Human Financial Advisors as Attainable Models: Advisor Source, Financial Self-Efficacy, and Financial Risk-Taking Propensity[1]

Abstract

Financial advice is increasingly delivered through both human professionals and AI-enabled advisory systems, yet advisor source may shape more than consumers' evaluations of the advice itself. This research identifies advisor source as a self-diagnostic cue that changes how consumers assess their own financial capability. Across three experiments, participants received equivalent financial analyses attributed either to a human financial advisor or to an AI financial advisor system. Human-sourced advice made the advisor's reasoning appear more attainable, meaning more understandable, learnable, and personally reproducible. This perceived attainability increased financial self-efficacy, which in turn increased financial risk-taking propensity. Study 1 established this serial process in a stock-analysis setting and showed that it was not reducible to perceived advice quality, advisor attitude, or general risk aversion. Study 2 replicated the first-stage process in a retirement-fund context and showed that the human-advisor advantage was stronger among consumers with lower measured financial literacy. Study 3 further demonstrated that the effect was stronger when consumers held a growth rather than a fixed financial-ability mindset. These findings shift the analysis of AI-enabled financial advice from advisor-directed evaluations to self-directed capability inferences. They suggest that human advisors can function as attainable models of financial reasoning, while also highlighting the need for hybrid advisory services to pair understandable reasoning with safeguards against overconfidence in risk-bearing decisions.

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Introduction

AI-enabled financial advice is reshaping consumer financial services. Consumers now receive investment guidance from human advisors and from AI-enabled advisory interfaces, including robo-advisers and generative AI tools. Robo-advisers use consumer information to create and manage portfolios (SEC, 2025; SEC Office of Investor Education and Advocacy, 2017). Platforms also provide automated portfolio construction, rebalancing, and hybrid human support (Vanguard, 2024). Advisor source has therefore become a salient cue.

This development raises a theoretical question. AI advice can expand access to scalable and analytically sophisticated guidance. Yet confidence in an advice source does not necessarily create confidence in the self. Consumers may view an AI advisor as accurate while seeing its reasoning as distant from what they could understand or reproduce. The same reasoning may feel more attainable when attributed to a human advisor. Advisor source may therefore shape consumers' evaluations of themselves as financial decision makers, not only their evaluations of the advisor or recommendation.

Prior research has mainly examined advisor-directed outcomes. Robo-advice research shows that automated systems can expand access to advice, alter household-advice markets, and sometimes substitute for traditional human advice (Brenner & Meyll, 2020; Cardillo & Chiappini, 2024; D'Acunto et al., 2019; D'Acunto & Rossi, 2023). Consumer and algorithmic-advice research examines acceptance, trust, reliance, and advice following (Bonaccio & Dalal, 2006; Castelo et al., 2019; Chua et al., 2023; Dietvorst et al., 2015; Logg et al., 2019; Northey et al., 2022; Yaniv, 2004; Zhang et al., 2021). Chang et al. (2026) show that trust in AI financial services can foster vicarious learning, strengthen financial self-efficacy, and promote AI-service adoption. We build from this insight but shift the theoretical target. Rather than examine trust in an AI service, we examine whether identical financial reasoning changes consumers' beliefs about their own capability when attributed to a human

rather than an AI advisor. This also shifts the outcome from AI-service adoption to financial risk-taking propensity.

We propose that human advisors increase financial self-efficacy relative to AI advisors when the advisor's reasoning appears attainable. Financial self-efficacy refers to consumers' perceived capability to manage financial tasks and decisions (Lown, 2011). The key psychological shift is not perceived advisor competence or recommendation accuracy. It is whether the reasoning behind the recommendation feels understandable, learnable, and personally reproducible. We call this perceived attainability of advisor reasoning. Consumers may view an AI recommendation as accurate without seeing its reasoning as personally attainable. They may also understand a recommendation without believing that they could learn to reason in the same way.

The mechanism rests on a self-directed inference. Human advisor source makes financial reasoning more self-diagnostic because the reasoning is attributed to another person. Consumers are more likely to view it as humanly learnable financial judgment. AI advisor source instead encourages attribution to computational capacity, data access, or algorithmic processing. These attributions provide weaker evidence for consumers' own capability. This distinction links advisor source to financial risk-taking propensity. Financial decisions involve uncertain returns, potential losses, and tradeoffs. When consumers feel less capable of understanding a decision, risk-bearing options seem opaque and hard to manage. When they feel more capable, the same options appear more evaluable and manageable. We therefore predict a serial process. Human advisor source increases perceived attainability of advisor reasoning. Perceived attainability increases financial self-efficacy, which then increases financial risk-taking propensity.

We identify two first-stage boundary conditions. Financial literacy shapes reliance on advisor source when consumers judge perceived attainability of advisor reasoning.

Consumers with greater financial knowledge have stronger internal standards for evaluating financial reasoning, so advisor source should provide less incremental information. Consumers with lower financial literacy have fewer internal standards, so the human-advisor advantage should be stronger. Financial-ability mindset also moderates the first stage. When consumers believe that financial reasoning can be developed, human-sourced reasoning is interpreted as learnable and transferable to the self. Under a fixed financial-ability mindset, the same human advisor may signal an ability gap, weakening perceived attainability.

Across three experiments, we test this attainability-based self-efficacy account. Study 1 examines whether human advisor source increases perceived attainability of advisor reasoning, financial self-efficacy, and financial risk-taking propensity relative to AI advisor source. Study 2 tests financial literacy as a measured first-stage boundary condition. Study 3 manipulates growth versus fixed financial-ability mindset. Together, the studies show when advisor source becomes self-diagnostic and how this process links human support to financial risk-taking propensity.

This research makes three contributions. First, it separates AI-financial-service adoption from advisor-source-based self-inference. Advisor source changes what consumers infer about their own financial capability even when advice content is held constant. Second, it identifies perceived attainability of advisor reasoning as the mechanism that makes human-sourced financial reasoning self-diagnostic. Third, it links this self-directed inference to financial risk-taking propensity. The findings specify when human support increases financial agency and why advisory design should pair attainable reasoning with suitability safeguards.

Theoretical Framework and Hypothesis Development

Advisor-Source Cues in Financial Decisions

Consumers often approach financial decisions with incomplete knowledge, uncertain outcomes, and limited confidence in their own judgment. Even routine investment decisions require consumers to compare uncertain returns, evaluate downside risk, and judge whether available information is diagnostic. Under these conditions, advisors do more than provide choice inputs. They can shape how consumers interpret the task, how capable consumers feel, and how willing consumers are to choose risk-bearing financial options.

The present research focuses on one feature of financial advice: advisor source. Advice-taking research shows that decision makers revise judgments in response to external advice, but they do not treat all advice sources as interchangeable (Bonaccio & Dalal, 2006; Yaniv, 2004). In consumer decision-aid contexts, interactive tools and advisors guide search, comparison, and choice construction. They therefore become part of the decision environment rather than passive information displays (Häubl & Trifts, 2000). This logic is especially relevant for AI-enabled financial advice. Consumer-AI interactions involve information provision, delegation, and social experience, each of which can alter consumers' sense of agency and competence in the decision process (Puntoni et al., 2021).

Recent service research reinforces that human and AI sources carry different psychological meanings. Consumers prefer AI agents for objective disclosures but human agents for subjective disclosures, partly because source type changes trust in recommendation capability (Dai et al., 2026). AI-generated personalized solutions are also perceived as less unique than human-provided solutions (Hou et al., 2026). In high-uncertainty advice contexts, human sources are evaluated more favorably and as more diagnostic than AI sources (Niu et al., 2026; Söderlund, 2026). Together, these findings show that advisor source can affect how consumers interpret advice beyond the informational content of the recommendation.

Most existing accounts emphasize advisor-directed evaluation. They examine whether consumers view the advisor as expert, trustworthy, accurate, personalized, or humanlike. We focus on a different consequence of advisor source: self-directed inference. In financial decisions, the same recommendation may be interpreted as humanly learnable reasoning or as the output of an external computational system. This distinction shifts the question from whether consumers trust the advisor to whether the advisor's reasoning changes consumers' confidence in themselves.

We define perceived attainability of advisor reasoning as the extent to which consumers view the advisor's reasoning as understandable, learnable, and personally reproducible by people like themselves. This construct differs from perceived advice quality. A recommendation can seem accurate without making the underlying reasoning feel attainable. It also differs from comprehensibility. Consumers may understand the content of an AI recommendation while still attributing the reasoning to computational capacities they do not possess. Perceived attainability of advisor reasoning captures whether the reasoning functions as a model for consumers' own possible capability.

This distinction separates advisor-directed evaluation from self-directed inference. Advisor-directed evaluation concerns whether consumers see the advisor as competent, trustworthy, accurate, or reliable. Self-directed inference concerns whether consumers see the advisor's reasoning as relevant to their own possible capability. Prior research on human versus algorithmic advice has mainly emphasized the first consequence. Our account centers on the second. Human advisor source makes financial reasoning appear more attainable for the self, whereas AI advisor source directs attention to computational resources that are external to the consumer.

This account identifies a self-efficacy pathway through which advisor source affects financial risk-taking propensity. It complements AI-financial-service trust models in which

trust enables vicarious learning, financial self-efficacy, and adoption (Chang et al., 2026). We examine whether identical financial reasoning becomes more self-diagnostic when attributed to a human advisor rather than to an AI advisor. Human-sourced reasoning appears more attainable, learnable, and self-relevant, increasing financial self-efficacy. AI-sourced reasoning may still appear competent, but it provides weaker evidence about consumers' own capabilities. This distinction explains how advisor source can shape financial risk-taking propensity when advice content is held constant.

Human Advisors as Attainable Models of Financial Reasoning

Self-efficacy theory identifies vicarious experience as a source of efficacy beliefs. Observing another actor perform a task can change whether observers believe that they can perform or cope with similar tasks (Bandura, 1977; Gist & Mitchell, 1992; Schunk & Hanson, 1985). This process is strongest when the observed actor is informative for the self. Social comparison theory makes a similar point. When objective standards are ambiguous, people evaluate their abilities by comparing themselves with others (Festinger, 1954). The proxy model of social comparison further suggests that comparison targets are especially useful when they help answer the question, "Can I do this?" (Wheeler et al., 1997).

A human financial advisor can serve as such a comparison target because human-sourced reasoning is more likely to be categorized as learnable human judgment. Consumers do not need to see themselves as already comparable to a professional advisor. Instead, the advisor's reasoning can make financial analysis appear understandable, practicable, and developable. When a human advisor explains tradeoffs, interprets risk, and translates financial information into clear steps, consumers may infer that the task is not only solvable by an expert but also belongs to a domain of reasoning that people can learn.

