seeking Behavior: Consumers' Use of AI and Financial Planners on Saving for Retirement

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Abstract

This study examines the effectiveness of three sources of retirement planning advice (AI tools, financial planners, and their combined use) in shaping retirement saving behavior. We introduce the Technology-Enabled Financial Help-Seeking (TEFHS) framework, which extends earlier models of financial help-seeking by incorporating technology adoption theory and resource-based perspectives. Using weighted survey data from 2,000 state and local government employees, we employ logistic regression to test Stage 5 of the TEFHS framework. Results show that all advice sources are associated with higher odds of saving for retirement compared to using no formal guidance. AI-only users demonstrate 75% higher odds, financial planner–only users 181% higher odds, and combined use 254% higher odds. These patterns are consistent with a complementary model in which AI reduces friction for standardized, rules-based choices while planners provide coordination and coaching for complex decisions. Findings extend help-seeking theory into a technology-enabled environment and indicate that expanding access to both AI-enabled tools and financial planners remains important for improving retirement saving behavior, particularly among individuals who do not currently engage with professional advisors.

Keywords: artificial intelligence, financial planning, retirement saving, technology adoption, Technology-Enabled Financial Help-Seeking framework

Introduction

Households increasingly face complex retirement planning decisions, yet access to professional advice remains uneven. Lower-income households, minorities, and less-educated individuals are substantially less likely to obtain financial advice, often due to cost barriers (Collins, 2012; Ludwig et al., 2023; Lusardi & Mitchell, 2014). Professional financial advisors have been shown to add value through portfolio guidance, risk management (Hanna & Lindamood, 2010), and improvements in retirement-related attitudes and behaviors (Joo & Grable, 2001). At the same time, the rapid emergence of artificial intelligence (AI) in financial services raises new questions about how technology may extend, complement, or substitute for human advice (Belanche et al., 2019; Ludwig & Bennetts, 2023).

While first-generation robo-advisors focused on automated portfolio construction (D'Acunto et al., 2019), recent advances in generative AI have introduced conversational interfaces capable of personalized guidance and behavioral nudges at scale. Early evidence suggests these tools can match or exceed automated robo-advisors on diversification and rule-based tasks, though performance is sensitive to prompts and evaluation criteria (Oehler & Horn, 2024; Fieberg, 2024). Yet little empirical work has examined how AI use alone, planner use alone, and combined use jointly relate to retirement saving behavior, particularly among workers facing the decline of defined benefit (DB) pensions and growing self-directed responsibility (Munnell et al., 2007).

To address this gap, we propose the Technology-Enabled Financial Help-Seeking (TEFHS) framework, the first formal extension of Grable and Joo's (1999) seminal help-seeking model to incorporate AI advice sources. Drawing on resource-based theory (Barney, 1991) and task-technology fit theory (Goodhue & Thompson, 1995), TEFHS reconceptualizes advice sources as contributing distinct forms of capital: AI tools provide informational capital through computational efficiency and consistent rule application, while financial planners provide human and social capital through expertise, accountability, and relational support. This study tests Stage 5 of TEFHS (advice source effectiveness) by examining

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retirement saving behavior across four advice-seeking patterns: no formal advice, AI only, financial planner only, and combined use.

We test three hypotheses. H1a: The odds of saving for retirement will be higher for individuals using AI tools than for those using no formal source. H1b: The odds of saving for retirement will be higher for individuals using professional financial planners than for those using no formal source. H1c: The odds of saving for retirement will be higher for individuals using both AI tools and professional planners than for those using either source alone.

Methods

Data were collected by Morning Consult in January 2025 from a national sample of full-time state and local government employees in the United States. Sampling quotas and population targets were derived from the 2023 Current Population Survey Annual Social and Economic Supplement (U.S. Census Bureau, 2023). The completion rate among respondents who began the survey was 87%. Survey weights were constructed using iterative proportional fitting (raking) to align the sample with CPS population benchmarks across age, gender, race, Hispanic ethnicity, educational attainment, geographic region, and K-12 education employment. The resulting design effect was 1.7. The final analytic sample comprised 2,000 respondents with complete data on analysis variables. All analyses use sampling weights to generate population-representative estimates.

The dependent variable was retirement saving behavior, a binary indicator coded 1 if respondents reported saving through an employer-sponsored plan (e.g., 401(k), 457) or outside their workplace (e.g., IRA, personal savings), and 0 if they reported not currently saving. DB plan coverage was treated as a separate control rather than included in the saving measure because it reflects employer-provided benefits rather than active individual saving.

