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Technology-Enabled Financial Help-Seeking: Evidence of AI and Financial Planners on Retirement Saving Behavior

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ABSTRACT

This study aims to examine 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 survey data from 2000 state and local government employees, we employ logistic regression to test Stage 5 of the TEFHS framework: advice source effectiveness. Results show that all advice sources are associated with higher odds of saving for retirement compared to individuals reporting no formal guidance. AI-only users demonstrate higher odds of saving, financial planner-only users show stronger associations, and combined use of AI and financial planners produces the highest odds. These patterns are consistent with a combined model in which AI reduces friction for standardized, rules-based choices while planners provide coordination and coaching for complex decisions. This study extends help-seeking theory into a technology-enabled environment while providing evidence relevant to the future of financial planning practice. The results 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 financial advisors. This study advances understanding of how AI tools and human advisors contribute to retirement saving behavior, providing empirical support that these advice sources can reinforce each other. Results suggest that AI and human advisors provide distinct value in supporting retirement saving behavior. We conclude with implications for practitioners and policymakers seeking to expand access to comprehensive financial guidance.

1 | Introduction

While some households work with professional financial advisors for retirement planning, others navigate these decisions independently or through informal advice channels. Prior research suggests that financial advisors contribute value by guiding portfolio choices and risk management (Hanna and Lindamood 2010) and improving clients' retirement-related attitudes and behaviors (Joo and Grable 2001). Together, this work implies that the advisor–client relationship can enhance retirement readiness and overall financial goal achievement. Researchers have highlighted a persistent access gap: lower-income households, minorities, and less-educated individuals are much less likely to obtain financial advice, often due to cost barriers (Collins 2012; Ludwig et al. 2023). Likewise, this literacy gap is especially concerning because it is most pronounced among younger workers, women, and minority groups (Lusardi and Mitchell 2014), the very populations now bearing greater responsibility for their own retirement security as traditional defined benefit pensions give way to defined contribution plans.

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The emergence of artificial intelligence in financial services offers potential to address this access challenge, but critical questions remain about optimal implementation approaches. While earlier robo-advisors focused primarily on portfolio management (Belanche et al. 2019), recent advances in generative AI have introduced conversational interfaces that can provide personalized guidance and behavioral nudges at scale (Ludwig and Bennetts 2023). These tools represent a potential advancement beyond traditional robo-advisory platforms, enabling natural language interactions about complex financial decisions like retirement saving decisions rather than simple portfolio optimization. However, this technological evolution raises an important question for researchers and practitioners: can AI deliver retirement-saving benefits for underserved populations, and are AI and financial advisors most effective when used independently or in combination?

This question has significant implications for expanding retirement planning access among populations not typically served by traditional financial planners. If AI tools can deliver meaningful retirement saving benefits for underserved populations—either independently or in combination with human advisors, they could help address persistent gaps in retirement preparedness. The stakes are considerable, as Benartzi (2025) estimates that holistic financial advice can deliver benefits equivalent to a 7.5% increase in annual income or roughly a 24.7% boost in the median retirement account balance. Yet, such guidance remains inaccessible to many due to cost barriers.

Prior research highlights technology's opportunities and limitations in retirement planning advice delivery. Belanche et al. (2019) demonstrate that AI-driven tools such as robo-advisors and conversational agents are increasingly viewed as legitimate providers of financial guidance, capable of offering scalable and personalized support. At the same time, Collins (2012) emphasized that professional human advisors remain especially important for complex or high-stakes financial decisions, given the limitations of technology and the unequal financial literacy distribution. Most importantly, Benartzi (2025) suggests that holistic advice, covering savings, debt, insurance, and investments, can generate significant household gains. Combined models combining human expertise with AI delivery may be the most effective way to expand access to financial guidance. Building on this foundation, our study directly addresses this question by examining retirement saving behavior, a fundamental component of financial wellness across four distinct advice-seeking patterns: no formal advice, AI only, professional advisor only, and combined approaches using both channels. Early experimental and field evidence echoes this duality: large language models can deliver surprisingly strong portfolio and planning guidance, yet quality varies by prompt and task, and the risks of hallucination and over-confidence remain salient (Oehler and Horn 2024; Schlosky et al. 2024).

Building on this evidence for combined approaches, we propose a novel Technology-Enabled Financial Help-Seeking framework, the first formal extension of Grable and Joo's (1999) seminal model to incorporate AI advice sources. While Grable and Joo's framework has generated substantial scholarly impact over the past 25 years across diverse populations and financial contexts, existing research has not theoretically or empirically addressed how AI-powered tools alter help-seeking dynamics. The TEFHS framework's central innovation lies in reconceptualizing advice sources through a resource-based lens, proposing that different advice sources contribute distinct forms of capital that can work synergistically to improve retirement savings and other financial wellness outcomes. AI tools primarily contribute informational capital through computational efficiency, consistent application of rules, and accessible guidance. Professional advisors provide specialized human capital through expertise and behavioral coaching, and social capital through accountability and trust-based relationships. By theorizing how these distinct resources operate together, the framework addresses a critical gap: understanding when, why, and how individuals optimally combine technology and human guidance. This theoretical innovation is particularly timely given a recently reported survey suggesting that 67% of Gen Z use AI for personal finance decisions (Menton 2024), yet no existing framework explains when, why, or how individuals optimally combine technology and human guidance.

We test these theoretical predictions using survey data from 2000 full-time state and local government employees by examining retirement saving behavior across the four advice-seeking patterns. Compared to individuals using no formal advice sources, those using AI-only demonstrate 75% higher odds of retirement saving, professional-advisors-only show 181% higher odds, and individuals employing combined approaches exhibit 254% higher odds. These findings provide empirical support for the TEFHS framework, suggesting that AI tools and human advisors contribute distinct value to retirement saving behavior.

2 | Literature Review

2.1 | Financial Help-Seeking and Advisory Relationships

The theoretical foundation for understanding financial advice-seeking behavior draws on health services research. Suchman's (1965) model of illness behavior conceptualized help-seeking as a staged process. Grable and Joo (1999) adapted this framework to personal finance, identifying four categories of determinants: predisposing characteristics (e.g., demographics and personality), enabling resources (e.g., income, education, and access), perceived need (e.g., financial stress and uncertainty), and attitudes toward help sources (e.g., trust and perceived competence). However, their framework predated online and AI-enabled financial tools, making it insufficient for understanding today's environment, where individuals increasingly access multiple advice sources simultaneously.

Empirical research suggests that professional financial advice is often associated with improved retirement saving outcomes, but these benefits remain unevenly distributed. More specifically, Hanna and Lindamood (2010) used theoretical models to demonstrate that financial planning advice can increase wealth, reduce risk, and smooth consumption, while also noting that households who report using financial planners tend to have higher wealth, though causality is uncertain. Using propensity score matching, Kim et al. (2018) found that households working with financial planners were significantly more

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likely to set retirement saving goals. These positive associations raise important questions about access and scalability. If professional advice generates meaningful retirement savings benefits, how can technology extend guidance to populations historically excluded from traditional advisory relationships? Evidence suggests that advice often works synergistically with self-directed actions, with coaching and accountability amplifying follow-through on saving intentions (Gennaioli et al. 2015; Joo and Grable 2001).