This logic is consistent with role-model theory. Role models influence observers because they make desired end states appear attainable and clarify paths to attainment

(Morgenroth et al., 2015). In the present context, the relevant end state is not becoming a professional advisor. It is feeling capable of understanding, evaluating, and acting on a financial decision. A human advisor can make this state appear attainable when the advisor's reasoning is construed as humanly learnable. The advisor therefore functions not only as a source of advice but also as a model of possible financial reasoning.

Attainability is central to this process because upward comparisons can produce either assimilation or contrast. When a comparison target feels reachable, it can improve self-evaluation. When the target feels distant or impossible to emulate, it can instead highlight an ability gap (Collins, 1996; Lockwood & Kunda, 1997). Social comparison also depends on whether consumers attend to similarities or differences between the self and the target (Mussweiler et al., 2004). Thus, human advisors increase financial self-efficacy when their reasoning appears understandable, learnable, and relevant to people like the consumer.

AI advisors provide a useful contrast. AI can be perceived as highly competent in analytic and utilitarian domains. Consumers may prefer algorithmic advice in judgment tasks (Logg et al., 2019), especially when the task appears objective, analytical, or quantitative (Castelo et al., 2019). The key distinction is not whether AI advice seems competent. It is whether AI-sourced reasoning provides self-diagnostic information for the consumer. AI competence is often attributed to data access, computational capacity, or machine-learning processes. These capacities are external to the consumer. As a result, AI advice may increase confidence in the recommendation without increasing confidence in the self. Consumers may conclude that "the AI can do this" without concluding that "I can do this."

This distinction is central to our account. A human advisor and an AI advisor may provide the same recommendation and may be evaluated similarly for usefulness or accuracy. Yet their reasoning differs in self-diagnostic value. Human-sourced reasoning implies that the task belongs to a domain of learnable human judgment. AI-sourced reasoning implies that the

task is handled through computational capacity external to the consumer. Advisor source can therefore determine whether advice becomes a model for consumers' own possible competence.

Recent work on generative AI as a social referent clarifies this boundary. Reich and Teeny (2026) show that AI-generated creative output can increase people's confidence in their own creative abilities when AI is treated as a lower social referent. They also show that this effect is weaker in fact-based domains, where AI is less likely to be seen as a lower social referent. Financial analysis fits the latter domain. It is fact-based, competence-intensive, and high-stakes. Consumers must interpret quantitative information, downside risk, time horizon, and loss exposure. In this setting, AI is more likely to function as an external computational referent than as a peer-like comparison target. AI advice may therefore appear competent without making the reasoning feel personally attainable. The relevant contrast is whether the source helps consumers infer that they can understand and manage the financial task.

Financial Self-Efficacy and Financial Risk-Taking

Self-efficacy refers to people's belief that they can organize and execute the actions required to perform a task (Bandura, 1977). It is task-focused and differs from general optimism, self-esteem, and expectations of favorable outcomes. In financial contexts, financial self-efficacy captures consumers' perceived capability to manage financial tasks and decisions (Lown, 2011). This perceived capability matters because financial self-efficacy predicts financial behavior beyond objective financial literacy alone (Farrell et al., 2016). Financial literacy and financial education are relevant, but they often explain limited variance in downstream financial behaviors (Fernandes et al., 2014). Consumers' financial behavior therefore depends not only on what they know, but also on what they believe they can understand and do.

In the present context, financial self-efficacy refers to consumers' perceived capability to understand, evaluate, and act on financial decisions involving uncertainty. It does not refer to perceived advice quality, perceived recommendation accuracy, or general optimism about financial outcomes. It captures whether consumers feel more capable of making financial judgments after encountering the advisor's reasoning. Vicarious experience describes one route through which this belief can arise. Consumers observe a model of financial reasoning and infer that the task is more personally manageable.

Human advisors should be especially likely to activate this route when their reasoning appears attainable. The advisor is not only an external source of information. The advisor is a human performer in the same broad domain of action. When the advisor's reasoning appears understandable and learnable, consumers may assimilate upward from it and update their perceived capability. This process is a vicarious route to financial self-efficacy, not a separate construct.

Financial self-efficacy should then increase financial risk-taking propensity. Financial risk-taking requires consumers to tolerate uncertainty, evaluate potential losses, and act despite incomplete information. It is domain-specific because financial choices involve distinct perceptions of loss, return, knowledge, and control (Duclos et al., 2013; Grable & Lytton, 1999; Weber et al., 2002). A consumer who feels unable to understand a financial decision may view a risky option as opaque and hard to manage. A consumer who feels capable may view the same option as more evaluable and manageable, even when objective risk is unchanged.

The proposed mechanism therefore concerns evaluable financial risk-taking, not impulsive risk-seeking. When consumers feel capable of understanding the financial tradeoff, they should be more willing to choose a risk-bearing option because uncertainty appears more manageable. Evidence from financial self-efficacy research supports this link. Financial

self-efficacy is associated with saving, investment-related behavior, and financial product holding (Farrell et al., 2016; Hoffmann & Plotkina, 2021; Lown, 2011). Investment-risk research also links financial self-efficacy to willingness to take investment risk (Montford & Goldsmith, 2016). Related behavioral-finance work shows that perceived competence and confidence are associated with more active and risk-bearing investment behavior (Graham et al., 2009).

The focal outcome in this research is financial risk-taking propensity, not financial performance. Higher financial risk-taking propensity does not imply better decision quality. The same perceived-capability process that makes risk-bearing options feel manageable may also produce overconfidence when perceived capability exceeds actual competence (Moore & Healy, 2008). We therefore treat financial risk-taking propensity as a behavioral tendency shaped by perceived manageability, rather than as evidence of objectively superior financial choice.

Main Effect and Serial-Mediation Hypotheses

The preceding theoretical account yields two predictions. First, when recommendation content is held constant, consumers should report greater financial risk-taking propensity after receiving advice from a human advisor than from an AI advisor. This prediction captures the overall effect of advisor source on the focal behavioral outcome.

Second, this effect should operate through a serial psychological process. Human advisor source should increase perceived attainability of advisor reasoning. When the same financial analysis is attributed to a human advisor, consumers should view the reasoning as more understandable, learnable, and personally reproducible than when it is attributed to an AI advisor. This perception makes the advisor's reasoning more informative for consumers' own possible competence. It should therefore increase financial self-efficacy. Higher

financial self-efficacy should then increase financial risk-taking propensity because the financial decision feels more evaluable and personally manageable.

This serial-mediation logic clarifies the theoretical mechanism. Advisor source matters because it changes whether the advisor's reasoning is perceived as relevant to consumers' own possible capability. Human advisor source makes financial reasoning appear more attainable for the self. This perceived attainability then translates the advice context into greater financial self-efficacy and stronger willingness to choose risk-bearing financial options.

The account also separates the proposed mechanism from advisor-directed explanations. Consumers may perceive one source as providing higher-quality advice. They may also feel greater trust or liking toward one advisor type. In addition, resistance to AI advice may arise from autonomy concerns (André et al., 2018), perceived intrusiveness and trust concerns (Chen & Cheng, 2026), loss of cognitive engagement and autonomy threat (Sreejesh et al., 2025), or conflict between algorithmic recommendations and consumer intuition (Sreejesh & Singha, 2026). These explanations concern evaluations of the advisor or the decision process. Our account concerns self-directed inference. The key question is whether the advisor's reasoning makes consumers feel more capable of handling the financial task.

This distinction also separates the proposed account from stable risk preference. Consumers differ in their general willingness to take risks, but our mechanism concerns a source-induced change in perceived financial task capability. Advisor source should affect financial risk-taking propensity through a specific pathway. Human-sourced reasoning increases perceived attainability of advisor reasoning. Perceived attainability of advisor reasoning increases financial self-efficacy. Financial self-efficacy, in turn, increases financial risk-taking propensity.

H1: In a financial-advice context where recommendation content is held constant, consumers who receive advice from a human advisor, rather than an AI advisor, will report greater financial risk-taking propensity.

H2: Perceived attainability of advisor reasoning and financial self-efficacy will serially mediate the effect of advisor source on financial risk-taking propensity. Specifically, compared with AI-sourced advice, human-sourced advice will make the advisor's reasoning seem more understandable, learnable, and personally reproducible, which will increase financial self-efficacy and subsequently increase financial risk-taking propensity.

Boundary Conditions: Financial Literacy and Financial-Ability Mindset

The proposed process should vary across consumers. If human advisors increase financial risk-taking propensity by making advisor reasoning feel attainable, the effect should depend on when consumers rely on source cues to judge attainability. It should also depend on whether consumers construe financial reasoning as learnable. We therefore examine two first-stage boundary conditions: financial literacy and financial-ability mindset. Financial literacy captures consumers' measured knowledge base for evaluating financial reasoning. Financial-ability mindset captures whether financial reasoning is construed as learnable. Both conditions specify when advisor source affects perceived attainability of advisor reasoning, rather than whether human advice is more accurate or more credible than AI advice.

Financial Literacy

Financial literacy should qualify the effect of advisor source at the first stage of the serial process. Objective financial knowledge shapes how much consumers need source information to judge whether financial reasoning is personally attainable. Financial literacy captures basic knowledge about interest compounding, inflation, and risk diversification that

supports household financial decision making (Lusardi & Mitchell, 2014). It is distinct from prior investing exposure, general confidence, and financial self-efficacy. It provides a domain-specific basis for interpreting financial information and assessing whether similar reasoning can be understood and reproduced by the self.

Consumers with higher financial literacy should have stronger internal standards for evaluating advisor reasoning. For these consumers, advisor source should add less incremental self-diagnostic information. They may still value the advice, but they are less dependent on whether the reasoning comes from a human advisor or an AI advisor when judging whether it is attainable. Their own financial knowledge provides a basis for assessing the reasoning.

Consumers with lower financial literacy should be more responsive to the human-advisor cue. With fewer domain-specific knowledge anchors, they have less basis for independently judging whether the analysis is understandable and reproducible. In this context, human-sourced reasoning can signal that the task belongs to a learnable human domain. The same analysis attributed to AI may still appear competent, but its competence is more likely to be attributed to computational capacity. It is therefore less informative about the consumer's own possible capability.

