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

Abstract

Financial service providers increasingly deliver investment advice through both human professionals and AI-enabled advisory systems, but the same recommendation may have different consequences for how consumers evaluate their own financial capability. This research examines whether advisor source changes consumers' financial self-efficacy and financial risk-taking propensity when advice content is held constant. 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 feel more attainable, which increased financial self-efficacy and, 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 or advisor attitude. 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 showed that the effect was stronger under a growth financial-ability mindset rather than fixed. The findings identify perceived attainability of advisor reasoning as a self-directed mechanism through which advisor source shapes consumer financial agency.

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Introduction

AI-enabled financial advice is changing not only how consumers receive investment guidance, but also how they understand their own role in financial decision-making. Consumers may now receive similar investment recommendations from a human advisor in a branch, online consultation, or wealth-management service encounter, or from an AI-enabled advisory interface such as a robo-advisory platform or consumer-facing generative AI tool. Robo-advisers are commonly described as automated digital investment advisory programs that collect information about consumers' goals, investment horizon, income, assets, and risk tolerance, and then use that information to create and manage investment portfolios (U.S. Securities and Exchange Commission, 2025; U.S. Securities and Exchange Commission Office of Investor Education and Advocacy, 2017). Financial-service providers and fintech platforms increasingly offer automated portfolio construction, low-minimum digital advice, automatic rebalancing, and hybrid forms of human support (Vanguard, 2024). As a result, advisor source—whether advice comes from a human or an AI advisor—has become a highly visible feature of consumer financial services.

The rise of AI-enabled advice creates a theoretically important question for consumer research. AI advice may be scalable, analytically sophisticated, and useful for expanding access to financial guidance. Yet confidence in an advice source need not translate into confidence in the self. A consumer may regard an AI advisor as accurate or powerful while still experiencing its reasoning as distant from what they themselves could understand or reproduce. Conversely, a human advisor may make the same financial reasoning feel more attainable because the source is another person rather than an external computational system. Thus, advisor source may shape not only how consumers evaluate the advisor or the recommendation, but also how consumers evaluate themselves as financial decision makers.

Prior research has examined robo-advice and AI-enabled financial advice from several important perspectives. Work on robo-advice shows that automated advisory systems can expand access to financial guidance, change the economics of household advice, and sometimes substitute for traditional human advice (Brenner & Meyll, 2020; Cardillo & Chiappini, 2024; D'Acunto et al., 2019; D'Acunto & Rossi, 2023). Related consumer research has examined when people accept, reject, or rely on AI-enabled investment advice, including the roles of perceived accuracy, firm type, trust, and willingness to follow recommendations (Chua et al., 2023; Northey et al., 2022; Zhang et al., 2021). Broader advice-taking and algorithmic-advice research similarly shows that consumers do not treat all advice sources as equivalent and may rely on, discount, or avoid algorithmic judgment depending on task characteristics and experience with algorithmic error (Bonaccio & Dalal, 2006; Castelo et al., 2019; Dietvorst et al., 2015; Logg et al., 2019; Yaniv, 2004).

Recent retailing and consumer-services research has begun to specify these processes within AI financial services and AI-generated advice. The closest adjacent work is Chang et al. (2026), who show that credibility- and benevolence-based trust in AI financial services can foster vicarious learning, strengthen financial self-efficacy, and promote adoption of AI-enabled financial services. We build from this insight but shift the theoretical target. Chang et al. explain how trust supports adoption of AI financial services. We ask whether identical financial reasoning changes consumers' beliefs about their own capability when it is attributed to a human rather than AI advisor. This distinction moves the explanatory focus from trust in an AI service to advisor source under constant advice content, and it moves the outcome from AI-service adoption to financial risk-taking propensity. Other AI-advice work similarly explains acceptance, resistance, satisfaction, helpfulness, perceived value, and intrusiveness (Huang, 2026; Meng & Xiao, 2026; Zobair et al., 2026). These studies leave

open whether advisor source changes consumers' self-directed inferences about financial capability.

This literature establishes that human and AI advisors are psychologically consequential sources of financial advice. However, much of it focuses on advisor-directed evaluations: whether consumers perceive the advisor as competent, trustworthy, accurate, useful, or worth following. Less is known about a self-directed consequence of advisor source: whether the source of financial advice changes what consumers infer about their own capability to understand and handle financial decisions. This distinction matters because financial advice is not only information to be accepted or rejected. It can also serve as a model of reasoning. When consumers encounter an advisor's reasoning, they may ask not only "Is this advisor competent?" but also "Is this kind of reasoning something I could understand, learn, or use?"