The mechanisms through which financial advice can create value for retirement savings are increasingly well documented. Financial decisions such as retirement savings often involve complex trade-offs, long time horizons, and compounding effects that make minor errors costly over time (Foerster et al. 2017). Research in behavioral economics further demonstrates that individuals frequently struggle with procrastination, inertia, and other biases that undermine saving, and structured interventions can help overcome these barriers (Thaler and Benartzi 2004). Professional advisors traditionally add value by reducing information frictions, translating technical knowledge into actionable recommendations, and providing ongoing accountability—functions that vary in their technological replicability. This creates a critical access paradox: while professional advice generates meaningful retirement planning benefits, cost barriers and advisor scarcity leave vulnerable populations significantly less likely to receive such guidance (Burke and Hung 2015; Collins 2012; Ludwig et al. 2023; Lusardi and Mitchell 2014), precisely the populations who could benefit most from structured retirement saving interventions (Thaler and Benartzi 2004).

2.2 | Financial Stress and Financial Behavior

Financial stress has emerged as an important factor affecting retirement saving behavior and advice-seeking decisions, though its effects appear more nuanced than traditionally assumed. It is commonly conceptualized as psychological strain resulting from the perceived inadequacy of financial resources to meet current and future needs (Archuleta et al. 2013). Research suggests that financial stress can shape saving behavior through multiple, and sometimes opposing, pathways. On one hand, uncertainty may motivate precautionary saving, as households seek to buffer against risk. Nevertheless, Lusardi (2011) documents that fewer than half of Americans have set aside emergency funds, and Lusardi et al. (2011) report that many Americans say they could not come up with even $2000 in the face of a modest shock, underscoring widespread financial fragility.

On the other hand, financial stress can deplete cognitive resources and increase cognitive load, undermining decision-making capacity and long-term planning (Assenza et al. 2023; Sergeyev et al. 2023). Evidence also indicates that subjective financial scarcity is associated with lower retirement saving rates (Pulk et al. 2025) and that financial worries contribute to elevated psychological distress, particularly among socioeconomically vulnerable groups (Ryu and Fan 2023). At the same time, proactive financial planning has been linked to reductions in stress and improved well-being (Adee 2024). These dynamics underscore the importance of designing interventions that account for the complex effects of financial stress. In this regard, AI-enabled advice may hold considerable promise by offering low-cost, scalable support to financially stressed populations who lack access to traditional advisory services.

Research on financial stress and retirement saving reveals contradictory patterns that may help explain complex relationships in contemporary data. Some evidence suggests that individuals facing financial fragility attempt to build savings buffers to increase resilience (Lusardi et al. 2011). Conversely, other research documents that financial stress impairs decision-making through cognitive load mechanisms, with Mani et al. (2013) demonstrating that financial scarcity creates a cognitive burden that reduces decision-making capacity for long-term planning. These competing effects may explain why the relationship between financial stress and retirement saving behavior appears more nuanced when individuals have access to structured guidance sources.

The relationship between financial stress and advice-seeking behavior adds additional complexity. Grable and Joo (1999) found that financial stress may increase individuals' motivation to seek help, yet limited enabling resources, such as income or access, can restrict their ability to obtain advice. This paradox suggests a potential role for AI tools, which may provide low-cost guidance to financially stressed populations.

2.3 | Defined Benefit Plans and Retirement Saving Behavior

The presence of defined benefit (DB) pension plans creates unique dynamics in retirement saving behavior that have important implications for understanding advice-seeking patterns and AI guidance effectiveness. DB plans provide guaranteed retirement income based on salary and years of service, creating theoretical tensions about whether such benefits reduce perceived need for additional retirement savings or provide financial security that enables additional savings (Munnell and Sundén 2004). Understanding these dynamics is particularly important for AI-enabled retirement guidance, as the ongoing decline of DB plans means growing numbers of workers must rely on self-directed savings and may represent prime candidates for accessible technological advice.

Research evidence supports the substitution hypothesis, with estimates indicating that each dollar of DB pension wealth (i.e., the present value of expected future pension payments) reduces other retirement savings by roughly 50–80 cents (Engelhardt and Kumar 2011). The substitution effect occurs because rational households optimize total retirement savings across all vehicles, reducing voluntary contributions when DB benefits are substantial (Gale 1998). This relationship directly influences advice-seeking behavior, as DB plan participants may have reduced perceived need for retirement planning guidance given their guaranteed income benefits.

The interaction between DB coverage and financial advice-seeking creates important considerations for interpreting AI advice effectiveness. While DB participants may seek less retirement planning advice due to guaranteed benefits, they may

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also represent more sophisticated retirement planners who actively seek advice to optimize strategies across multiple vehicles. As DB plans continue declining in private sector employment, understanding how AI-enabled advice can help workers transition from institutional retirement security to self-directed savings becomes increasingly critical for expanding access to retirement planning guidance (Munnell et al. 2007).

2.4 | The Evolution of FinTech and AI in Financial Planning

The transformation of retirement planning advice delivery through technology has accelerated dramatically, with important implications for expanding access to retirement guidance. First-generation robo-advisors, emerging around 2010, focused narrowly on automated portfolio construction and rebalancing (D'Acunto et al. 2019). While these platforms successfully reduced costs and improved diversification, adoption was concentrated among younger and more affluent investors rather than addressing the broader retirement savings needs of middle-income households who lack access to traditional advisory services (Brenner and Meyll 2020). Recent tests suggest LLM-based systems can match or at times exceed automated robo-advisors on diversification and rule-based advice, with performance susceptible to prompts and evaluation criteria (Oehler and Horn 2024; Fieberg 2024). These findings reinforce the premise that AI may substitute for standardized planning components while underscoring the importance of rigorous evaluation protocols.

The current generation of AI-powered financial tools represents a qualitative leap in capability and scope. Advances in large language models and conversational AI now enable natural language interactions about complex financial decisions like retirement planning, personalized goal-setting, and contextual guidance that adapts to individual circumstances (Huang and Rust 2018; Ludwig and Bennetts 2023). These systems can integrate multiple data sources to provide retirement planning guidance that approaches the comprehensiveness traditionally associated with human advisors (Benartzi 2025).

Modern AI financial tools increasingly incorporate insights from behavioral economics to influence decision-making. Research on "nudge" interventions shows that small changes in how choices are presented, such as automatic enrollment defaults, can dramatically improve participation rates even though contribution levels often remain anchored at the default (Madrian and Shea 2001). AI tools can deliver personalized retirement saving nudges based on individual behavior patterns, with timing and frequency impossible for human advisors to match alone. This capability suggests distinct roles where AI handles routine behavioral interventions while human advisors focus on complex planning and relationship management.

2.5 | Trust and Equity Considerations in AI-Enabled Advice

While AI-enabled retirement planning tools offer the promise of scalable and low-cost guidance, their adoption depends critically on trust, a factor that may explain the effectiveness of combined approaches. Research shows that individuals often display "algorithm aversion," resisting automated decision-making even when algorithms outperform human experts (Dietvorst et al. 2015). Biases in how clients and advisors interpret or interact with AI may further limit effective use, as shown in recent analyses of planner–client dialogs with ChatGPT (Bennetts and Ludwig 2025). In retirement planning, this reluctance may be amplified by the high stakes of long-term financial security and the perception that algorithms lack empathy or individualized judgment about personal retirement goals (Burton et al. 2020). Importantly, combined models that combine AI-generated retirement guidance with human relational support appear to be more effective in overcoming these trust barriers than fully automated approaches (Benartzi 2025). Consistent with this, nationally representative polling indicates that while many consumers experiment with AI for money questions, trust in AI advice still trails trust in human professionals, and comfort levels differ sharply by age, education, and digital familiarity (FINRA Investor Education Foundation 2024).