The first stage of the serial process should therefore vary with measured financial literacy. The human-advisor advantage on perceived attainability of advisor reasoning should be stronger among consumers with lower financial literacy and weaker among consumers with higher financial literacy. Because perceived attainability of advisor reasoning increases financial self-efficacy, and financial self-efficacy increases financial risk-taking propensity, the full serial indirect effect should also be stronger among lower-literacy consumers.

H3: Financial literacy will moderate the effect of advisor source on perceived attainability of advisor reasoning. The positive effect of a human advisor, relative to an

AI advisor, on perceived attainability of advisor reasoning will be stronger among consumers with lower financial literacy than among those with higher financial literacy. Consequently, the serial indirect effect of advisor source on financial risk-taking propensity through perceived attainability of advisor reasoning and financial self-efficacy will be stronger among consumers with lower rather than higher financial literacy.

Financial-Ability Mindset

A second boundary condition concerns whether consumers view financial reasoning as developable. Implicit-theory research distinguishes fixed views of ability from growth views, in which ability can improve through effort, strategy, and learning (Dweck & Leggett, 1988; Hong et al., 1999). These beliefs shape how people interpret difficulty, ability gaps, and models of successful performance. When complex decision-making ability is framed as acquirable rather than fixed, people maintain stronger self-efficacy and use more adaptive analytic strategies (Wood & Bandura, 1989). Consumer research also links growth mindsets to learning-oriented self-enhancement (Burnette et al., 2013; Mathur et al., 2016).

A growth financial-ability mindset should make human advisor reasoning more useful as a model for the self. When consumers believe that financial reasoning can be learned, a competent human advisor is more likely to prompt assimilation. If another person can reason this way, then similar reasoning may also be personally learnable. Under this view, the advisor's reasoning signals not only that the task can be solved, but also that the relevant capability can be acquired.

Under a fixed financial-ability mindset, the same human advisor may instead signal a stable ability gap. The advisor's reasoning can still appear impressive, accurate, or useful, but it is less likely to feel personally attainable. Consumers may interpret the advisor's performance as evidence that some people possess the relevant ability and others do not. In that case, the human advisor remains competent but becomes less useful as a model of the

consumer's own potential. This logic is consistent with evidence that implicit theories shape whether successful role models increase confidence and identification (Hoyt et al., 2012).

AI-sourced reasoning should be less affected by this mindset process. When AI performance is attributed to data access, algorithmic processing, or machine-learning infrastructure, consumers' beliefs about whether human financial ability can grow are less relevant to perceived attainability of advisor reasoning. The proposed moderation therefore concerns whether advisor reasoning is construed as humanly acquirable. A growth financial-ability mindset should strengthen the effect of human advisor source because it makes human reasoning more likely to be interpreted as learnable and self-relevant.

Financial-domain research also suggests that implicit self-theories shape consumer financial risk preferences, although through mechanisms adjacent to the present attainability account (Rai & Lin, 2019; Montford, Leary, & Nagel, 2019). Our theory focuses on the first stage of the process. A growth financial-ability mindset should strengthen the effect of human advisor source on perceived attainability of advisor reasoning. This stronger perceived attainability should then increase financial self-efficacy and, in turn, financial risk-taking propensity.

H4: Financial-ability mindset will moderate the effect of advisor source on perceived attainability of advisor reasoning. The positive effect of a human advisor, relative to an AI advisor, on perceived attainability of advisor reasoning will be stronger when consumers hold a growth financial-ability mindset than when they hold a fixed financial-ability mindset. Consequently, the serial indirect effect of advisor source on financial risk-taking propensity through perceived attainability of advisor reasoning and financial self-efficacy will be stronger under a growth financial-ability mindset than under a fixed financial-ability mindset.

Figure 1 presents the conceptual model.

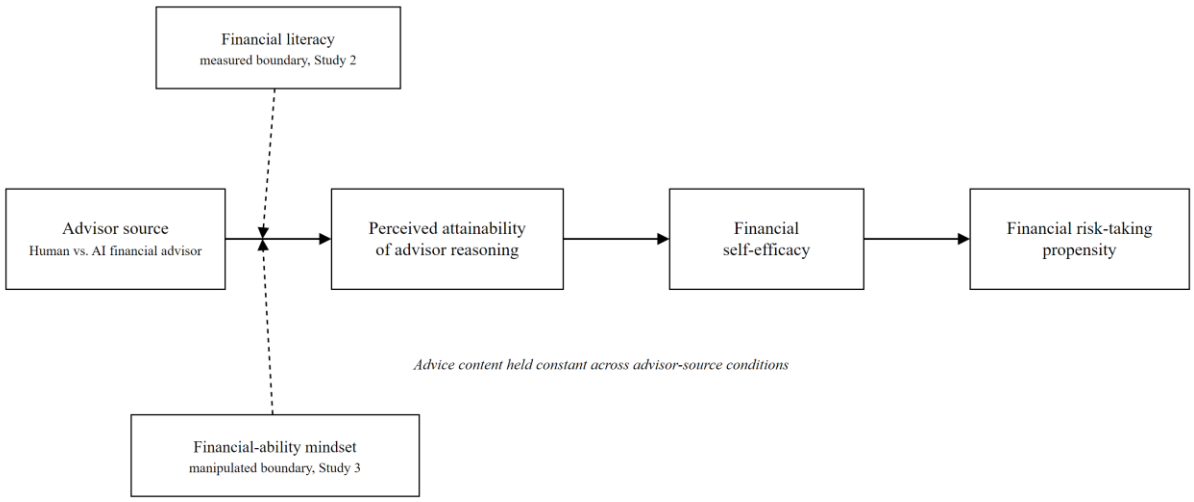


Figure 1. Conceptual Model

Overview of Studies

Across three experiments, we test an attainability-based self-efficacy account of advisor-source effects in financial decision-making. Study 1 tests the full serial process in a stock-analysis context. Holding advice content constant, human advisor source increases perceived attainability of advisor reasoning, which increases financial self-efficacy and, in turn, increases preference for a higher-risk investment portfolio. Study 2 extends the first-stage test to a retirement-fund allocation context and examines financial literacy as a measured boundary condition. Study 3 tests financial-ability mindset as an experimentally manipulated boundary condition in a savings-allocation context involving a guaranteed account and a diversified mutual fund. Together, the studies examine the same psychological process across distinct financial decisions and identify when human advisor source becomes self-diagnostic.

Study 1: Full Mechanism Test

Study 1 tests whether human advisor source increases financial risk-taking propensity through perceived attainability of advisor reasoning and financial self-efficacy. It also

examines whether this process is distinct from advice quality, advisor attitude, and stable risk aversion.

Method

Study 1 used data from 200 U.S.-based participants recruited through Prolific (Mage = 33.93 years, SD = 11.76; 102 females). The study used a two-condition between-subjects design. Participants imagined that an investing or finance platform had introduced a new advice service. All participants read the same financial-advice scenario and stock-analysis sample about Northbridge Technology, a fictional publicly traded company. The only intended difference was whether the analysis was attributed to an AI financial advisor system or to a human financial advisor.

The financial risk-taking task was adapted from Duclos, Wan, and Jiang (2013). Participants imagined having $5,000 to invest for 12 months and indicated their relative preference between a lower-risk portfolio and a higher-risk portfolio with the same expected value. The dependent variable was preference for the higher-risk portfolio on a 1–7 scale. Full portfolio descriptions are reported in the Appendix.

Perceived attainability of advisor reasoning was measured with three items adapted from Gartzia et al. (2021). Financial self-efficacy was measured with four items from Han et al. (2019). The study also measured advice quality, advisor attitude, and risk averseness using items adapted from Wixom and Todd (2005), Khoso et al. (2026), and Nenkov et al. (2009), respectively.

Results

The source manipulation worked as intended. Participants in the AI-advisor condition perceived the source as substantially less human than participants in the human-advisor condition (AI: M = 1.73, SD = 0.96; human: M = 5.81, SD = 1.37). The risk perception check

confirmed that the higher-risk portfolio was perceived as riskier than the lower-risk portfolio ($M = 5.51$, $SD = 1.27$). Reliability was high for perceived attainability of advisor reasoning ($\alpha = .90$), financial self-efficacy ($\alpha = .88$), advice quality ($\alpha = .87$), advisor attitude ($\alpha = .88$), and risk averseness ($\alpha = .92$).

Participants in the human-advisor condition perceived the advisor's reasoning as more attainable than those in the AI-advisor condition ($M = 4.95$, $SD = 1.39$ vs. $M = 4.20$, $SD = 1.27$), $t(198) = 3.97$, $p < .001$, $d = 0.56$. They also reported higher financial self-efficacy ($M = 4.78$, $SD = 1.42$ vs. $M = 3.88$, $SD = 1.35$), $t(198) = 4.60$, $p < .001$, $d = 0.65$, and stronger preference for the higher-risk portfolio ($M = 4.48$, $SD = 1.50$ vs. $M = 3.63$, $SD = 1.23$), $t(198) = 4.40$, $p < .001$, $d = 0.62$. These results support H1 and the first-stage logic of H2.

Serial mediation analyses using PROCESS Model 6 tested the proposed pathway. Advisor source was coded 0 = AI advisor and 1 = human advisor. Human advisor source increased perceived attainability of advisor reasoning ($b = 0.75$, $p < .001$). Perceived attainability of advisor reasoning positively predicted financial self-efficacy, controlling for condition ($b = 0.52$, $p < .001$). Financial self-efficacy positively predicted financial risk-taking propensity, controlling for condition and perceived attainability of advisor reasoning ($b = 0.56$, $p < .001$). The focal serial indirect effect through perceived attainability of advisor reasoning and financial self-efficacy excluded zero ($Ind3 = 0.22$, 95% CI [0.10, 0.37]), supporting H2.

Figure 2 displays the complete PROCESS Model 6 path estimates from Study 1.