The present research examines this self-evaluative consequence of advisor source. We propose that human financial advisors can increase consumers' financial self-efficacy relative to AI advisors when the advisor's reasoning appears attainable to consumers. Financial self-efficacy refers to consumers' perceived capability to manage financial tasks and make financial decisions (Lown, 2011). The key psychological shift is not simply that the advisor seems competent or that the recommendation seems accurate. Rather, human-sourced advice may make the reasoning behind the recommendation feel more understandable, learnable, and personally reproducible by people like the consumer. We refer to this judgment as perceived attainability of advisor reasoning.

Perceived attainability of advisor reasoning is distinct from perceived advice quality, advisor trust, and recommendation acceptance. A consumer may believe that an AI recommendation is accurate without seeing the underlying reasoning as personally attainable. Similarly, a consumer may understand the content of a recommendation without feeling that

they could learn to reason in that way. Our account therefore shifts the focus from confidence in the advisor to confidence in the self. We argue that human advisor source can make financial reasoning more self-diagnostic: because the reasoning is attributed to another person, consumers may be more likely to see it as a form of humanly learnable financial judgment. AI advisor source, by contrast, may lead consumers to attribute the same reasoning to computational capacity, data access, or algorithmic processing that does not imply greater personal capability.

This self-efficacy pathway has implications for financial risk-taking. Financial decisions often involve uncertain returns, potential losses, and tradeoffs that consumers may find difficult to evaluate. When consumers feel less capable of understanding the decision, risk-bearing options may seem opaque and hard to manage. When they feel more capable, the same options may appear more evaluable and manageable. We therefore predict that human-sourced advice, relative to AI-sourced advice, will increase financial risk-taking propensity through a serial process: human advisor source increases perceived attainability of advisor reasoning, perceived attainability of advisor reasoning increases financial self-efficacy, and financial self-efficacy increases financial risk-taking propensity. Importantly, this prediction does not assume that human advice is objectively better than AI advice. The proposed effect arises because advisor source changes whether the reasoning feels relevant to the consumer's own possible capability.

We further propose that this process is bounded by consumers' financial literacy and financial-ability mindset. Financial literacy should qualify the first stage of the process because consumers with more financial knowledge have stronger internal standards for judging whether financial reasoning is understandable and reproducible. For these consumers, advisor source should provide less incremental information about whether the reasoning is personally attainable. Consumers with lower financial literacy, by contrast, may rely more on

the source cue when deciding whether the reasoning belongs to a humanly learnable domain. Thus, the human-advisor advantage in perceived attainability of advisor reasoning should be stronger among lower-literacy consumers. Financial-ability mindset should also moderate the first stage. When consumers believe that financial reasoning can be developed, human-sourced reasoning should be more readily interpreted as learnable and transferable to the self. Under a fixed financial-ability mindset, the same human advisor may instead signal an ability gap, weakening the effect on perceived attainability of advisor reasoning.

Across three experiments, we test this attainability-based self-efficacy account. Study 1 tests the proposed serial process by examining whether human, compared with AI, advisor source increases perceived attainability of advisor reasoning, financial self-efficacy, and financial risk-taking propensity. Study 2 examines financial literacy as a measured first-stage boundary condition, testing whether the human-advisor advantage in perceived attainability of advisor reasoning is stronger among consumers with lower financial literacy. Study 3 manipulates growth versus fixed financial-ability mindset, testing whether human advisor source has a stronger effect when consumers construe financial reasoning as learnable.

This research makes three contributions. First, it separates AI-financial-service adoption from advisor-source-based self-inference. Recent work shows that trust in AI financial services can strengthen financial self-efficacy and adoption (Chang et al., 2026). We show a different effect: advisor source can change what consumers infer about their own financial capability even when advice content is held constant. Second, it contributes to self-efficacy, social comparison, and role-modeling research by identifying perceived attainability of advisor reasoning as the mechanism that makes human-sourced financial reasoning self-diagnostic. Third, it contributes to consumer financial services and welfare research by linking this self-directed inference to financial risk-taking propensity rather than to service adoption. The findings specify when human support is most likely to increase financial

agency: among consumers with lower measured financial literacy and when financial-ability mindset is construed as developable. They also qualify the welfare implications of human support. A human advisor source may help consumers approach financial risk as more understandable and manageable, but it may also require safeguards against overconfidence and unsuitable risk-taking.