Equity represents an equally important consideration in deploying AI-enabled retirement planning advice. Access to professional financial advisors has long been stratified by income, race, and education (Collins 2012; Ludwig et al. 2023; Lusardi and Mitchell 2014). Regulatory and supervisory guidance has begun articulating those expectations, emphasizing transparency, explainability, and non-discrimination when automated tools influence consumer financial outcomes (National Institute of Standards and Technology [NIST] 2023; OECD 2024). While AI tools have the potential to democratize access to retirement guidance by lowering costs, they may also replicate or amplify existing disparities if trained on biased data or designed without attention to underserved groups (O'Neil 2016). Research on machine learning in credit markets finds that minority borrowers often face structural disadvantages, with Black and Hispanic households disproportionately less likely to benefit from predictive technologies (Fuster et al. 2022), raising questions about whether AI-enabled retirement advice can meaningfully reduce demographic disparities in retirement saving behavior. Understanding these equity implications is critical to realizing the inclusive potential of AI-enabled retirement planning advice.

Together, this literature establishes that professional advice can improve retirement saving outcomes, but access remains stratified by demographic and socioeconomic factors. While AI-enabled retirement planning tools offer promise for expanding access through lower costs and greater scalability, questions remain about their effectiveness relative to human advisors and whether combined approaches might optimize outcomes. Despite growing theoretical interest in how AI and human guidance interact, little empirical evidence exists quantifying these effects on retirement saving behavior across different advice-seeking patterns. To address this gap, we propose the Technology-Enabled Financial Help-Seeking (TEFHS) framework and empirically examine retirement saving behavior among individuals using AI-only, human-only, combined, and no formal advice approaches.

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3 | Theoretical Framework and Hypotheses

3.1 | Technology-Enabled Evolution of Financial Help-Seeking Theory

Building on Grable and Joo's (1999) pioneering application of help-seeking theory to financial contexts, we extend their framework to accommodate contemporary technology-enabled advice sources. While Grable and Joo demonstrated that financial stress and behavioral factors drive help-seeking from human advisors, the emergence of AI tools requires re-conceptualizing both the sources and types of capital available to help-seekers. Grable and Joo's framework, adapted from Suchman's (1965) health care help-seeking model, established that individuals progress through predictable stages when seeking financial assistance: exhibiting financial behaviors, evaluating those behaviors, determining causes, deciding whether to seek help, choosing specific assistance sources, and maintaining treatment relationships. Their empirical work with 184 clerical workers demonstrated that financial stressors, poor financial behaviors, age, and homeownership status significantly predicted help-seeking behavior, with younger non-homeowners experiencing financial difficulties most likely to seek assistance.

However, the financial advice landscape has transformed dramatically since 1999. Grable and Joo's (1999) adaptation of Suchman's (1965) help-seeking model provided a foundation for understanding advice-seeking, but it reflected a context where options were primarily human advisors, such as financial planners, counselors, attorneys, and informal networks. Today's environment includes online and AI-enabled tools alongside traditional advisors, creating opportunities for combined approaches that draw on multiple sources of advice.

3.2 | Technology-Enabled Financial Help-Seeking (TEFHS) Framework

We propose a Technology-Enabled Financial Help-Seeking (TEFHS) framework that preserves Grable and Joo's (1999) core insights while incorporating critical advances in our understanding of technology adoption and resource-based decision-making. Financial planners primarily contribute human capital through specialized training, professional certifications, and experiential knowledge accumulated across diverse client retirement situations. They also provide social capital through relationship building, accountability mechanisms, and ongoing emotional support during financial transitions. These resources prove particularly valuable in complex, ambiguous, or emotionally charged planning contexts where professional judgment, empathy, and cultural sensitivity are essential. In operational terms, TEFHS treats "facilitating conditions" to include an organization's AI risk-management practices (documentation, bias and robustness testing, human review, and incident response) aligning the framework with contemporary governance standards (NIST 2023; NIST 2024; OECD 2024).

AI-enabled tools contribute informational capital characterized by rapid computation, consistent rule application, access to vast datasets, and scalable personalization capabilities. AI tools excel at processing structured information, executing standardized calculations, and providing timely behavioral prompts without the cost and scheduling constraints associated with human advisors. These capabilities align with structured financial and retirement planning decisions involving explicit rules and quantifiable optimization criteria.

The framework incorporates task-technology fit theory (Goodhue and Thompson 1995) to predict when different advice sources will be most effective and how they might work together. High task-technology fit occurs when the capabilities of an advice source align well with the demands of a specific financial task. Retirement saving decisions, for example, exhibit strong fit with AI capabilities because they involve standardized calculations, clear optimization criteria, and benefit from consistent behavioral prompting over time. However, optimal outcomes may result from combining AI's computational strengths with human advisors' relational and judgment capabilities, creating additive rather than competing relationships between advice sources. Figure 1 below illustrates the Technology-Enabled Financial Help-Seeking (TEFHS) framework, which extends classic help-seeking models (Suchman 1965; Grable and Joo 1999) by incorporating technology and, in this study, specifically AI as a source of informational capital alongside professional planners.

The TEFHS framework encompasses multiple stages of technology-enabled help-seeking behavior, from initial problem recognition through advice source selection to outcome evaluation. This study focuses specifically on Stage 5: Advice Source Effectiveness, examining how combinations of AI and human advice sources influence retirement saving outcomes. Rather than predicting why individuals choose particular advice sources (Stages 1–4), we analyze the behavioral consequences of those choices to quantify the relative effectiveness of AI-only, human-only, and combined approaches for promoting retirement saving behavior.

While this study focuses on artificial intelligence applications, the TEFHS framework is designed to accommodate the rapidly evolving financial technology landscape, including online financial tools, virtual reality planning environments, and automated coaching systems that contribute distinct forms of capital to the financial help-seeking process.

3.2.1 | Combined Effects of AI and Financial Planners

A key prediction of the TEFHS framework is that using AI tools and financial planners together will be associated with stronger retirement saving outcomes than relying on either source alone. The rationale is that each provides distinct resources: AI delivers consistent, low-cost, and scalable guidance, while planners offer expertise, accountability, and relational support. Combined, these forms of guidance encourage initial participation and sustained engagement in retirement saving.