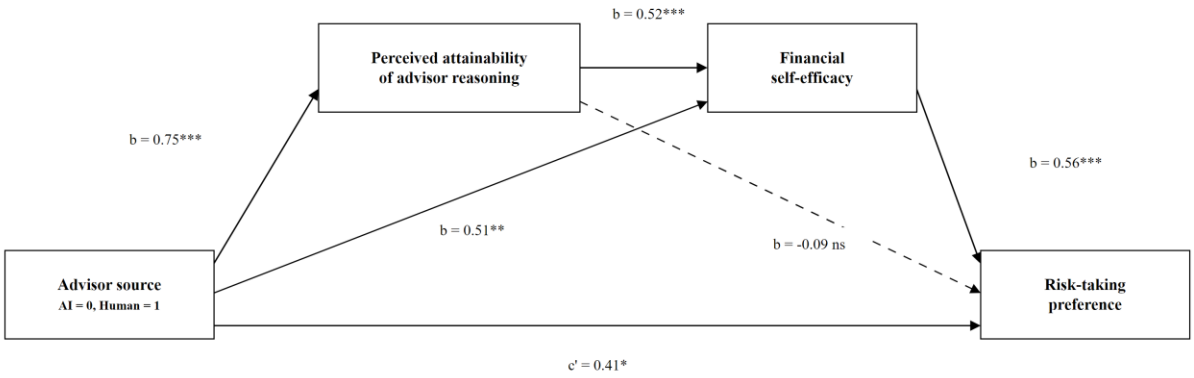


Figure 2. PROCESS Model 6 serial mediation path in Study 1

A competing-mediator regression distinguished the proposed process from advisor-evaluation alternatives. Financial self-efficacy remained a significant predictor of financial risk-taking propensity when advice quality, advisor attitude, risk averseness, condition, and perceived attainability of advisor reasoning were entered simultaneously ($b = 0.56$, $p < .001$). Perceived attainability of advisor reasoning was not significant in this full model ($b = -0.09$, $p = .211$), consistent with the serial account in which attainability affects risk-taking primarily through financial self-efficacy. Advisor attitude ($b = 0.06$, $p = .700$), risk averseness ($b = -0.06$, $p = .632$), and advice quality ($b = -0.01$, $p = .949$) did not significantly predict financial risk-taking propensity. The direct condition effect remained significant ($b = 0.42$, $p = .019$), indicating partial mediation.

Discussion

Study 1 provides evidence for the proposed serial process. Human advisor source increased perceived attainability of advisor reasoning, which predicted higher financial self-efficacy and, in turn, stronger preference for the higher-risk investment portfolio. The competing-mediator analysis shows that this process is not reducible to advice quality, advisor attitude, or stable risk aversion. These findings support the attainability-based self-efficacy account of advisor-source effects on financial risk-taking propensity.

Study 2: Financial Literacy as a Boundary Condition

Study 2 tests whether measured financial literacy qualifies the first stage of the proposed process in a retirement-fund allocation context. Consumers with lower financial literacy should rely more on an advisor source when judging whether financial reasoning is personally attainable. Thus, a human advisor source should have a stronger effect on the perceived attainability of advisor reasoning among lower-literacy consumers.

Method

Study 2 used data from 300 U.S.-based participants recruited through Prolific (Mage = 35.44 years, SD = 11.64; 153 females). The study used the same advisor-source manipulation and process measures as Study 1, but placed the advice in a retirement-account planning context. Participants imagined contributing $5,000 to a retirement account and read an advisor's analysis comparing a stable-income fund with a diversified-growth fund. The dependent variable was relative preference for the diversified growth fund on a 1–7 scale.

Financial literacy was measured with the three standard financial literacy questions summarized by Lusardi and Mitchell (2014), covering compound interest, inflation, and risk diversification. Correct answers were coded as 1, and incorrect or “do not know” answers were coded as 0. The three items were summed to form a 0–3 financial literacy score. Financial literacy was treated as a measured continuous moderator and mean-centered before constructing the advisor source × financial literacy interaction term.

Results

The source manipulation worked as intended. Participants in the AI-advisor condition perceived the source as less human than participants in the human-advisor condition (AI: M = 1.67, SD = 0.83; human: M = 6.11, SD = 0.91). The risk perception check confirmed that the diversified growth fund was perceived as riskier than the stable income fund (M = 5.62, SD =

1.27). Reliability was strong for perceived attainability of advisor reasoning (α = .93) and financial self-efficacy (α = .89).

Descriptively, participants in the human-advisor condition reported higher perceived attainability of advisor reasoning than those in the AI-advisor condition (M = 4.78, SD = 1.49 vs. M = 4.16, SD = 1.37), higher financial self-efficacy (M = 4.51, SD = 1.55 vs. M = 3.82, SD = 1.46), and stronger preference for the diversified growth fund (M = 4.19, SD = 1.35 vs. M = 3.68, SD = 1.48).

Consistent with H3, measured financial literacy qualified the effect of advisor source on perceived attainability of advisor reasoning. The advisor-source effect was positive overall (b = 0.57, SE = 0.16, t = 3.54, p < .001), and the advisor source × financial literacy interaction was negative and significant (b = −0.51, SE = 0.17, t = −3.07, p = .002). Conditional effects showed that the human-advisor advantage was stronger among participants with lower measured financial literacy (b = 1.27, SE = 0.28, t = 4.55, p < .001) and was not significant among those with higher measured financial literacy (b = −0.17, SE = 0.29, t = −0.58, p = .562). Figure 3 summarizes the Johnson-Neyman analysis for the first-stage moderation in Study 2.

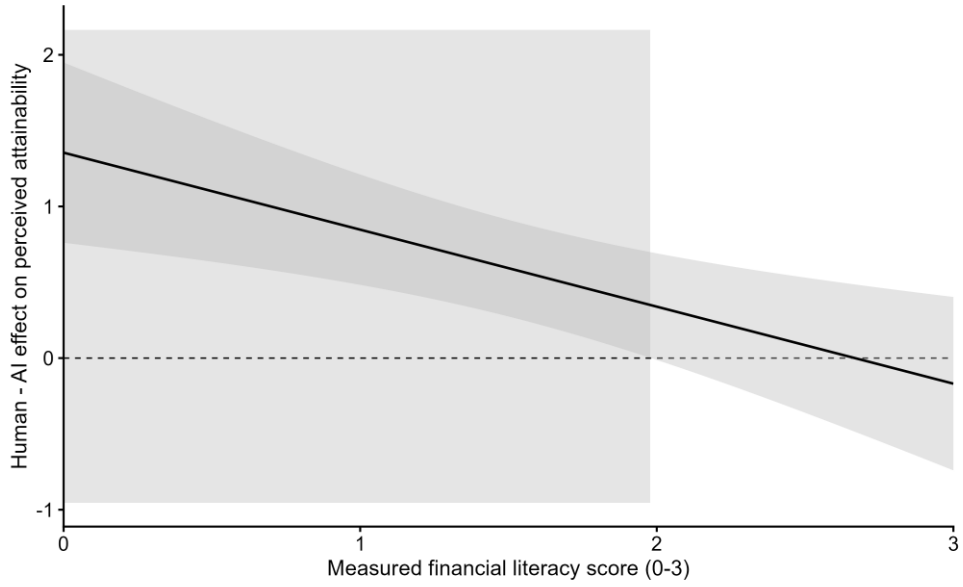


Figure 3. Study 2 Johnson-Neyman analysis.

The downstream serial path was also consistent with the proposed mechanism. Perceived attainability of advisor reasoning positively predicted financial self-efficacy, controlling for condition and financial literacy ($b = 0.64$, $p < .001$). Financial self-efficacy positively predicted financial risk-taking propensity, controlling for condition, perceived attainability of advisor reasoning, and financial literacy ($b = 0.46$, $p < .001$).

PROCESS Model 83 with 5,000 bootstrap samples tested the first-stage conditional serial indirect effect. The index of moderated mediation for the serial path was negative and excluded zero (index = −0.15, 95% CI [−0.26, −0.05]), indicating that the estimated indirect effect was smaller at higher measured financial literacy. The conditional serial indirect effect was positive among participants with lower measured financial literacy (effect = 0.37, 95% CI [0.21, 0.57]) and not significant among those with higher measured financial literacy (effect = −0.05, 95% CI [−0.22, 0.12]).

Discussion

Study 2 provides measured-moderator evidence consistent with financial literacy as a first-stage boundary condition. The human-advisor effect on perceived attainability of advisor reasoning was stronger among participants with lower measured financial literacy and weaker among those with higher measured financial literacy. This pattern supports the claim that consumers with fewer financial knowledge anchors rely more on advisor source when judging whether financial reasoning is personally attainable.

Study 3: Financial-Ability Mindset as a Boundary Condition

Study 3 tests whether financial-ability mindset moderates the effect of advisor source on perceived attainability of advisor reasoning. If human advisors operate as attainable models for the self, the human-advisor effect should be stronger when financial reasoning is

framed as developable rather than fixed. Study 3 tests this prediction in a savings-allocation context.

Method

Study 3 used data from 400 U.S.-based participants recruited through Prolific (Mage = 34.84 years, SD = 11.49; 204 females). The study used a 2 (advisor source: AI advisor vs. human advisor) × 2 (financial-ability mindset: fixed vs. growth) between-subjects design.

Before the advisor-source manipulation, participants completed an article-based mindset manipulation adapted from prior implicit self-theory manipulations in financial decision-making research (Rai & Lin, 2019; Montford et al., 2019). In the growth financial-ability mindset condition, the summary stated that financial reasoning can become stronger through practice, feedback, and exposure to clear examples. In the fixed financial-ability mindset condition, the summary stated that people differ in their natural aptitude for analyzing financial information and that this ability tends to be relatively stable.

Participants then completed a forced-choice engagement item before proceeding to the advisor-source manipulation. In the savings-allocation context, they imagined using a banking or savings app allocation service and read an advisor analysis comparing a guaranteed account with a diversified mutual fund. The dependent variable was relative preference for the diversified mutual fund on a 1–7 scale, with higher values indicating greater willingness to choose the risk-bearing savings option.

Perceived attainability of advisor reasoning and financial self-efficacy were measured as in the prior studies. The financial-ability mindset manipulation check used four items adapted from Levy et al. (1998), Rai and Lin (2019), and Montford et al. (2019). The focal conditional-process model tested whether financial-ability mindset moderated the effect of advisor source on perceived attainability of advisor reasoning and whether this first-stage moderation carried through financial self-efficacy to financial risk-taking propensity. Advisor

source was coded 0 = AI advisor and 1 = human advisor. Financial-ability mindset was coded 0 = fixed mindset and 1 = growth mindset.

Results

The perceived-source check indicated the intended advisor-source perception. Scores were low in the AI-advisor cells (fixed mindset: M = 1.65, SD = 0.86; growth mindset: M = 1.78, SD = 0.91) and high in the human-advisor cells (fixed mindset: M = 6.08, SD = 0.97; growth mindset: M = 6.22, SD = 0.89). The risk perception check confirmed that the diversified mutual fund was perceived as riskier than the guaranteed account (M = 5.76, SD = 1.28).