Theoretical Framework and Hypothesis Development

Advisor-Source Cues in Financial Decisions

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

The present research focuses on one specific feature of financial advice: its 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 can guide search, comparison, and choice construction, making the aid part of the decision environment rather than a passive information display (Häubl & Trifts, 2000). This logic is especially relevant for AI-enabled financial advice because consumer-AI interactions involve not only information provision but also delegation and social experience, both 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 are not psychologically interchangeable. Consumers may 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), and AI-generated personalized solutions may be perceived as less unique than human-provided solutions (Hou et al., 2026). In high-uncertainty advice contexts, human sources can also be evaluated more favorably or as more diagnostic than AI sources (Niu et al., 2026; Söderlund, 2026). These findings support the premise that source labels can carry psychological meanings beyond the informational content of advice.

Recent consumer-AI research suggests that agent source can alter how consumers interpret otherwise similar recommendations. However, most existing accounts emphasize confidence in the advisor, such as perceived expertise, trustworthiness, personalization quality, or humanlikeness. We focus on a different implication of source: whether the reasoning behind the recommendation is perceived as attainable for the consumer. In financial decisions, the same advice may be interpreted either as a form of humanly learnable reasoning or as the output of an external computational system. This distinction shifts the focus 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 is distinct from perceived advice quality. A recommendation may appear accurate without making the underlying reasoning feel attainable. It is also distinct from mere comprehensibility. Consumers may understand the content of an AI recommendation while still attributing the reasoning to computational capacities that are unavailable to them. perceived attainability of advisor reasoning captures whether the reasoning functions as a model for the consumer's own possible capability.

Accordingly, we distinguish 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 work on human versus algorithmic advice has primarily emphasized the first consequence. Our account focuses on the second. A human advisor may make financial reasoning appear more attainable for the self, whereas AI advice may be attributed to computational resources that do not imply greater personal capability. Therefore, the proposed effect does not require consumers to believe that human advice is objectively superior to AI advice. It requires only that human-sourced reasoning be more self-diagnostic.

This research therefore contributes to advice-taking and consumer-AI research by identifying a self-efficacy pathway through which advisor source affects financial risk-taking. This pathway complements, but differs from, AI-financial-service trust models in which trust enables vicarious learning, financial self-efficacy, and adoption (Chang et al., 2026). We do not ask whether consumers trust AI enough to adopt an AI-enabled service. We ask whether the same financial reasoning becomes more self-diagnostic when it is attributed to a human advisor rather than to AI. When financial reasoning is attributed to a human advisor, it may appear more attainable, learnable, and self-relevant, thereby increasing consumers' financial self-efficacy. When the same reasoning is attributed to AI, consumers may still view the recommendation as competent, but the reasoning may be less informative about their own capability. This distinction explains how source cues can shape financial risk-taking propensity even when advice content is held constant.

Human Advisors as Attainable Models of Financial Reasoning

Self-efficacy theory identifies vicarious experience as one 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 similarly argues that people evaluate their abilities by comparing themselves with others when objective standards are ambiguous (Festinger, 1954). The proxy model of social comparison sharpens this point: 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 the same reasoning, when attributed to a person, is more likely to be categorized as humanly learnable. This claim does not require consumers to believe that they are already as skilled as a professional advisor. Rather, the argument is that a human advisor's reasoning can make financial analysis feel like a form of reasoning that people can understand, practice, and develop. If the advisor explains tradeoffs, interprets risk, and translates financial information into understandable steps, consumers may infer that the task is not merely solvable by an external system but is also within the broader domain of human reasoning.

This argument is consistent with role-model theory. Role models influence observers not simply because they display high performance, but because they can make desired end states appear attainable and clarify possible paths to attainment (Morgenroth et al., 2015). In the present context, the relevant end state is the consumer's perceived ability to understand, evaluate, and act on a financial decision. A human advisor can make this state appear attainable not because consumers expect to become experts, but because the advisor's reasoning can be construed as humanly learnable. Thus, the advisor functions not only as a source of advice but also as a model of possible financial reasoning.

This emphasis on attainability is important because upward comparisons do not always improve self-evaluation. They can also produce contrast when the comparison target feels distant, elite, or impossible to emulate (Collins, 1996). Role models are more likely to

inspire self-enhancement when their success seems attainable rather than unreachable (Lockwood & Kunda, 1997). Likewise, social comparison can produce assimilation or contrast depending on whether people focus on similarities or dissimilarities between the self and the target (Mussweiler et al., 2004). Thus, our account does not assume that human advisors are automatically proximal. The predicted self-efficacy benefit should arise when the advisor's reasoning appears understandable, learnable, and relevant to people like the consumer.