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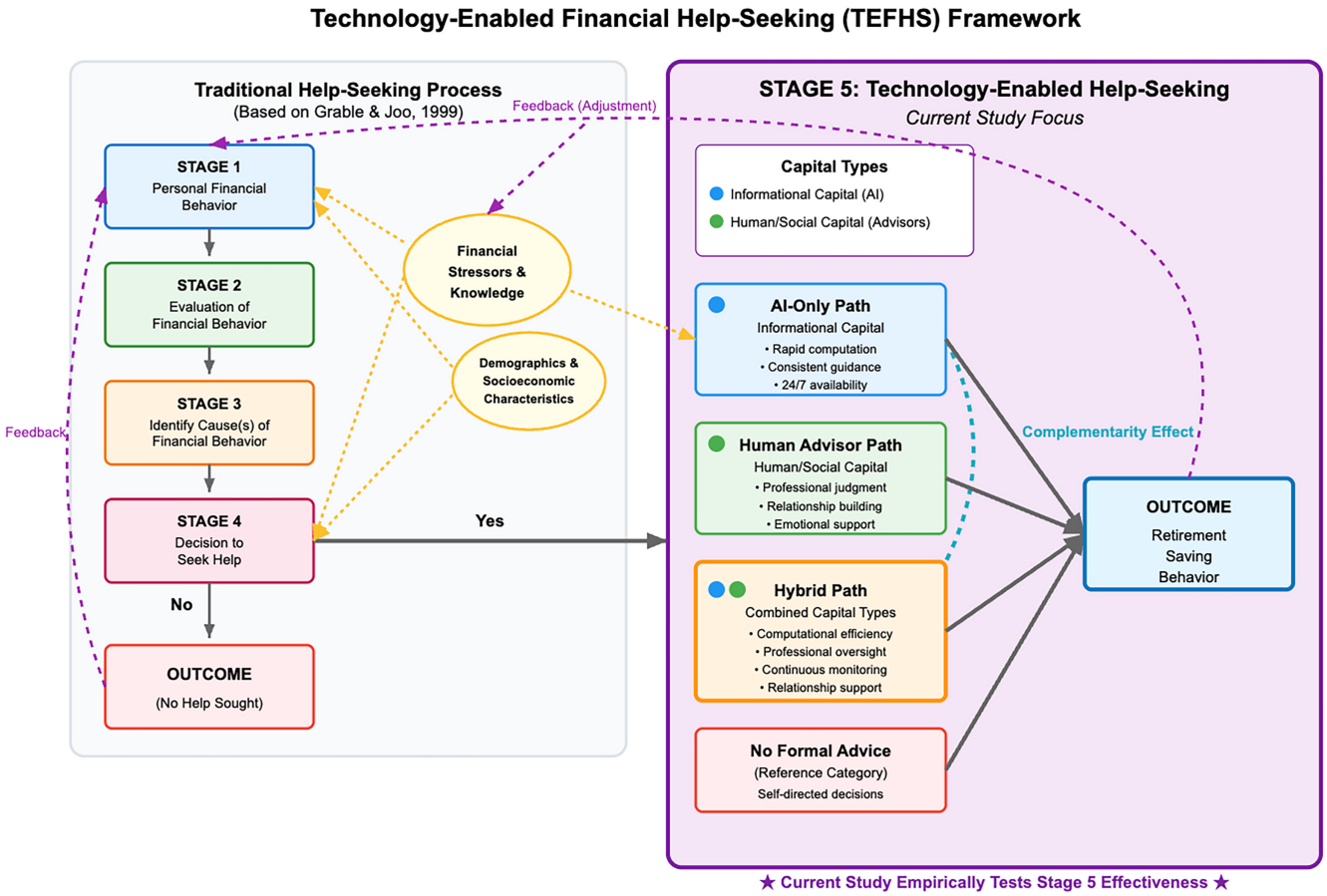


FIGURE 1 | Technology-enabled financial help-seeking (TEFHS) framework. Figure created by the authors, adapted from general help-seeking theory (Suchman 1965) and its financial application (Grable and Joo 1999).

3.2.2 | Hypotheses

Drawing on Stage 5 of the TEFHS framework and evidence from technology adoption research, we propose three primary hypotheses:

H1a. *The odds of saving for retirement will be higher for individuals who use AI tools than for those who use no formal advice source.*

H1b. *The odds of saving for retirement will be higher for individuals who use professional financial advisors than those with no formal advice source.*

H1c. *The odds of saving for retirement will be higher for individuals using both AI tools and professional advisors than those using either source alone.*

Together, these hypotheses operationalize Stage 5 of the TEFHS framework by focusing on the effectiveness of different advice source combinations. Rather than examining antecedents of advice-seeking behavior, the analysis evaluates outcomes by estimating the odds of saving for retirement across AI-only, human-only, and combined approaches. This design allows us to test the central prediction of the TEFHS framework that combining AI and human advice is associated with a greater likelihood of saving for retirement compared to relying on single-source strategies. The following section describes the data, measures, and methods used to test these hypotheses.

4 | Methods

4.1 | Data and Sample

This study employed a cross-sectional survey design to examine the relationship between different sources of retirement planning guidance and retirement saving behavior among public sector employees in the United States. Data were collected through an online survey administered in January 2025 to full-time employees of state and local government organizations. The target population consisted of adults aged 18 and older currently employed in state and local government positions, representing a significant segment of the American workforce with distinct financial planning needs and benefit structures. The sample was drawn to include public sector employees accross different employment sectors within state and local goverment.

The survey was administered by Morning Consult in January 2025 using their online opt-in panel of respondents. Sampling quotas and population targets were derived from the 2023 Current Population Survey Annual Social and Economic Supplement (CPS ASEC), which is widely regarded as the gold standard for labor force data (U.S. Census Bureau 2023). State and local public employees were identified based on

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employment status, occupation, and industry. Sampling quotas were established using the joint distribution of age, gender, and industry among public sector employees. The completion rate among those who began the survey was 87%. The final analytic sample comprised 2000 respondents who completed the survey instrument without missing data on the variables used in the analysis. Analyses use unweighted logistic regression and describe associations within the sample of state and local government employees.

4.2 | Measures

4.2.1 | Dependent Variable

The dependent variable was retirement saving behavior, measured as a binary indicator derived from responses to the survey question: "Are you currently saving for retirement (either through an employer retirement plan or on your own)? Please select all that apply." Respondents could select from four options: (1) "Yes, I save for retirement through an employer sponsored plan (e.g., 401(k), 457)," (2) "Yes, I have a defined benefit pension plan (from a current/previous employer)," (3) "Yes, I save for retirement outside my work (using IRA, personal savings, etc.)," and (4) "No, I am not saving for retirement currently." The retirement saving variable was coded as 1 if respondents selected either option 1 (employer-sponsored plan) or option 3 (outside employer retirement saving), and 0 if they selected only option 4 (not currently saving). Defined benefit plan coverage (option 2) was treated as a separate control variable rather than included in the retirement saving measure, as defined benefit plans represent employer-provided benefits rather than individual saving decisions. This coding approach captures active retirement saving behavior across both employer-sponsored and individual retirement accounts.

4.2.2 | Independent Variables

The primary independent variable was advice source, operationalized as a four-category variable created from responses to two survey questions about financial guidance usage. Financial planner usage was measured with the question: "Do you currently work with one or more financial professionals?" with response options of "Yes" or "No". AI usage for retirement planning was assessed with the question: "Have you used AI tools to improve your understanding of retirement savings options?" with response codes 1 = "Yes" and 2 = "No". This retirement-specific AI question was designed to capture AI usage directly relevant to retirement planning decisions rather than general financial advice. Based on responses to these questions, participants were classified into four mutually exclusive advice source categories: (0) Neither AI nor financial planners (reference group), (1) AI only, (2) Financial planners only, and (3) Both AI and financial planners. The survey item asked broadly about 'AI tools to improve understanding of retirement savings options' without specifying tool type. Respondents may have been referencing robo-advisors, AI-powered retirement calculators, conversational AI systems such as ChatGPT, or other AI-enabled financial tools. The measure therefore captures general AI tool usage for retirement planning rather than any specific AI application. This measurement approach reflects the current state of the field, where boundaries between AI tool categories remain fluid and consumer awareness of underlying technologies varies considerably.