The primary independent variable was a four-category advice source measure constructed from two items: whether the respondent currently worked with one or more financial professionals, and whether the respondent had used AI tools to improve their understanding of retirement savings options. Categories were: (0) neither AI nor financial planners (reference), (1) AI only, (2) financial planners only, and (3) both AI and financial planners. Control variables included financial stress, DB plan coverage, gender, marital status, education, age, income, homeownership, investment level, and race. Analyses were conducted in Stata version 19.5 using weighted logistic regression with all controls included simultaneously. Multicollinearity was acceptable (all VIF values below 3.0; mean VIF = 1.56).

Results

In the full sample, 75.0% of respondents reported saving for retirement; 42.0% used neither AI nor financial planners, 15.7% used AI only, 13.5% used financial planners only, and 28.8% used both. Financial stress was reported by 42.8% of respondents, and 28.5% had access to a DB plan from a current or former employer. The logistic regression model exhibited acceptable fit (McFadden pseudo-R^2 = 0.33; N = 2,000).

All three advice source categories showed significantly higher odds of retirement saving relative to using neither source. AI-only users had 75.3% higher odds of saving for retirement (OR = 1.75, p = .003), financial planner–only users had 181.4% higher odds (OR = 2.81, $p < .001$), and individuals using both sources had 254.0% higher odds (OR = 3.54, $p < .001$). To formally test H1c, the model was re-estimated using different reference categories. Compared with AI-only users, those using both sources had significantly higher odds of saving for retirement (OR = 2.02, p = .003). However, compared with financial planner–only users, the difference for combined users was not statistically significant (OR = 1.26, p = .37).

Several control variables were meaningfully associated with retirement saving. DB plan coverage was associated with 93.8% lower odds of additional retirement saving (OR = 0.06, $p < .001$), consistent with substitution effects (Engelhardt & Kumar, 2011). Educational attainment showed strong gradient effects, with graduate degree holders exhibiting 313.1% higher odds of saving than those with high school education or less (OR = 4.13, $p < .001$). Investment level was the strongest predictor, with those holding investments above $50,000 showing 719.8% higher odds of saving than non-investors (OR = 8.20, $p < .001$). Women had 31.1% lower odds of saving than men (OR = 0.69, p = .012), and Black respondents had 31.0% lower odds than White respondents (OR = 0.69, p = .032). Financial stress was not significantly associated with retirement saving (OR = 0.94, p = .626).

Hypotheses H1a and H1b were supported. H1c received mixed support: combined use yielded the highest odds ratio relative to no advice and significantly outperformed AI-only use, but did not significantly outperform financial planner–only use in this sample.

Discussion and Implications

Findings provide empirical support for core predictions of the TEFHS framework while refining expectations about combined advice. Consistent with task-technology fit theory (Goodhue & Thompson, 1995), AI tools appear well suited to standardized, rules-based retirement saving decisions and were independently associated with higher odds of saving among individuals who might otherwise lack access to formal guidance. This finding is consistent with the view that AI can help bridge persistent advice gaps for middle-income and underserved households (Collins, 2012; Ludwig et al., 2023).

The strongest association with retirement saving was observed when individuals used AI and financial planners together, consistent with the resource-based prediction that informational, human, and social capital reinforce one another (Barney, 1991). At the same time, the lack of a statistically significant difference between combined use and financial planner–only use suggests that, for the specific outcome of retirement saving participation, the incremental contribution of AI on top of an existing planner relationship is more modest than commonly assumed. This pattern is consistent with a complementary model in which AI provides meaningful incremental value when added to no-advice or AI-only baselines, while human advisors remain a powerful independent driver of saving behavior.

The substantial negative association between DB plan coverage and additional saving (OR = 0.06) underscores the continued relevance of substitution effects (Engelhardt & Kumar, 2011) and highlights that workers transitioning away from DB coverage may particularly benefit from accessible AI tools and planner relationships. Persistent demographic disparities by gender and race, even after controlling for income, education, and advice access, suggest that expanding advice access alone is unlikely to fully resolve inequities in retirement preparedness (Lusardi & Mitchell, 2014).

For consumer interests, three implications follow. First, practitioners should treat AI as a complement rather than a substitute for human advice, integrating AI tools into workflows to expand the reach of planning services to underserved households. Second, employers can strengthen plan effectiveness by making both AI-enabled guidance and planner access available, since combined use is associated with the highest odds of saving relative to no advice. Third, policymakers and consumer protection agencies should encourage adoption of established AI governance frameworks (NIST, 2023; OECD, 2024) to ensure that AI-enabled retirement guidance is transparent, accurate, and equitable. The cross-sectional design and public-sector sample limit causal inference and generalizability, and future work should employ longitudinal designs and richer measures of advice quality, contribution adequacy, and downstream financial well-being.

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