AI advisors provide a useful contrast. AI may be perceived as competent in analytic and utilitarian domains, and consumers may sometimes prefer or weight algorithmic advice in judgment tasks (Logg et al., 2019). Algorithmic advice may also be especially acceptable when the task appears objective, analytical, or quantitative (Castelo et al., 2019). The present theory therefore does not require AI to be viewed negatively or seen as low quality. Instead, it distinguishes perceived advisor competence from perceived self-capability. AI competence may be attributed to data access, computational capacity, or machine-learning processes that are not available to the consumer. When that happens, AI advice may increase confidence in the recommendation without increasing confidence in the self. The consumer may think "the AI can do this" without concluding "I can do this."

This distinction is central to the present account. A human advisor and an AI advisor may provide the same recommendation and may even be evaluated similarly in terms of accuracy or usefulness. Yet their reasoning can differ in self-diagnostic value. Human-sourced reasoning may imply that the task belongs to a domain of learnable human judgment. AI-sourced reasoning may imply that the task is handled through computational capacity external to the consumer. Thus, advisor source can shape whether the advice becomes a model for the consumer's own possible competence.

Recent work on generative AI as a social referent clarifies the boundary of this argument. 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 attenuated in fact-based domains, where AI is less likely to be seen as a lower social referent. Financial analysis fits the latter class more closely than the former. 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 less likely to operate as a downward or peer-like comparison target and more likely to function as an external computational referent. AI advice may therefore appear competent without making the reasoning feel personally attainable. The relevant contrast is not whether AI is capable, but whether its reasoning lets consumers infer that they themselves 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). The construct is task-focused. It is not the same as general optimism, self-esteem, or belief that an outcome will be favorable. In financial contexts, financial self-efficacy captures consumers' perceived capability to manage financial tasks and decisions (Lown, 2011). This perceived capability has behavioral relevance because financial self-efficacy predicts financial behavior beyond objective financial literacy alone (Farrell et al., 2016). This distinction is important because financial literacy and financial education, although relevant, often explain only limited variance in downstream financial behaviors (Fernandes et al., 2014). Consumers' financial behavior therefore cannot be reduced to objective knowledge; perceived capability also matters.

We define financial self-efficacy in this context as consumers' perceived capability to understand, evaluate, and act on financial decisions involving uncertainty. This definition is

task-specific. It does not refer to perceived advice quality, perceived recommendation accuracy, or general optimism about financial outcomes. Rather, it captures whether consumers feel more capable of handling the financial judgment after encountering the advisor's reasoning. We use the term vicarious only to describe one route through which such efficacy beliefs may arise: consumers observe a model of financial reasoning and infer that the task is more personally manageable.

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

Financial self-efficacy should then increase financial risk-taking propensity. Financial risk-taking requires consumers to tolerate uncertainty, evaluate possible losses, and act despite incomplete information. It is also domain-specific: financial risk-taking and financial risk tolerance are commonly treated as distinct from general risk preference because financial choices involve particular 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 difficult to evaluate and hard to control. A consumer who feels capable may view the same option as more manageable, even when the objective risk is unchanged.

The proposed mechanism concerns financial risk-taking propensity that feels evaluable, not impulsive risk seeking. When consumers feel capable of understanding the financial tradeoff, they may be more willing to choose a risk-bearing option because uncertainty appears more manageable. Thus, financial self-efficacy should increase financial

risk-taking propensity through perceived manageability rather than through a generalized preference for risk.

Evidence from financial self-efficacy research supports this link. Financial self-efficacy is associated with consequential financial behaviors, including saving, investment-related behavior, and financial product holding (Farrell et al., 2016; Hoffmann & Plotkina, 2021; Lown, 2011). More directly, investment-risk research links financial self-efficacy to willingness to take investment risk (Montford & Goldsmith, 2016). Related behavioral-finance work also 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 necessarily imply better decision quality. The same perceived-capability process that helps consumers choose risk-bearing options 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 that consumers make objectively superior choices.

Main Effect and Serial-Mediation Hypotheses

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

Second, this effect should operate through a serial psychological process. Human advisor source cues should first increase perceived attainability of advisor reasoning. When the same financial analysis is attributed to a human advisor, consumers should be more likely

to see the reasoning as understandable, learnable, and personally reproducible than when it is attributed to AI. This perception makes the advisor's reasoning more informative for the consumer's own possible competence. As a result, consumers should report greater financial self-efficacy. Higher financial self-efficacy should then increase financial risk-taking propensity because the decision feels less opaque and more personally manageable.

This serial-mediation logic clarifies the contribution of the theory. The proposed effect is not that human advisors are objectively better than AI advisors, nor that consumers simply evaluate human advisors more favorably. The effect arises because human advisors can make financial reasoning appear more attainable for the self. The source cue matters because it changes whether the advisor's reasoning is perceived as relevant to the consumer's own possible capability.