4.2.3 | Control Variables

Several demographic and socioeconomic variables were included as control variables based on their established associations with retirement saving behavior. Financial stress was measured as a binary indicator derived from the question "What are your biggest sources of stress right now? Please select all that apply," where respondents could select "Your personal finances" as a primary source of stress from a list of common life stressors (e.g., work, health, family relationships, finances). See Appendix A for the complete list of stressor items. The variable was coded as 1 if personal finances were selected and 0 if not selected. Defined benefit plan coverage was measured as a binary variable indicating whether respondents reported having a defined benefit pension plan from a current or previous employer. Gender was coded as a binary variable (male/female), and marital status was categorized into six groups: never married, married, separated, divorced, widowed, and living with a partner. This detailed marital status categorization recognizes that individuals who are single due to life circumstances (divorce or widowhood) may have different financial behaviors than those who have never married.

Educational attainment was measured in four categories: high school or less, some college/associate degree, bachelor's degree, and graduate degree. Age was categorized into four groups: under 35, 35–44, 45–64, and 65+. Household income was measured in four categories: under $50,000, $50,000–$99,999, $100,000–$199,999, and $200,000 or more. Homeownership was coded as a binary variable (owned vs. rented/other arrangement). Investment level was categorized as none, below $50,000, or above $50,000. Race was categorized into three groups: White, Black, and Other.

4.3 | Analytical Approach

Our analytical approach aligns with Stage 5 of the TEFHS framework by treating advice source usage as the independent variable and retirement saving behavior as the dependent variable, thereby testing the effectiveness of different advice source combinations rather than predicting advice-seeking decisions. All analyses were conducted using Stata version 19.5. Given the binary nature of the dependent variable (retirement saving behavior), logistic regression was employed to examine the associations between advice source and retirement saving while controlling for demographic and financial characteristics. The logistic regression model estimated the odds of saving for retirement across the four advice source categories, with "Neither AI nor financial planners" serving as the reference group. Results are presented as odds ratios where OR greater than 1.0 indicate higher odds of retirement saving than the reference group, while OR less than 1.0 indicate lower odds. The model specification included all control variables simultaneously to isolate the independent association of

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TABLE 1 | Sample descriptive statistics.

	Full sample	Is saving ($n = 1501$)	Not saving ($n = 499$)
How respondents save for retirement			
ER plan only	55.1%	73.4%	—
Outside ER plan only	7.1%	9.5%	—
Use both	12.9%	17.2%	—
Do not save for retirement	25.0%	—	100.0%
Financial advice source			
Neither	42.0%	35.6%	61.3%
AI only	15.7%	15.4%	16.6%
FP only	13.5%	15.1%	8.8%
Both	28.8%	34.0%	13.2%
Financial stress			
No	57.2%	59.6%	50.1%
Yes	42.8%	40.4%	49.9%
Has a defined benefit plan			
No	71.6%	78.0%	52.3%
Yes	28.5%	22.1%	47.7%
Gender			
Male	37.7%	40.9%	27.9%
Female	62.4%	59.1%	72.1%
Marital status			
Never married	31.4%	26.7%	45.5%
Married	54.0%	59.8%	36.7%
Separated	1.1%	0.9%	1.8%
Divorced	5.1%	4.9%	5.4%
Widowed	1.2%	0.7%	2.4%
Living with a partner	7.3%	7.0%	8.2%
Education			
High school or less	11.3%	7.1%	24.1%
Some college/ associate degree	24.8%	22.9%	30.3%
Bachelor's Degree	31.5%	33.5%	25.5%
Graduate Degree	32.5%	36.5%	20.2%
Age category			
Under 35	42.3%	39.2%	51.7%
35–44	34.0%	36.4%	26.7%
45–64	22.3%	23.3%	19.4%
65+	1.4%	1.1%	2.2%
Income			
Under $50 k	22.8%	16.1%	42.9%
$50 k–$99 k	42.2%	44.4%	35.5%
$100 k–$199 k	22.2%	24.9%	13.9%
$200 k+	12.9%	14.5%	7.8%
Homeownership			
Rent/Other	31.4%	25.6%	48.9%
Owned	68.6%	74.4%	51.1%
Investment level			
None	32.7%	22.5%	63.1%
Below $50 k	28.9%	31.9%	19.6%
Above $50 k	38.5%	45.6%	17.2%
Race/Ethnicity			
White	76.7%	79.2%	68.9%
Black	16.1%	13.3%	24.3%
Other	7.3%	7.5%	6.8%

Note: Unweighted sample statistics. Column Ns shown in headers. Values may not sum to 100% due to rounding. An em (—) dash indicates not applicable.

advice source with retirement saving behavior. Model fit was assessed using the McFadden pseudo-R^2 statistic, which indicates the proportion of variation in the dependent variable explained by the model. Multicollinearity among predictor variables was assessed using variance inflation factors (VIF), with all VIF values below 3.0 indicating acceptable levels of multicollinearity.

5 | Results

5.1 | Descriptive Statistics

Descriptive statistics for the full sample are presented in Table 1. Regarding retirement saving behaviors, 55.1% of respondents saved through employer-sponsored plans only, 7.1% saved outside employer plans only, 12.9% used both employer and outside retirement saving vehicles, and 25.0% reported not saving for retirement. The distribution of advice sources showed that 42.0% used neither AI nor financial planners, 15.7% used AI only, 13.5% used financial planners only, and 28.8% used both

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TABLE 2 | Logistic regression analysis predicting retirement saving behavior.

Category	OR	SE	*p*
Advice source (ref. = Neither)			
AI only	1.753**	0.334	0.003
Planner only	2.814***	0.621	< 0.001
Both	3.540***	0.738	< 0.001
Financial stress (Yes; ref. = No)	0.936	0.128	0.626
Has defined benefit plan (ref. = No)	0.062***	0.011	< 0.001
Gender (ref. = Male)			
Female	0.689*	0.102	0.012
Marital status (ref. = never married)			
Married	1.482*	0.251	0.020
Separated	0.599	0.362	0.397
Divorced	1.731	0.537	0.077
Widowed	0.346	0.194	0.059
Living with a Partner	2.126**	0.541	0.003
Education (ref. = high school or less)			
Some college/associate	1.826**	0.384	0.004
Bachelor's degree	2.412***	0.554	< 0.001
Graduate degree	4.131***	1.029	< 0.001
Age category (ref. = Under 35)			
35–44	1.615**	0.275	0.005
45–64	1.478*	0.293	0.048
65+	0.886	0.461	0.816
Income (ref. = Under $50 k)			
$50–99 k	2.127***	0.377	< 0.001
$100–199 k	1.633*	0.392	0.041
≥ $200 k	0.845	0.248	0.567
Homeownership (ref. = rent/other)			
Owned	1.220	0.188	0.198
Investment level (ref. = none)			
Below $50 k	5.770***	1.030	< 0.001
Above $50 k	8.198***	1.742	< 0.001
Race (ref. = White)			
Black	0.690*	0.120	0.032
Other	1.333	0.337	0.255
Constant	0.374***	0.097	< 0.001

Note: Estimates from unweighted logistic regression. $N = 2000$; McFadden Pseudo $R^2 = 0.33$.
Abbreviations: OR = odds ratio; SE = standard error; ref. = reference category.
***$p < 0.001$.
**$p < 0.01$.
*$p < 0.05$.

sources. Financial stress was reported by 42.8% of respondents, while 28.5% had access to defined benefit pension plans from current or former employers.