Reliability was strong for perceived attainability of advisor reasoning (α = .88), financial self-efficacy (α = .90), and the financial-ability mindset check (α = .93). The mindset manipulation check was successful. Participants in the growth financial-ability mindset condition agreed more strongly that financial reasoning can improve than did participants in the fixed financial-ability mindset condition (b = 1.33, SE = 0.12, t = 11.14, p < .001).

Descriptively, perceived attainability of advisor reasoning followed the predicted source-by-mindset pattern. The human-advisor advantage was larger in the growth financial-ability mindset condition (human: M = 5.19, SD = 1.40; AI: M = 4.21, SD = 1.52) than in the fixed financial-ability mindset condition (human: M = 4.46, SD = 1.48; AI: M = 4.12, SD = 1.33). Financial self-efficacy and financial risk-taking propensity showed the same directional pattern. Figure 4 summarizes the descriptive means from Study 3.

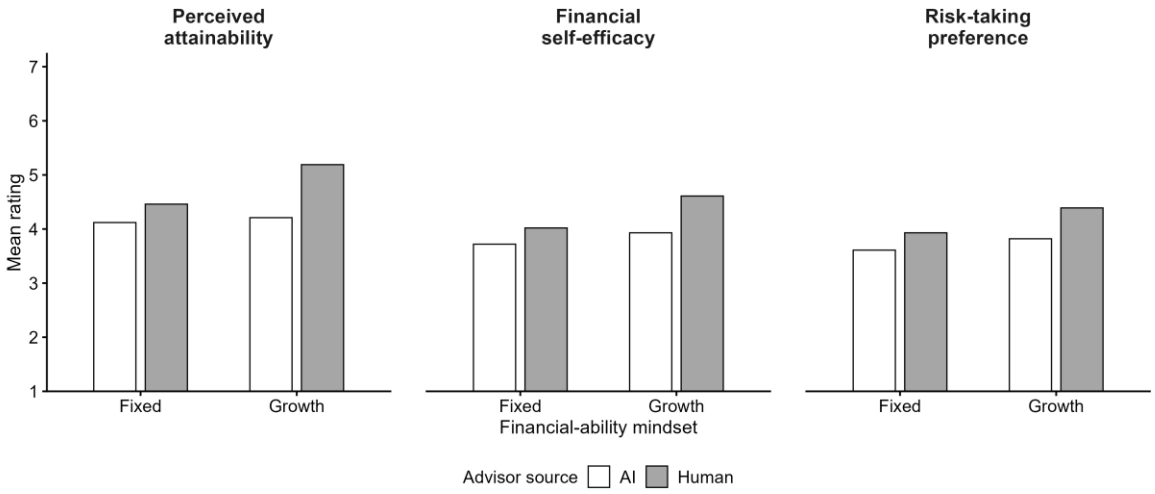


Figure 4. Study 3 descriptive means by advisor source and financial-ability mindset.

Consistent with H4, financial-ability mindset moderated the effect of advisor source on perceived attainability of advisor reasoning. In the fixed financial-ability mindset condition, the human-advisor effect was positive but not significant ($b = 0.34$, $SE = 0.20$, $t = 1.67$, $p = .096$). The advisor source × financial-ability mindset interaction was positive and significant ($b = 0.64$, $SE = 0.29$, $t = 2.23$, $p = .026$), indicating that the human-advisor advantage was stronger under a growth financial-ability mindset. The implied human-advisor effect under a growth financial-ability mindset was 0.98 scale points ($SE = 0.20$, $t = 4.84$, $p < .001$).

The downstream serial path was also consistent with the proposed mechanism. Perceived attainability of advisor reasoning positively predicted financial self-efficacy, controlling for condition and financial-ability mindset ($b = 0.56$, $p < .001$). Financial self-efficacy positively predicted financial risk-taking propensity, controlling for condition, financial-ability mindset, and perceived attainability of advisor reasoning ($b = 0.51$, $p < .001$).

PROCESS Model 83 with 5,000 bootstrap samples tested the first-stage conditional serial indirect effect. The index of moderated mediation for the serial path was positive and

excluded zero (index = 0.19, 95% CI [0.03, 0.37]), indicating that the serial indirect effect was stronger under a growth financial-ability mindset than under a fixed financial-ability mindset. The conditional serial indirect effect was not significant in the fixed financial-ability mindset condition (effect = 0.10, 95% CI [−0.01, 0.21]) but was positive in the growth financial-ability mindset condition (effect = 0.29, 95% CI [0.16, 0.43]).

Discussion

Study 3 supports financial-ability mindset as a first-stage boundary condition. Human advisor source increased perceived attainability of advisor reasoning more strongly under a growth financial-ability mindset than under a fixed financial-ability mindset. This first-stage moderation carried through financial self-efficacy to financial risk-taking propensity. The findings show that human advisor reasoning becomes more self-diagnostic when consumers construe financial reasoning as learnable.

General Discussion

Consumers increasingly encounter financial advice in service environments where human professionals and AI-enabled advisory systems coexist. This research examines a self-evaluative consequence of advisor source. Specifically, it tests whether the source of financial advice changes consumers' perceived capability to understand and handle financial decisions. Across three experiments, we develop and test an attainability-based self-efficacy account. Human advisors, relative to AI advisors, increase perceived attainability of advisor reasoning. This perception strengthens financial self-efficacy, which in turn increases financial risk-taking propensity.

The central insight is that advisor source affects not only how consumers evaluate advisors, but also how they evaluate themselves. A human advisor can function as an attainable model of financial reasoning. When financial analysis is attributed to another

person, consumers are more likely to view the reasoning as understandable, learnable, and personally reproducible. When the same analysis is attributed to AI, it can still appear competent, accurate, and useful. However, that competence is more likely to be located in computational capacity rather than in a form of reasoning consumers can map onto their own capability. The key psychological shift is therefore from externally located competence to self-relevant capability.

This distinction clarifies the role of financial advice in consumer service experiences. Financial advice is not only information that consumers accept or reject. It can also model how financial reasoning is performed. In service environments that include robo-advisers, digital investment platforms, automated advisory tools, and human professionals, advisor source becomes a design cue. It shapes whether consumers feel able to understand financial products, evaluate risk, and take an active role in the decision.

Study 1 established the proposed serial process in a stock-analysis context. Participants exposed to a human advisor perceived the advisor's reasoning as more attainable, reported higher financial self-efficacy, and showed greater financial risk-taking propensity than participants exposed to an AI advisor. The serial mediation results supported the pathway from advisor source to perceived attainability of advisor reasoning, from perceived attainability of advisor reasoning to financial self-efficacy, and from financial self-efficacy to financial risk-taking propensity. Competing-mediator analyses further showed that this process was not reducible to perceived advice quality, advisor-directed trust and liking, or stable risk preference.

Studies 2 and 3 identified first-stage boundary conditions and extended the evidence beyond the stock-analysis setting. Study 2 showed that financial literacy qualified the effect of advisor source in a retirement-fund allocation context. The human-advisor advantage in perceived attainability of advisor reasoning was stronger among participants with lower

measured financial literacy. This pattern indicates that consumers with fewer domain-specific knowledge anchors rely more on advisor source when judging whether financial reasoning is personally attainable. Study 3 then showed that financial-ability mindset shaped the same first-stage process in a guaranteed-account versus mutual-fund context. The human-advisor advantage was stronger under a growth financial-ability mindset than under a fixed financial-ability mindset. Together, the studies show when human advisors become self-diagnostic: when consumers have fewer internal knowledge anchors and when financial reasoning is construed as learnable.

Theoretical Contributions

This research makes three theoretical contributions. First, it contributes to research on AI-enabled financial services, robo-advice, and algorithmic advice by separating advisor-directed evaluation from consumer self-evaluation. Prior work shows that trust in AI financial services can support vicarious learning, financial self-efficacy, and adoption. The present research asks a different question: when the financial reasoning is held constant, does advisor source change what consumers infer about their own ability to understand and manage the decision? This distinction is theoretically important because advisor competence, trust, and consumer self-efficacy are separable constructs. Consumers may evaluate an AI advisor favorably without seeing its reasoning as personally attainable, just as they may view a human advisor as fallible while still finding the advisor's reasoning more self-relevant and learnable. Thus, advisor source can shape self-directed capability inferences even when advice content is equivalent.

Second, the research extends self-efficacy, social comparison, and role-modeling perspectives by identifying perceived attainability of advisor reasoning as a process variable that determines when financial advice becomes self-diagnostic. Human advisors do not automatically increase consumers' capability beliefs. Their reasoning must appear

sufficiently understandable, learnable, and relevant to the consumer's own possible competence. In the fact-based financial-analysis contexts examined here, human-sourced reasoning is more likely to function as an attainable model of financial reasoning, whereas AI-sourced reasoning may be attributed to external computational capacity and therefore appear less diagnostic of what the consumer can personally learn or do. This account also specifies boundary conditions. Human advisor reasoning is most likely to increase financial self-efficacy when consumers have fewer internal financial-knowledge anchors or when they construe financial reasoning as developable. In this way, the framework clarifies when advisor source invites assimilation to the self rather than remaining merely an external source of expertise.

Third, the research contributes to consumer financial risk-taking research by showing that advisor-source-based self-evaluation carries behavioral implications beyond AI-service adoption. The results indicate that financial self-efficacy increases willingness to allocate money to a higher-risk option because the decision feels more understandable and manageable. At the same time, greater financial risk-taking propensity is not necessarily better financial behavior. A service interface that increases perceived capability may help consumers engage with suitable financial products, but it may also raise the risk of overconfidence if perceived capability exceeds actual understanding. The theoretical contribution is therefore not that human advice objectively improves financial decisions, but that advisor source alters consumers' psychological readiness to engage with financial risk in a welfare-relevant but normatively ambiguous way.

Practical Implications

The findings inform the design of advisory services in which consumers encounter human advisors, AI advisors, or hybrid support. A central design objective is to make financial reasoning attainable while keeping confidence calibrated to consumers' goals,

liquidity needs, time horizon, risk tolerance, and loss capacity. This objective is important because advisor source can increase financial risk-taking propensity through perceived attainability of advisor reasoning and financial self-efficacy.

For robo-advisory platforms, hybrid advisory services, and digitally mediated wealth-management interfaces, the results identify distinct roles for AI and human support. AI advisors can deliver scalable analysis and standardized decision support. Human advisors add value when they make the reasoning behind advice understandable, personally relevant, and learnable. The human element therefore operates not only through reassurance or trust. It can also strengthen consumers' sense of personal financial capability.