This account also distinguishes the proposed mechanism from several adjacent explanations. One possibility is perceived advice quality: consumers may believe that one source provides more accurate recommendations. A second possibility is advisor-directed trust or liking: consumers may simply feel more favorable toward one advisor type. A third possibility is general algorithm aversion or autonomy concern: consumers may resist AI advice because it feels less self-directed (André et al., 2018). Recent AI-service research similarly shows that resistance can arise from perceived intrusiveness and trust concerns (Chen & Cheng, 2026), loss of meaningful cognitive engagement and autonomy threat (Sreejesh et al., 2025), or conflict between algorithmic recommendations and consumers' intuition (Sreejesh & Singha, 2026). These explanations concern evaluations of the advisor or the decision process. By contrast, our account concerns a self-directed inference: whether the advisor's reasoning makes consumers feel more capable of handling the financial task. The proposed serial pathway therefore requires changes in perceived attainability of advisor reasoning and financial self-efficacy, not merely more favorable evaluations of human advice.

This distinction also helps separate the present account from stable risk preference. Consumers may differ in their general willingness to take risks, but the proposed process concerns a source-induced change in perceived financial task capability. If consumers choose risk-bearing options merely because they are chronically less risk averse, the observed behavior would not support the proposed mechanism. The present account predicts that advisor source affects financial risk-taking propensity through a specific psychological pathway: human-sourced reasoning increases perceived attainability of advisor reasoning, perceived attainability of advisor reasoning increases financial self-efficacy, and financial self-efficacy increases financial risk-taking propensity.

H1: In a financial-advice context where recommendation content is held constant, consumers who receive advice from a human financial advisor, rather than an AI financial 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 not operate equally for all consumers. If human advisors increase financial risk-taking propensity because their reasoning appears attainable for the self, then the effect should depend on when consumers need external source information and when they construe the relevant ability as learnable. We therefore examine two boundary conditions that target the first stage of the serial process: financial literacy and mindset about

financial-ability mindset. Both concern when advisor source should change perceived attainability of advisor reasoning, rather than whether human advice is more accurate or more credible than AI advice. Financial literacy concerns consumers' measured knowledge base for evaluating financial reasoning. Financial-ability mindset concerns whether human financial reasoning is interpreted as developable.

Financial Literacy

Financial literacy should qualify the effect of advisor source at the first stage of the process because objective financial knowledge is associated with how much consumers need source information when judging 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. Financial literacy provides a domain-specific knowledge base that consumers can use when interpreting financial information and assessing whether they could understand similar reasoning themselves.

Consumers with higher financial literacy should have more internal basis for evaluating whether the advisor's reasoning is understandable and personally reproducible. For these consumers, whether the advisor is human or AI should add less incremental self-diagnostic information. They may still evaluate the advice positively and may still benefit from advice, but advisor source should be less important for judging whether the reasoning is attainable. Their own domain knowledge provides a standard for interpreting the reasoning, reducing reliance on the source cue.

Consumers with lower financial literacy should be more responsive to the human-advisor cue when forming perceived attainability of advisor reasoning. With less domain-specific knowledge available for independently evaluating the analysis, the source of the

reasoning can provide more information about whether the reasoning is humanly understandable. A human advisor's reasoning can signal that the task is not merely computationally solvable but can be interpreted through human financial reasoning. By contrast, the same analysis attributed to AI may still appear competent while remaining less informative about the consumer's own possible capability.

This argument is not that lower-literacy consumers are less intelligent or generally less capable. Rather, the claim is that measured financial knowledge is associated with the diagnostic value of the source cue. Higher-literacy consumers can use their own knowledge to evaluate whether the reasoning is understandable and reproducible, making source less informative for perceived attainability of advisor reasoning. Lower-literacy consumers have fewer internal standards for making this judgment, so the human source cue should be more diagnostic of whether the reasoning belongs to a learnable human domain.

Thus, the first stage of the serial process should vary with financial literacy. Because Study 2 measures rather than manipulates financial literacy, this prediction concerns an individual-difference pattern, not a causal effect of changing 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 is expected to increase financial self-efficacy, which then increases financial risk-taking propensity, the full serial indirect effect should also be stronger among consumers with lower rather than higher financial literacy.

H3: Financial literacy will moderate the effect of advisor source on perceived attainability of advisor reasoning, such that the positive effect of a human financial advisor, relative to an AI financial 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 consumers' beliefs about whether financial reasoning can be developed. 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 more adaptive analytic strategies (Wood & Bandura, 1989). Consumer research also links growth mindsets to learning-oriented forms of self-enhancement (Burnette et al., 2013; Mathur et al., 2016).