Demographic characteristics revealed a predominantly female sample (62.4%) with diverse marital status representation: 54.0% married, 31.4% never married, 7.3% living with a partner, 5.1% divorced, 1.2% widowed, and 1.1% separated. Educational attainment was high, with 32.5% holding graduate degrees, 31.5% bachelor's degrees, 24.8% some college or associate degrees, and 11.3% high school education or less. The age distribution showed 42.3% under 35 years, 34.0% aged 35–44, 22.3% aged 45–64, and 1.4% aged 65 or older ($M = 36.6$, SD = 11.3, range = 18–78). Household income was broadly distributed: 22.8% earned under $50,000, 42.2% earned $50,000–$99,999, 22.2% earned $100,000–$199,999, and 12.9% earned $200,000 or more. Additional characteristics included 68.6% homeownership and varied investment levels with 32.7% holding no investments, 28.9% with investments below $50,000, and 38.5% with investments above $50,000. The racial composition was 76.7% White, 16.1% Black, and 7.3% Other.

Notable differences emerged between participants who saved for retirement ($n = 1501$, 75.0%) and those who did not ($n = 499$, 25.0%). Among savers, 73.4% used employer-sponsored plans, 9.5% saved outside employer plans, and 17.2% used both saving vehicles. Advice-seeking patterns differed substantially between groups, with savers more likely to use AI and financial planners (34.0% vs. 13.2%) and less likely to use neither source (35.6% vs. 61.3%). Financial stress levels were similar between groups, with 40.4% of savers and 49.9% of non-savers reporting personal finances as a stress source. Access to defined benefit plans showed a notable inverse relationship with additional retirement saving, as 47.7% of non-savers had defined benefit coverage compared to 22.1% of savers.

Demographic differences between savers and non-savers revealed several patterns consistent with existing retirement literature. Savers were more likely to be male (40.9% vs. 27.9%), married (59.8% vs. 36.7%), and have higher educational attainment, with 70.0% of savers holding bachelor's degrees or higher, compared with 45.7% of non-savers. Age patterns showed savers concentrated in middle-aged groups, while non-savers were more heavily represented among younger participants (51.7% under 35 vs. 39.2% for savers). Income disparities were substantial, with 42.9% of non-savers earning

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TABLE 3 | Odds of retirement saving comparing both sources to single sources.

Comparison	OR	95% CI	*p*
Both vs. FP only	1.26	[0.75, 2.11]	0.37
Both vs. AI only	2.02**	[1.27, 3.21]	0.003

Note: Results from logistic regression models with different reference categories for advice source, controlling for all covariates from main model. $N = 2000$.
**$p < 0.01$.
Abbreviations: CI = confidence interval; FP = financial planner; OR = odds ratio.

under $50,000 compared to 16.1% of savers, while 39.4% of savers earned $100,000 or more compared to 21.7% of non-savers. Investment holdings showed the most substantial differences, with 63.1% of non-savers holding no investments compared to 22.5% of savers, while 45.6% of savers held investments above $50,000 compared to 17.2% of non-savers. Homeownership rates were higher among savers (74.4% vs. 51.1%). Racial composition also differed between groups, with savers more likely to be White (79.2% vs. 68.9%) and less likely to be Black (13.3% vs. 24.3%).

5.2 | Logistic Regression of Retirement Savings

Table 2 presents the logistic regression analysis results examining the association between advice source and retirement saving behavior, controlling for demographic and financial characteristics. The model demonstrated acceptable fit with a McFadden pseudo-R^2 of 0.33 ($N = 2000$), indicating the model explains substantial variation in retirement savings behavior. Odds ratios (OR) greater than 1 indicate higher odds of retirement saving relative to the reference category, while ORs less than 1 indicate lower odds. Variance inflation factor analysis confirmed that multicollinearity was not a concern, with all VIF values below 3.0 (mean VIF = 1.56). All three advice source categories showed significantly higher odds of retirement saving than using neither AI nor financial planners. Specifically, AI-only users had 75.3% higher odds of saving for retirement (OR = 1.753, $p = 0.003$), financial planner-only users had 181.4% higher odds (OR = 2.814, $p < 0.001$), and those using both sources had 254.0% higher odds (OR = 3.540, $p < 0.001$).

To formally test H1c, the model was re-estimated using different reference categories for advice source in Table 3. Compared to those using only a financial planner, those using both AI and a financial planner had 26% higher odds of saving for retirement, but this difference was not statistically significant (OR = 1.26, $p = 0.37$). Compared to those using only AI, those using both sources had 102% higher odds of saving for retirement (OR = 2.02, $p = 0.003$).

Several control variables demonstrated significant associations with retirement saving behavior. Financial stress showed no significant association with retirement saving (OR = 0.936, $p = 0.626$). Having a defined benefit plan was associated with 93.8% lower odds of additional retirement saving (OR = 0.062, $p < 0.001$), markedly stronger than other predictors. Gender differences were significant, with females having 31.1% lower odds of retirement saving than males (OR = 0.689, $p = 0.012$). Marital status showed varied effects, with married individuals having 48.2% higher odds (OR = 1.482, $p = 0.02$) and those living with a partner having 112.6% higher odds (OR = 2.126, $p = 0.003$) compared to never-married participants. Other marital status categories were not significantly associated with retirement saving.

Educational attainment showed strong positive associations with retirement saving. Compared to those with high school education or less, individuals with some college or associate degrees had 82.6% higher odds (OR = 1.826, $p = 0.004$), those with bachelor's degrees had 141.2% higher odds (OR = 2.412, $p < 0.001$), and those with graduate degrees had 313.1% higher odds (OR = 4.131, $p < 0.001$). Age categories revealed that those aged 35–44 had 61.5% higher odds of retirement saving compared to those under 35 (OR = 1.615, $p = 0.005$), while the 45–64 age group had 47.8% higher odds (OR = 1.478, $p = 0.048$). The oldest age group (65+) showed no significant difference from the youngest group (OR = 0.886, $p = 0.816$).