First, advisory interfaces should make reasoning attainable, not only recommendations available. A recommendation has limited developmental value when consumers cannot see how to evaluate it or how it fits their financial situation. Human advisors and human-supported digital interfaces can increase perceived attainability of advisor reasoning by explaining the logic of the recommendation, clarifying tradeoffs, and linking risk, return, time horizon, and loss capacity. The design goal is to make the reasoning process understandable and usable for consumers' own decision evaluation.

Second, advisory support should account for financial literacy. Study 2's measured pattern shows that the human-advisor advantage is stronger among consumers with lower financial literacy. These consumers have fewer domain-specific knowledge anchors for judging whether financial reasoning is personally attainable. For them, human advisors are most valuable when they explain the basis of the recommendation, clarify downside risk, and connect advice to goals and constraints. For consumers with higher financial literacy, advisor source alone is less diagnostic. Interfaces should provide transparent assumptions, detailed reasoning, and scenario analysis that support independent evaluation.

Third, advisory interfaces should frame financial reasoning as learnable. Study 3 shows that human advisor reasoning has a stronger effect on perceived attainability when consumers hold a growth financial-ability mindset. Platforms can support this mindset through step-by-step explanations, plain-language risk comparisons, interactive examples, and educational prompts. These features make the reasoning process less opaque and more usable for consumers' own decision evaluation.

Fourth, advisory systems should calibrate confidence as they increase agency. Because human advisor cues can increase financial self-efficacy and financial risk-taking propensity, interfaces should pair attainable reasoning with comprehension checks, suitability assessments, risk-disclosure prompts, portfolio stress tests, and opportunities to reconsider high-risk choices. These safeguards connect increased consumer agency to actual understanding and appropriate risk exposure.

Limitations and Future Research

This research has several limitations that open useful directions for future work. First, the studies use controlled experimental scenarios rather than naturally occurring advisory interactions. This design holds advice content constant and isolates advisor source, but actual financial service encounters include richer variation in interaction style, responsiveness, disclosure format, personalization, emotional tone, and regulatory positioning. Future research could test whether the same attainability-based self-efficacy process emerges in interactive settings, including chatbot-based investment guidance, video consultations, hybrid robo-advisory platforms, and branch-based advisory encounters.

Second, the studies measure financial risk-taking propensity through hypothetical allocation tasks. These tasks are well suited for testing the proposed psychological process, but they do not measure realized financial behavior or decision quality. Future work could examine consequential choices, longitudinal investment behavior, portfolio suitability,

learning outcomes, and post-decision satisfaction. A particularly important question is whether advisor-source-induced financial self-efficacy remains aligned with actual understanding over time, or whether it contributes to overconfidence, excessive trading, or unsuitable product adoption. These outcomes are central to household-investing research (Barber & Odean, 2001; Seru et al., 2010).

Third, the present research focuses on a human versus AI advisor-source distinction. Future research should examine the design features that make advice feel attainable within and across these source categories. AI advisors vary in anthropomorphism, transparency, explainability, autonomy, and human-in-the-loop review. Human advisors also vary in whether their recommendations are interactive, scripted, personalized, or opaque. Plain-language explanations, peer-like framing, human review, step-by-step reasoning, and interactive educational support may increase perceived attainability of advisor reasoning even when the recommendation is generated by AI.

Fourth, the present framework examines financial literacy and financial-ability mindset as first-stage boundary conditions. Other consumer characteristics may shape whether advisor source becomes self-diagnostic. Numeracy, financial experience, risk tolerance, technology readiness, algorithm aversion, income uncertainty, and prior experiences with financial institutions may affect how consumers interpret human and AI advice. Cultural context may also matter because social comparison, authority perception, and attitudes toward financial expertise vary across markets.

Fifth, future work should examine consumer welfare more directly. The present account treats financial risk-taking propensity as a behavioral outcome rather than a welfare criterion. A stronger welfare test would assess whether advisor-source design improves consumers' ability to choose products that fit their goals, constraints, liquidity needs, and loss capacity. Such work could distinguish calibrated financial self-efficacy from overconfidence

and would be valuable for regulators and service providers designing responsible AI-enabled financial advice.

In summary, this research shows that advisor source is not merely a label attached to financial advice. It shapes whether financial reasoning feels attainable and whether consumers feel capable of engaging with financial risk. Human advisors matter not only because consumers may trust them, but because their reasoning can become self-diagnostic. The broader implication is that financial advice should provide recommendations while also calibrating consumers' sense of what they can understand, evaluate, and act upon.

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Appendix: Study Stimulus Materials and Measures

Study 1 Stock-Analysis Stimulus

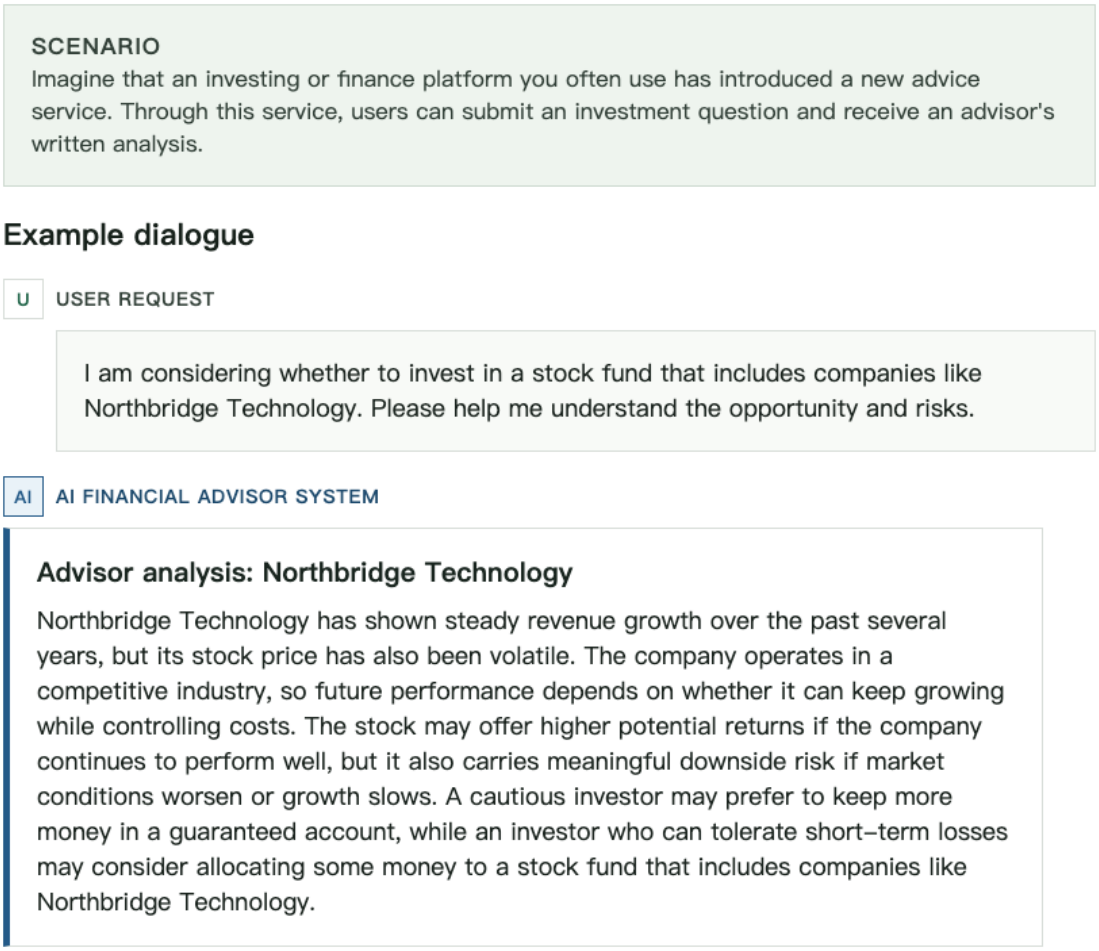


Figure A1. Study 1 AI-advisor HTML dialogue stimulus.

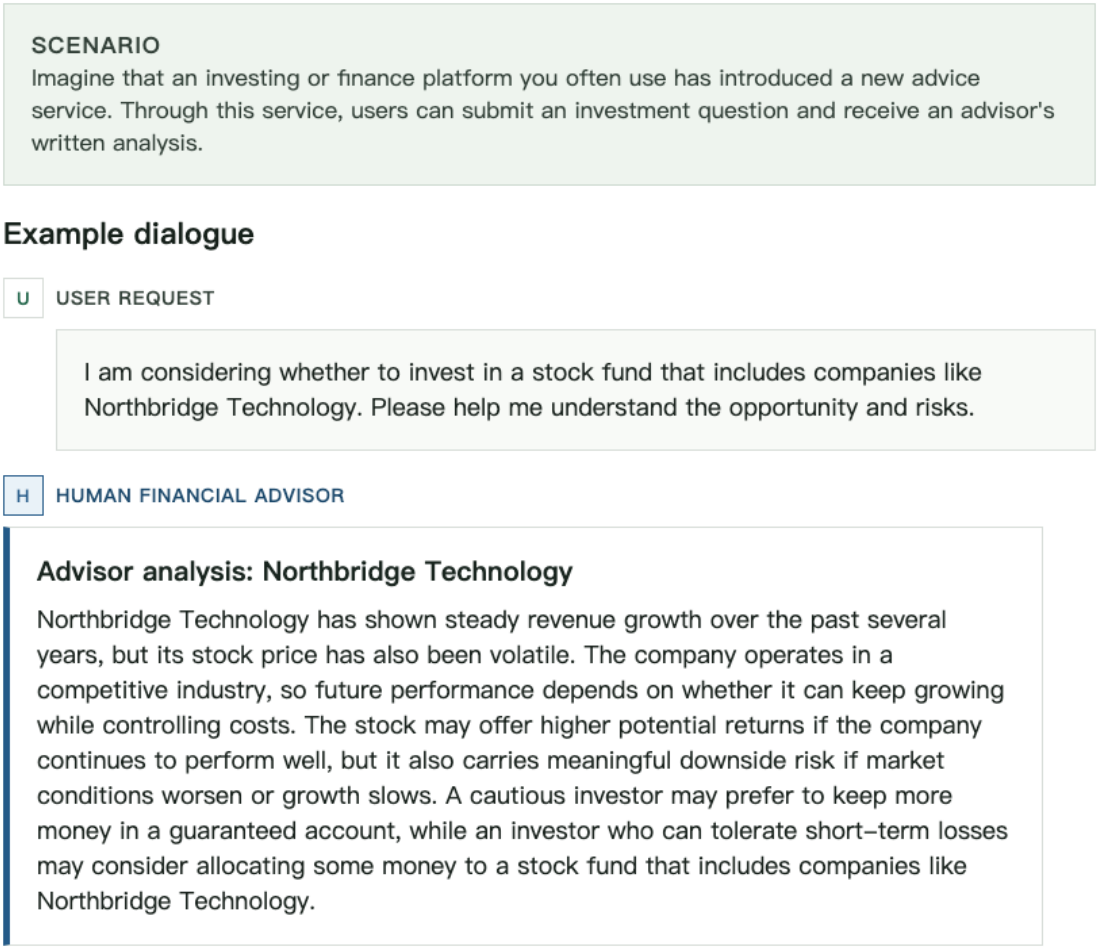


Figure A2. Study 1 human-advisor HTML dialogue stimulus.