A growth financial-ability mindset should make a human advisor's 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 a person can reason this way, then similar reasoning may be personally learnable. In other words, a growth mindset makes human financial reasoning psychologically transferable to the self. The advisor's reasoning signals not only that the task can be solved, but also that the relevant capability can be acquired.

In contrast, Under a fixed financial-ability mindset, the same human advisor may 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 who believe that financial-ability mindset is fixed may interpret the advisor's performance as evidence that some people

have the relevant ability and others do not. Under this interpretation, the human advisor remains competent but becomes less useful as a model for the consumer's own possible capability. This logic is consistent with evidence that implicit theories affect whether successful role models increase confidence and identification (Hoyt et al., 2012).

AI advisors should be less sensitive to this mindset process when AI performance is attributed to computational capacity rather than learnable human reasoning. If the AI's output is perceived as the product of data access, algorithmic processing, or machine-learning infrastructure, a consumer's belief that human financial ability can grow may have limited bearing on whether the AI's reasoning feels personally attainable. Thus, the proposed moderation concerns whether advisor reasoning is construed as humanly acquirable. A growth mindset should strengthen the effect of human advisor source because it increases the likelihood that human reasoning will be interpreted as learnable and self-relevant.

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

Accordingly, financial-ability mindset should moderate the effect of advisor source on perceived attainability of advisor reasoning. When consumers hold a growth mindset, human-sourced reasoning should be more likely to function as an attainable model and should therefore produce a stronger increase in perceived attainability of advisor reasoning. When consumers hold a fixed mindset, the same human-sourced reasoning should be less likely to be assimilated into the self and should therefore produce a weaker increase in perceived attainability of advisor reasoning. Because perceived attainability of advisor reasoning

increases financial self-efficacy and financial self-efficacy increases financial risk-taking propensity, the serial indirect effect should be stronger under a growth mindset than Under a fixed financial-ability mindset.

H4: Financial-ability mindset will moderate the effect of advisor source on perceived attainability of advisor reasoning, such that the positive effect of a human financial advisor, relative to an AI financial advisor, on perceived attainability of advisor reasoning will be stronger when consumers hold a growth mindset than when they hold a fixed 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 mindset than Under a fixed financial-ability mindset.

Figure 1 summarizes the proposed attainability-based self-efficacy process and the two first-stage boundary conditions.

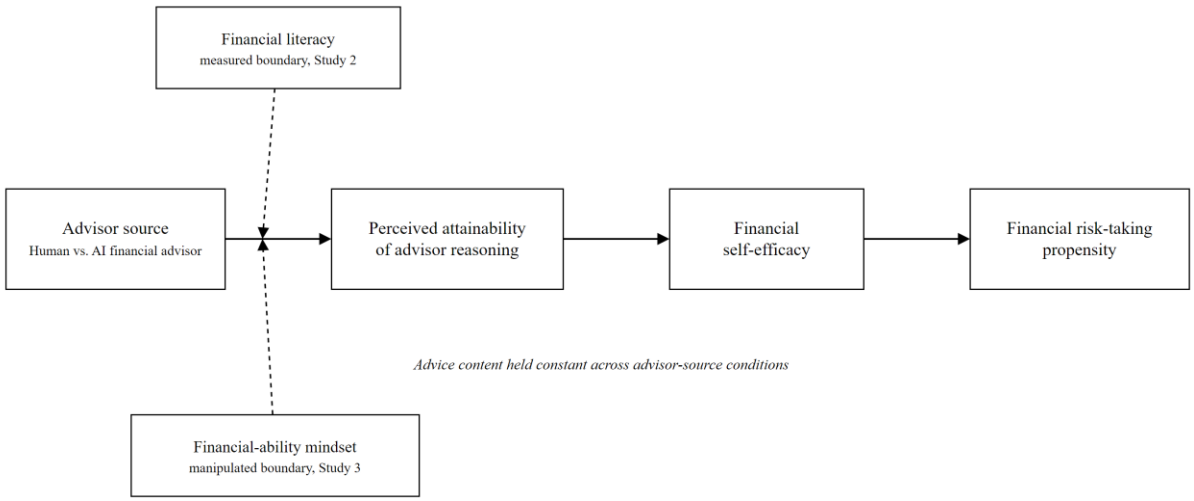


Figure 1. Proposed attainability-based self-efficacy process linking advisor source to financial risk-taking propensity. The model holds advice content constant across advisor-source conditions.