Income effects were substantial and consistent across categories. Compared to those earning under $50,000, individuals earning $50,000–$99,999 had 112.7% higher odds of retirement saving (OR = 2.127, $p < 0.001$), those earning $100,000–$199,999 had 63.3% higher odds (OR = 1.633, $p = 0.041$), while the highest income category ($200,000+) showed no significant difference (OR = 0.845, $p = 0.567$). Homeownership was not significantly associated with retirement saving (OR = 1.220, $p = 0.198$). Investment level showed the strongest associations in the model, with those holding investments below $50,000 having 477.0% higher odds (OR = 5.770, $p < 0.001$) and those with investments above $50,000 having 719.8% higher odds (OR = 8.198, $p < 0.001$) compared to non-investors. We acknowledge that the strong associations between investment holdings and retirement saving may reflect partially tautological relationships; however, a robustness check excluding investment level confirmed that all three advice source categories remained statistically significant and in the same rank order (AI only OR = 2.40; planner only OR = 3.80; both OR = 5.76; all $p < 0.001$). Race showed one significant difference, with Black participants having 31.0% lower odds of retirement saving than White participants (OR = 0.690, $p = 0.032$), while the Other race category showed no significant difference (OR = 1.333, $p = 0.255$).

5.3 | Hypotheses Testing Summary

The results support the study's primary hypotheses regarding the relationship between advice sources and retirement saving behavior. H1a predicted that individuals using AI tools would be more likely to save for retirement than those using neither AI nor financial planners. This hypothesis was supported, with AI-only users demonstrating significantly higher odds of retirement saving (OR = 1.753, $p = 0.003$). H1b predicted that individuals using financial planners would be more likely to save for retirement than those using neither source. This hypothesis was also supported, with financial planner-only users showing substantially higher odds of retirement saving (OR = 2.814, $p < 0.001$). H1c predicted that

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individuals using both AI and financial planners would be associated with higher odds of retirement saving than those using either source alone. This hypothesis received mixed support. While the combined approach yielded the highest odds ratio relative to using neither source (OR = 3.540, $p < 0.001$), formal comparisons with single-source categories revealed differential patterns. Compared to AI-only users, those using both sources had significantly higher odds of retirement saving (OR = 2.02, $p = 0.003$). However, compared to financial planner-only users, the difference was not statistically significant (OR = 1.26, $p = 0.37$).

6 | Discussion

This research aimed to examine the effectiveness of different sources of retirement planning guidance, specifically AI, financial planners, and their combined use, in promoting retirement saving among public sector employees. By situating the analysis within the Technology-Enabled Financial Help-Seeking (TEFHS) framework, this study extended earlier work on advice-seeking in financial contexts (Grable and Joo 1999; Suchman 1965). The TEFHS framework allowed for a focus on outcomes rather than antecedents, aligning with recent calls in the financial planning literature to assess the effectiveness of advice across multiple delivery channels (Foerster et al. 2017; Collins 2012). The results provide new empirical evidence that all advice sources are positively associated with retirement saving, with the strongest associations found among individuals who use both AI and financial planners together.

6.1 | Main Findings

This research produced three central findings. First, AI use was independently associated with higher odds of saving for retirement compared to individuals who reported no formal advice source. This result suggests that technology alone can support retirement saving behaviors, particularly when decisions involve standardized rules and structured optimization criteria (Goodhue and Thompson 1995). Second, using financial planners was also positively associated with saving, and the magnitude of this association exceeded that of AI alone. Third, individuals who reported using both AI and financial planners together demonstrated the highest odds of retirement saving relative to using neither source. However, formal comparisons revealed that this advantage was statistically significant when compared to AI only users but not when compared to financial planner only users. These findings suggest that AI provides incremental value when added to traditional advisory relationships, though the incremental value of adding AI to existing financial planner relationships could not be statistically confirmed in this sample (Ludwig and Bennetts 2023).

6.2 | Combined Use of AI and Human Advisors

The strongest associations with retirement savings were found among individuals who combined AI with financial planners. This result is consistent with the theoretical prediction that informational capital from AI and human and social capital from planners reinforce one another (Barney 1991). Prior research has suggested that advice quality is shaped by technical expertise and relational trust and accountability (Collins 2012; Grable and Joo 1999; Ludwig et al. 2023). By combining these sources of capital, participants in this study appeared more likely to engage in consistent saving behaviors than those who relied on a single source.

The mechanisms underlying these findings are consistent with task-technology fit theory. AI tools effectively handle structured computational tasks such as contribution calculations and reminders to increase savings (Goodhue and Thompson 1995). Financial planners, in contrast, provide professional judgment and relational support that is particularly valuable in complex or emotionally sensitive contexts (Foerster et al. 2017). When combined, these resources operate synergistically. AI reduces barriers to initial engagement by providing cost-effective and immediate guidance, while planners contextualize recommendations within the client's broader financial and life circumstances. This alignment of resources supports the TEFHS prediction that different advice sources contribute unique forms of capital to retirement saving behavior.

6.3 | AI as an Independent Source of Guidance

Although combined use yielded the strongest associations relative to using no advice, AI alone was positively associated with retirement saving. This finding is significant because it demonstrates that technology can reach individuals who may not otherwise engage with professional financial planners. Research has long documented the "advice gap," where traditional planning services underserve middle-income households due to cost or lack of access (Gennaioli et al. 2015; Glenn and Heckman 2020; Kimiyaghalam et al. 2016; White and Heckman 2016). AI-enabled tools may help bridge this gap by providing consistent, rule-based recommendations at a larger scale. Where personalization needs are moderate and rules are clear, AI's informational capital can substitute for aspects of human capital, extending planner-like benefits at lower marginal cost (Huang and Rust 2018).

The effectiveness of AI alone is consistent with theoretical perspectives on technology adoption and financial behavior. Because retirement saving often involves structured decisions with explicit contribution rules, AI is well-suited to supporting these actions (Goodhue and Thompson 1995). However, prior studies also suggest that individuals often exhibit algorithm aversion, resisting automated advice even when it performs well (Dietvorst et al. 2015). The positive association observed in this study suggests that, at least within the retirement domain, AI adoption may be growing as individuals become more familiar with these tools. The finding that combined use significantly outperformed AI alone indicates that human advisors provide meaningful value beyond AI's capabilities. However, the lack of statistical difference between combined use and financial planners alone suggests that for the outcome of retirement saving participation, AI's incremental contribution to traditional advisory relationships may be more modest than initially hypothesized.

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6.4 | Financial Stress and Retirement Saving

A surprising finding was the null association between financial stress and retirement saving behavior. Although 43% of participants reported finances as a primary stressor, stress did not predict saving outcomes. This result contrasts with literature on scarcity and decision-making, which finds that financial stress can consume cognitive bandwidth and impair planning capacity (Mani et al. 2013). Well-timed, simplified pathways may help households act even when they feel financially strained (Thaler and Benartzi 2004), whether human or AI-mediated.

Several explanations are possible, though the current data do not allow us to adjudicate among them. First, advice may buffer the adverse effects of stress by simplifying choices and providing concrete actions, thereby reducing decision paralysis. Second, retirement savings may function as a coping strategy, consistent with precautionary saving theory, where households save to manage uncertainty (Carroll 1997). Third, stress may be driven by immediate cash flow concerns, which do not necessarily prevent participation in employer-sponsored plans that are automatic or incentivized through matching contributions. Collectively, these explanations suggest that advice can mitigate the adverse effects of stress, reinforcing the importance of ensuring access to both AI and planners.