Study 2 Retirement-Fund Stimulus

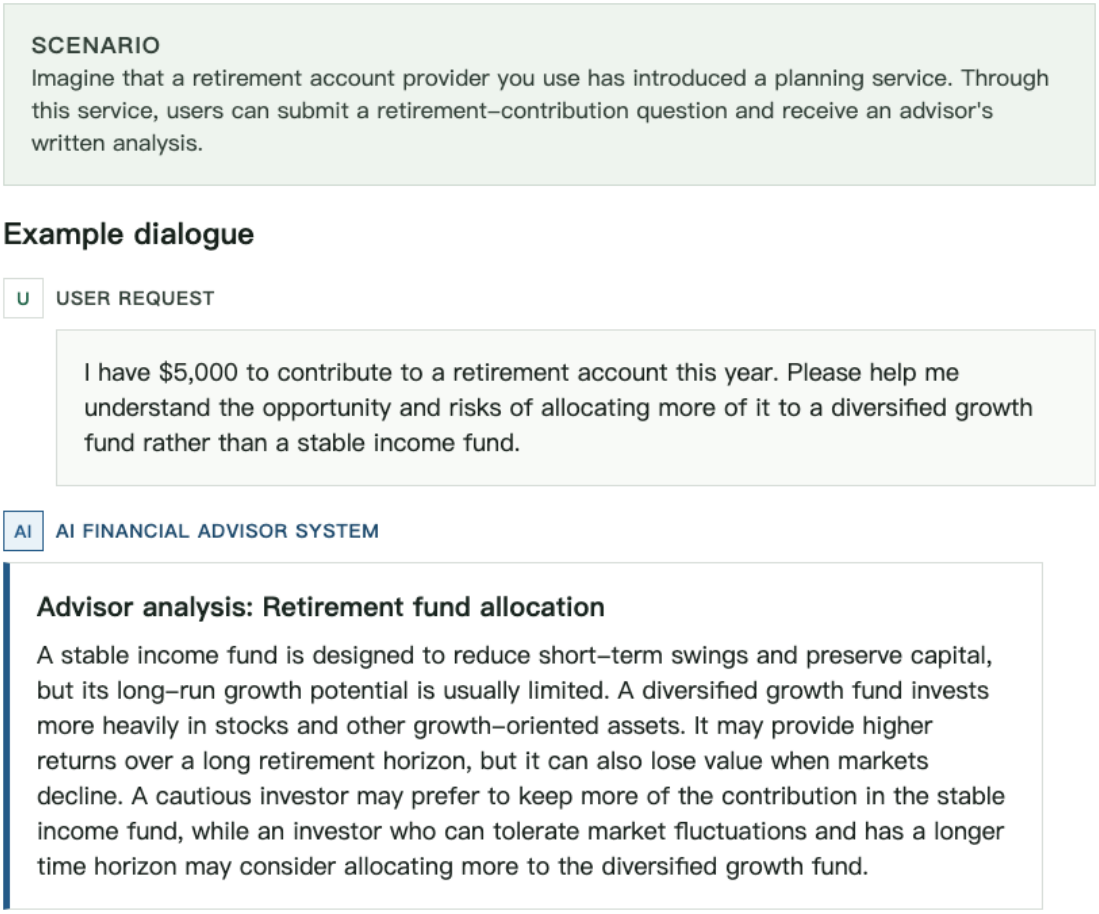


Figure A3. Study 2 AI-advisor HTML dialogue stimulus.

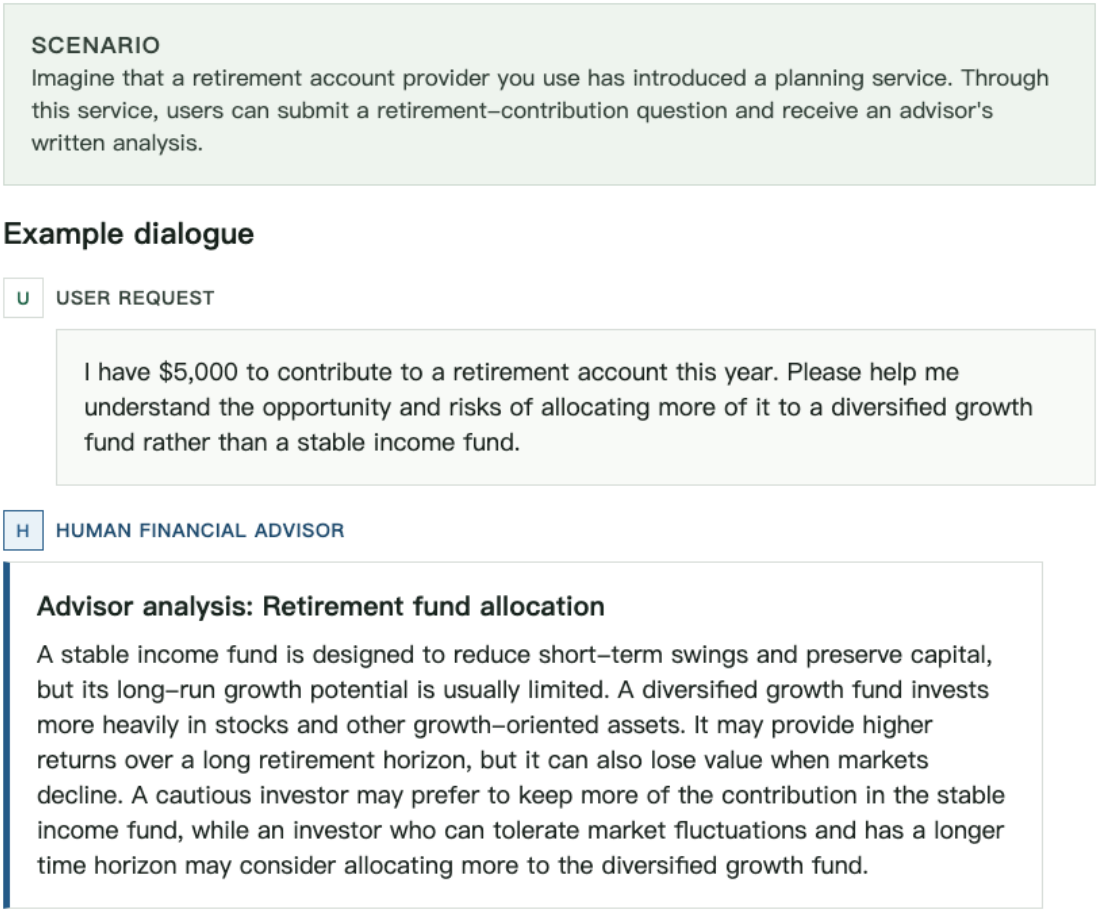


Figure A4. Study 2 human-advisor HTML dialogue stimulus.

Study 3 Financial-Ability Mindset and Savings-Allocation Stimuli

growth financial-ability mindset condition:

"Recent research on financial decision making suggests that people can improve their ability to analyze financial information. Although some people begin with more background knowledge than others, financial reasoning can become stronger through practice, feedback, and exposure to clear examples. Over time, people can learn to recognize patterns in financial information, evaluate risk-return tradeoffs, and understand the reasoning behind investment recommendations."

fixed financial-ability mindset condition:

"Recent research on financial decision making suggests that people differ in their natural aptitude for analyzing financial information. Although people can learn some basic facts, their ability to recognize patterns in financial information, evaluate risk-return tradeoffs, and understand investment recommendations tends to be relatively stable. Some people naturally find this kind of reasoning easier than others, even with practice and feedback."

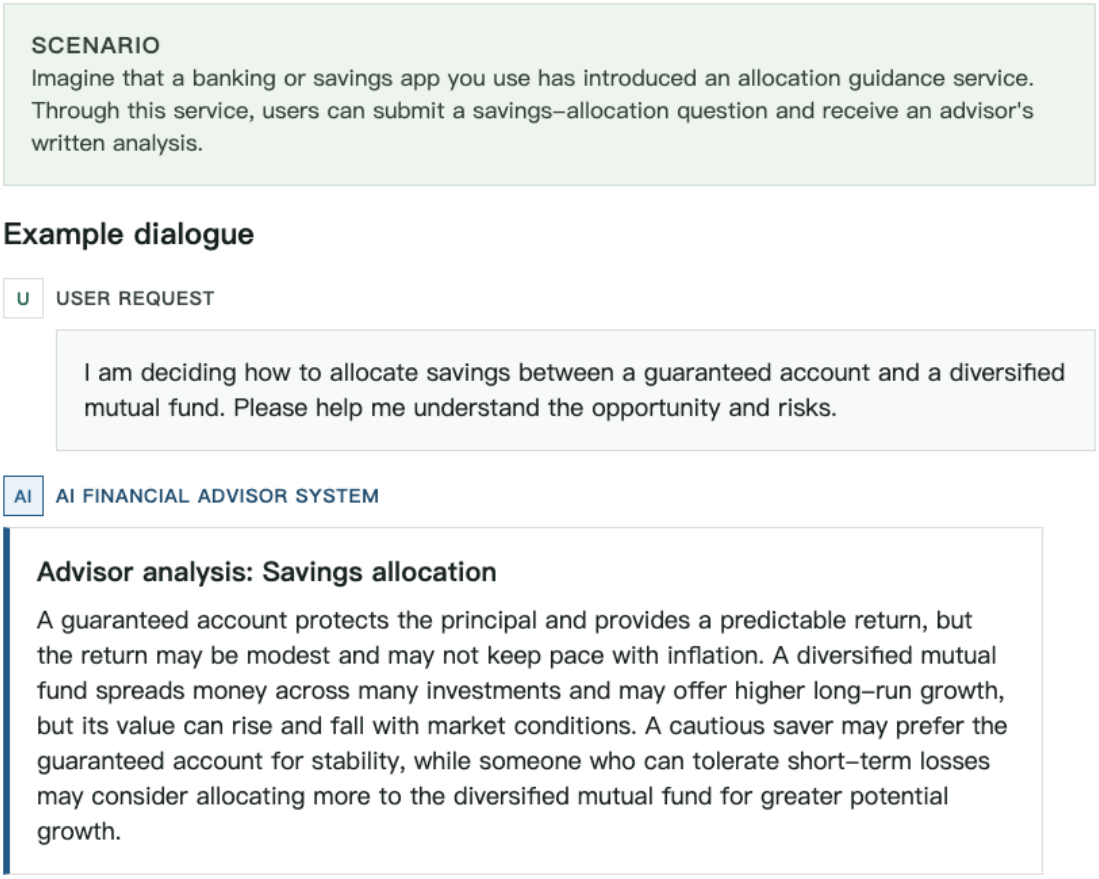


Figure A5. Study 3 AI-advisor HTML dialogue stimulus.