Overview of Studies

Across three studies, we test an attainability-based self-efficacy account of advisor-source effects in financial decision making. Study 1 provides initial evidence for the proposed serial process in a stock-analysis context: holding advice content constant, a human rather than AI advisor increases the perceived attainability of advisor reasoning, which enhances financial self-efficacy and, in turn, increases preference for a higher-risk investment portfolio. Study 2 conceptually replicates the first-stage process in a retirement-fund allocation context and provides measured-moderator evidence consistent with financial literacy as a boundary condition. Study 3 tests the mindset boundary condition in a savings-allocation context involving a guaranteed account and a diversified mutual fund. Together, the studies test the same psychological process across distinct financial decisions and show when human advisor cues become self-diagnostic.

Study 1: Full Mechanism Test

Study 1 examines whether a human, compared with an AI, advisor source increases perceived attainability of advisor reasoning, which in turn increases financial self-efficacy and strengthens preference for a higher-risk investment portfolio. The study also tests whether the proposed process can be distinguished from advice-quality, advisor-attitude, and stable risk-aversion explanations.

Method

Study 1 used data collected from 200 U.S.-based participants recruited through Prolific (*M*age = 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 they often use had introduced a new advice service. All participants read the same user request, financial-advice scenario, and stock-analysis sample

concerning 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. No certification, licensing, professional credential, or regulatory-status information was provided in either condition. The common analysis described steady revenue growth, stock-price volatility, competitive uncertainty, potential upside, and downside risk, and was framed as decision support only.

After reading the analysis, participants completed the focal process measures and the financial risk-taking task in the post-manipulation survey.

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 primary dependent variable was preference for the higher-risk portfolio on a 1–7 scale. The two portfolios were matched on expected value. The higher-risk option had greater return variance, a higher probability of loss, a larger maximum loss, and a larger potential gain. Full portfolio descriptions are reported in the Appendix.

Perceived attainability of advisor reasoning was measured with three items adapted from the attainable role-model measure in Gartzia et al. (2021) and reworded for advisor reasoning in an investment decision context. Financial self-efficacy was measured with four items from Han et al. (2019), assessing participants' perceived capability to handle unexpected financial events and financial trouble. Thus, the financial self-efficacy measure captures perceived financial coping capability after exposure to the advisor-source cue.

The study further measured competing explanations and controls. Advice quality was measured with items adapted from the information-quality scale in Wixom and Todd (2005). Advisor attitude was measured with items adapted from the Attitude Toward AI items in

Khoso et al. (2026) and reworded for the focal advisor. Risk averseness was measured with three items from Nenkov et al. (2009).

Results

The manipulation check was measured on a 1–7 scale indicating whether the investment analysis seemed to be provided by an AI financial advisor system or a human financial advisor, with higher values indicating stronger perceived human source. Responses indicated the intended source perception: 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 manipulation check was analyzed descriptively and was not used as an exclusion criterion. A portfolio risk perception check confirmed that Option B was perceived as riskier than Option A ($M = 5.51$, $SD = 1.27$).

The multi-item scales showed strong reliability. Reliability was high for perceived attainability of advisor reasoning ($\alpha = .90$) and financial self-efficacy ($\alpha = .88$). The competing-explanation and control measures also showed strong reliability, including advice quality ($\alpha = .87$), advisor attitude ($\alpha = .88$), and risk averseness ($\alpha = .92$).

Descriptively, participants in the human-advisor condition perceived the advisor's reasoning as more attainable than participants in the AI-advisor condition ($M = 4.95$, $SD = 1.39$ vs. $M = 4.20$, $SD = 1.27$). They also reported higher financial self-efficacy ($M = 4.78$, $SD = 1.42$ vs. $M = 3.88$, $SD = 1.35$) and showed stronger preference for the higher-risk portfolio ($M = 4.48$, $SD = 1.50$ vs. $M = 3.63$, $SD = 1.23$).

The corresponding equal-variance t tests supported H1 and the first-stage logic of H2. Participants in the human-advisor condition perceived the advisor's reasoning as more attainable than participants in the AI-advisor condition, $t(198) = 3.97$, $p < .001$, $d = 0.56$. Participants in the human-advisor condition also reported higher financial self-efficacy than those in the AI-advisor condition, $t(198) = 4.60$, $p < .001$, $d = 0.65$. Participants in the

human-advisor condition showed stronger preference for the higher-risk portfolio than those in the AI-advisor condition, $t(198) = 4.40$, $p < .001$, $d = 0.62$. This result should be interpreted as greater financial risk-taking propensity, not as evidence of objectively better financial behavior.