6.5 | Defined Benefit Substitution

Defined benefit pension coverage was strongly associated with lower odds of additional saving (OR = 0.062), a notably large effect. This strong negative association likely reflects that employees with guaranteed pension benefits have reduced need for supplemental retirement savings and may not categorize pension participation as active saving behavior when responding to survey items. This substitution effect is consistent with prior research showing that households optimize retirement wealth across vehicles, reducing voluntary saving when guaranteed pensions are available (Engelhardt and Kumar 2011). In this study, participants with DB coverage had substantially lower odds of engaging in additional saving, confirming the continuing relevance of substitution in contemporary retirement contexts.

The implications of this finding are considerable. As DB pensions decline in the private sector (Munnell et al. 2007), more workers will transition from guaranteed retirement benefits to self-directed saving. For these individuals, access to practical guidance is increasingly important. AI tools can provide scalable support, while planners can assist with more complex transition planning. The combined use of these sources may be particularly valuable as workers navigate the shift from institutional retirement security to personal responsibility for saving and investment.

6.6 | Demographic and Behavioral Patterns

The analysis revealed persistent demographic disparities in retirement savings. Women and Black participants were less likely to save than men and White participants, even after controlling for income, education, and advice access. These results are consistent with prior work showing that structural and cultural barriers influence financial behavior (Collins 2012; Lusardi and Mitchell 2014). Although advice sources were positively associated with saving across all groups, disparities were not eliminated.

The findings suggest that advice alone cannot fully overcome systemic inequities but can help narrow gaps. AI tools may improve access by offering consistent and low-cost support, particularly for underserved groups. However, financial planners remain critical for addressing context-specific needs, such as navigating cultural differences, building trust, and tailoring strategies to complex family or employment situations. These results highlight the ongoing need for multipronged approaches combining technological and human guidance to address structural and behavioral barriers.

Investment experience was also strongly associated with saving for retirement. Individuals with higher investment holdings were far more likely to save, reflecting both greater financial capacity and stronger engagement with financial markets. This result echoes prior research on financial literacy and preparedness, which shows that knowledge and prior engagement reinforce saving behavior (Lusardi and Mitchell 2014). For individuals without prior investments, AI-enabled tools may provide accessible entry points, while planners can build long-term strategies that sustain engagement. Combining both advice sources may be particularly effective in fostering initial participation and sustaining savings over time.

6.7 | Implications for Financial Planning Practice and Policy

6.7.1 | Financial Planning Practitioners

The findings have direct relevance for financial planners. Rather than viewing AI as a threat to traditional advisory services, planners should consider how technology can enhance their practices across multiple dimensions. AI tools are increasingly integrated into advisor workflows through several key applications: automated meeting note-taking and CRM updates, voice-activated plan building and updates, pre-meeting client research and information synthesis, and client communication drafting. These technologies can handle time-intensive administrative tasks such as meeting preparation, detailed note-taking, compliance documentation, and follow-up communications, freeing planners to focus on relationship building, complex planning, and behavioral coaching.

The division of labor extends beyond simple automation. AI tools excel at consistent application of rules-based guidance (contribution calculations, deadline reminders, portfolio monitoring) and can translate complex financial concepts into multiple explanatory approaches tailored to different client learning styles. Meanwhile, planners provide irreplaceable value through professional judgment in ambiguous situations, accountability during market volatility, and coordination across multiple life domains. This strategic allocation of tasks allows planners to serve more clients efficiently while potentially improving

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service quality through reduced administrative burden and enhanced preparation. For practices seeking to expand their reach to middle-income households who are often underserved (Collins 2012; Kimiyaghalam et al. 2016; Ludwig et al. 2023), AI tools may provide the operational efficiency necessary to serve these clients profitably while maintaining high service standards.

6.7.2 | Employers

Employers shape retirement savings through plan design and the availability of guidance. The results suggest that making both AI and planner access available can increase participation and savings. While AI tools alone are beneficial, the strongest outcomes occur when employees have access to both sources. Employers can strengthen plan effectiveness by integrating AI-enabled guidance with opportunities for professional advice, thereby accommodating diverse needs and preferences across their workforce.

6.7.3 | Policymakers

Policy initiatives should promote both access to AI-enabled tools and the affordability of professional financial planning. Regulatory frameworks will be necessary to ensure that AI systems are transparent, reliable, and equitable, given concerns about potential bias (Benartzi 2025; Bennetts and Ludwig 2025). At the same time, policies that expand affordable access to planners remain critical, especially for underserved populations. Encouraging integration rather than substitution may be the most effective strategy for strengthening retirement readiness at a national scale. Policymakers can accelerate safe deployment by mapping retirement-focused AI tools to established governance frameworks, such as the NIST AI Risk Management Framework and the NIST Generative AI Profile, and by encouraging outcome-based audits that track accuracy, fairness, and consumer comprehension over time (NIST 2023; NIST 2024). Complementary guidance that harmonizes financial services oversight with international best practice will further support trust and cross-market comparability (OECD 2024).

6.8 | Limitations

Several limitations qualify the interpretation of these findings. The cross-sectional design cannot establish causality. Individuals predisposed to save may also be more likely to seek advice from multiple sources, meaning that observed associations could reflect selection effects rather than the independent contributions of each advice source. Financially engaged individuals may both seek more advice and save more, independent of any causal effect on advice behavior. Longitudinal studies and quasi-experimental methods are needed to address this endogeneity concern and determine if a causal effect exists (Heckman et al. 2025). The dependent variable measured saving participation, but not contribution adequacy, asset allocation, or retirement income planning decisions, which are also critical aspects of preparedness. Measures of AI use were broad and did not capture variation in tool type or quality of guidance. The use of categorical response options for income and investment levels, while standard in survey research, limits our ability to detect variation within categories. The $50,000 investment threshold in particular may not fully differentiate among respondents with substantially higher wealth. Although the sample size was large, it was limited to state and local government employees. This sample of state and local government employees may differ from private sector workers in ways that affect generalizability. Public sector employees typically have higher rates of defined benefit pension coverage, greater job stability, and different demographic compositions than private sector counterparts. These factors may influence both advice-seeking behavior and retirement saving patterns, and findings should be generalized to other populations with caution. Future research should examine diverse populations, employ longitudinal designs, and incorporate richer measures of advice processes.

7 | Conclusion

This study provides new empirical evidence on the role of AI tools and financial planners in shaping retirement saving behavior. The results demonstrate that both sources are independently associated with higher odds of saving, with the strongest associations observed among individuals who use both AI and planners together compared to using neither source. However, formal comparisons revealed different patterns: using AI with a financial planner showed significantly higher odds than AI alone but not financial planners alone, suggesting that AI provides meaningful incremental value when added to traditional advisory relationships while the added value of incorporating AI into existing planner relationships requires further investigation. These findings extend help-seeking theory into a technology-enabled environment, supporting aspects of the TEFHS framework while also revealing the continued strength of traditional advisory relationships. The results suggest that technology may expand access to guidance for underserved groups while planners continue to provide value through judgment, empathy, and accountability. As defined benefit pensions decline and disparities in retirement preparedness persist, understanding how AI and human advisors can work together to support diverse populations becomes increasingly important. Future research should continue to explore how best to integrate technology into planning practice and policy, particularly examining the conditions under which combined approaches provide value beyond either source alone. By examining outcomes rather than only antecedents of advice use, this study advances theory and practice in retirement planning and offers a foundation for strategies promoting long-term financial security.

Disclosure

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