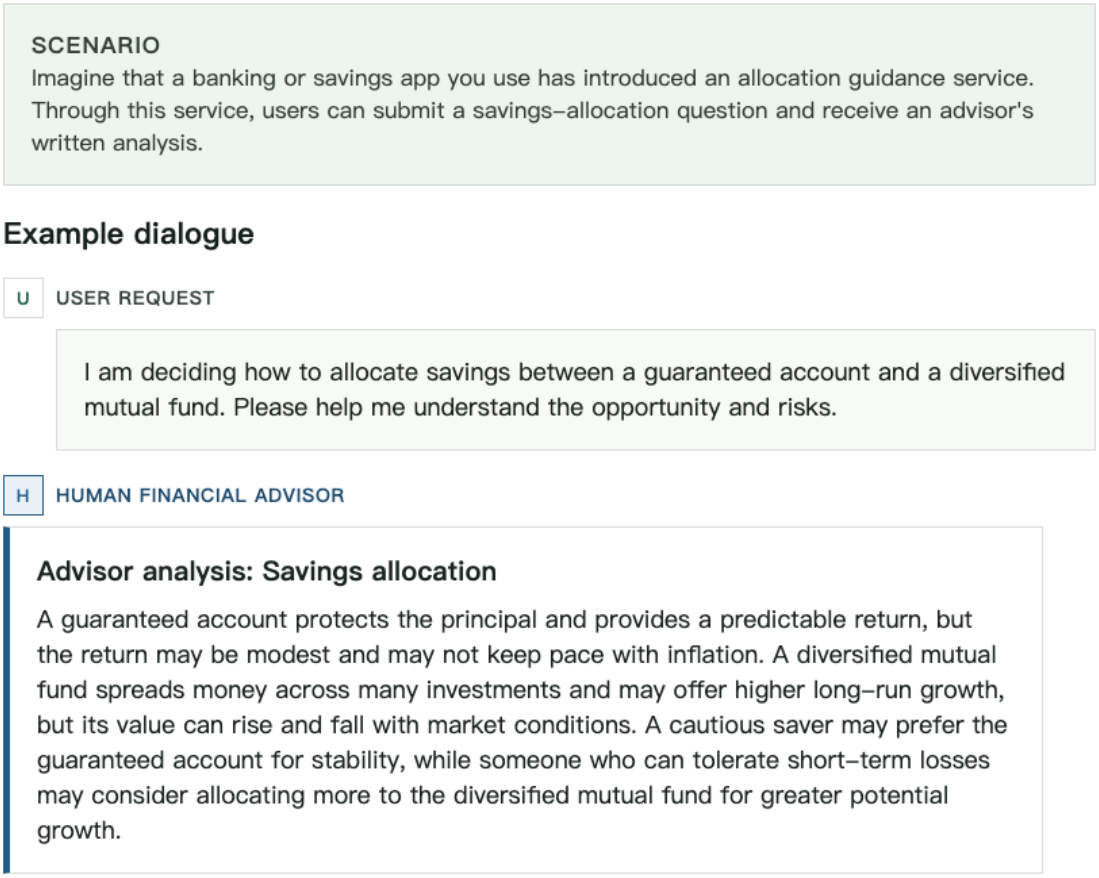


Figure A6. Study 3 human-advisor HTML dialogue stimulus.

Variable Items and Measures

The tables below list the study-specific choice tasks, common process measures, moderators and checks, and additional measures. Shared measures are listed once rather than repeated within each study.

Table A1. Study-specific financial risk-taking propensity tasks.

Study / variable	Task wording and coding
Study 1 stock-analysis task Financial risk-taking propensity Adapted from Duclos et al. (2013)	Stem: Based on the advisor's analysis, please imagine that you have $5,000 to invest for the next 12 months. Please indicate your relative preference between the following two investment portfolios. Option A: Lower-risk portfolio. This portfolio had a 90% chance of gaining $750 and a 10% chance of losing $500. Option B: Higher-risk portfolio. This portfolio had a 50% chance of gaining $2,500 and a 50% chance of losing $1,250. Note: Both portfolios have the same expected value. Scale: 1 = Strongly prefer Option A; 4 = No preference between the two options; 7 = Strongly prefer Option B.
Study 2 retirement-fund task Financial risk-taking propensity Adapted from Duclos et al. (2013)	Stem: Based on the advisor's analysis, please imagine that you have $5,000 to contribute to a retirement account this year. Please indicate your relative preference between the following two options. Option A: Stable income fund. Option B: Diversified growth fund. Scale: 1 = Strongly prefer the stable income fund; 4 = No preference between the two options; 7 = Strongly prefer the diversified growth fund.
Study 3 savings-allocation task Financial risk-taking propensity Adapted from Duclos et al. (2013)	Stem: Based on the advisor's analysis, please imagine that you have $5,000 in savings available for the next 12 months. Please indicate your relative preference between the following two options. Option A: Guaranteed account. Option B: Diversified mutual fund. Scale: 1 = Strongly prefer the guaranteed account; 4 = No preference between the two options; 7 = Strongly prefer the diversified mutual fund.

Table A2. Common advisor-source and process measures.

Construct / source	Item wording, scale, and scoring
Relative risk perception check Author-created check	Item: Which option do you perceive as riskier? Scale: 1 = Option A is much riskier; 4 = The two options are equally risky; 7 = Option B is much riskier.
Advisor-source manipulation check Author-created check	Item: Who did the advisor's financial analysis seem to be provided by? Scale: 1 = Definitely an AI financial advisor system; 4 = Not sure / equally AI and human; 7 = Definitely a human financial advisor.
Perceived attainability of advisor reasoning Adapted from Gartzia et al. (2021)	Stem: To what extent do you agree with the following statements about the advisor's reasoning? Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. Being able to reason like this advisor seems attainable to me. 2. I think I can learn to evaluate financial options like this advisor if I want to. 3. Being like this advisor in evaluating financial decisions seems unrealistic to me. (reverse-coded) Scoring: Mean of the three scored items after reverse-coding the reverse-coded item.

Financial self-efficacy Han et al. (2019)	Stem: To what extent do you agree with the following statements? Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. I am confident that I could deal efficiently with unexpected financial events. 2. Thanks to my resourcefulness, I know how to handle unforeseen financial situations. 3. If I am in financial trouble, I can usually think of a solution. 4. I can usually handle whatever comes my way financially. Scoring: Mean of the four items.
Advice quality Adapted from Wixom and Todd (2005)	Stem: To what extent do you agree with the following statements about the advisor and the analysis? Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. Overall, I would give the advisor's analysis high marks. 2. Overall, I would give the advisor's analysis a high rating in terms of quality. 3. In general, the advisor's analysis provides me with high-quality information. Scoring: Mean of the three items.
Advisor attitude Adapted from Khoso et al. (2026)	Stem: To what extent do you agree with the following statements about the advisor and the analysis? Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. I feel positive toward the advisor described in this scenario. 2. I feel that using this advisor's financial analysis is pleasant. 3. Using this advisor's financial analysis is a good idea. 4. Using this advisor's financial analysis is a smart way to make financial decisions. Scoring: Mean of the four items.

Table A3. Study-specific moderators and manipulation checks.

Study / source	Item wording, response options, and scoring
Study 2 financial literacy moderator Lusardi and Mitchell (2014)	Measure: Three standard financial literacy questions summarized by Lusardi and Mitchell (2014). Items: 1. 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? Response options: More than $102; Exactly $102; Less than $102; Do not know. Correct answer: More than $102. 2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account? Response options: More than today; Exactly the same as today; Less than today; Do not know. Correct answer: Less than today. 3. True or false: Buying a single company stock usually provides a safer return than a stock mutual fund. Response options: True; False; Do not know. Correct answer: False. Scoring: Correct answer = 1; incorrect or do-not-know answer = 0; sum of the three scored items, ranging from 0 to 3. In the Study 2 analysis, financial literacy was mean-centered and treated as a continuous moderator.

Study 3 mindset engagement item Author-created comprehension check	Item: Which statement best summarizes the research summary you just read? Response options: Items: A. People can improve their financial reasoning over time. B. People's financial reasoning ability is relatively stable. C. The summary compared AI advisors and human advisors. Scoring: Growth financial-ability mindset condition correct answer = A; fixed financial-ability mindset condition correct answer = B; option C is a distractor indicating confusion with the advisor-source manipulation. This item was used as an engagement/comprehension item rather than as the focal manipulation check.
Study 3 financial-ability mindset manipulation check Adapted from Levy et al. (1998), Rai and Lin (2019), and Montford et al. (2019)	Stem: Please indicate how much you agree with each statement. Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. People can substantially improve their ability to analyze financial investments. 2. No matter who they are, people can significantly improve their financial reasoning. 3. A person's ability to evaluate investment information is something basic about them, and it cannot be changed very much. (reverse-coded) 4. People can learn new ways to recognize risk-return patterns in financial information. Scoring: Mean of the four scored items after reverse-coding the reverse-coded item.

Table A4. Additional measures and demographics.

Measure / source	Item wording, response options, and scoring
Risk averseness Nenkov et al. (2009)	Stem: In your daily life, to what extent do you agree with the following statements? Scale: 1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree. Items: 1. I would rather be safe than sorry. 2. I want to be sure before I purchase anything. 3. I avoid risky things. Scoring: Mean of the three items.
Demographics Author-created demographics	Biological sex assigned at birth: Male = 0; Female = 1; Intersex = 2; Prefer not to say = 3. Age in years.