Serial mediation analyses using PROCESS Model 6 tested the proposed serial 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 ($b = 0.52$, $p < .001$), and financial self-efficacy positively predicted financial risk-taking propensity controlling for condition and perceived attainability of advisor reasoning ($b = 0.56$, $p < .001$), consistent with H2.

A PROCESS Model 6 analysis with 5,000 bootstrap samples showed that the serial indirect effect from advisor source to financial risk-taking propensity through perceived attainability of advisor reasoning and financial self-efficacy excluded zero (Ind3 = 0.22, 95% CI [0.10, 0.37]). The indirect path through perceived attainability of advisor reasoning alone did not exclude zero (Ind1 = −0.07, 95% CI [−0.18, 0.03]), whereas the indirect path through financial self-efficacy alone excluded zero (Ind2 = 0.29, 95% CI [0.07, 0.52]). Thus, the data support the hypothesized serial pathway while also showing an additional indirect component through financial self-efficacy alone, which suggests that perceived attainability of advisor reasoning may not capture all routes through which advisor source affects efficacy beliefs.

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

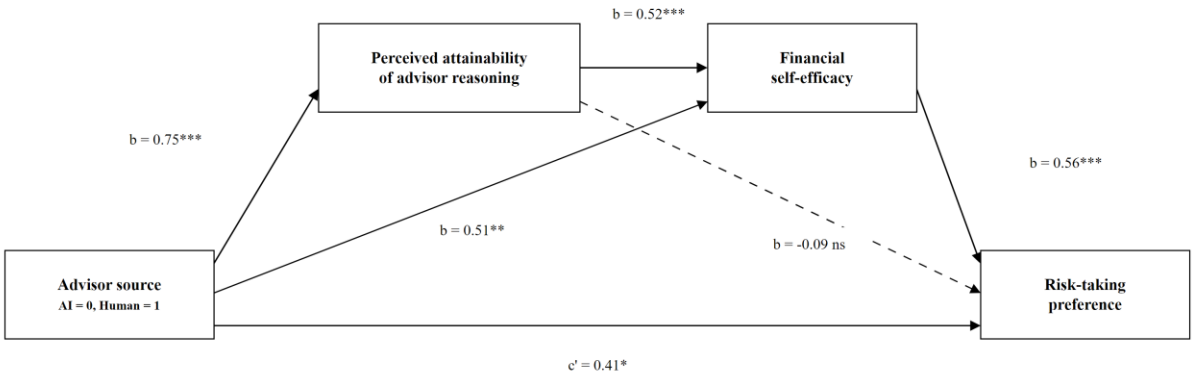


Figure 2. Complete PROCESS Model 6 serial mediation path estimates in Study 1. Coefficients are unstandardized. Dashed path is not significant. The indirect effect through perceived attainability of advisor reasoning alone was −0.07, 95% CI [−0.18, 0.03]; the indirect effect through financial self-efficacy alone was 0.29, 95% CI [0.07, 0.52]; and the serial indirect effect was 0.22, 95% CI [0.10, 0.37].

A competing-mediator regression provided evidence against several 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 ($b = −0.09$, $p = .211$), which is consistent with the serial account: attainability is theorized to affect risk-taking primarily through financial self-efficacy rather than through a direct path to risk preference. 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 in the full model ($b = 0.42$, $p = .019$), indicating that the focal self-efficacy process explains part of the observed condition difference while leaving some residual condition variance.

Discussion

Study 1 provides initial evidence for the proposed serial mechanism. 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 helps distinguish this process from advice-quality and advisor-attitude explanations, suggesting that the effect is not simply driven by the measured favorable evaluations of human advisors.

These findings support the proposed attainability-based mechanism: when advisor reasoning appears more humanly attainable, participants appear more likely to translate the advice context into confidence in their own financial capability. This self-efficacy pathway helps explain why a human advisor source can increase financial risk-taking propensity relative to an AI advisor source.

At the same time, the behavioral implication should be interpreted carefully. The higher-risk portfolio preference observed in the human-advisor condition reflects greater financial risk-taking propensity, not necessarily superior financial decision-making. The task held expected value constant across portfolios and was designed to capture risk preference in an investment context rather than objective investment performance. Thus, Study 1 supports the proposed psychological process while leaving open whether human-advisor-induced self-efficacy improves or worsens downstream financial outcomes in more consequential settings.

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. The logic is that consumers with lower financial literacy have fewer internal knowledge anchors when evaluating a financial task and should therefore rely more on external source cues when judging whether the reasoning is personally manageable. For these consumers, a human advisor's reasoning should feel especially attainable relative to an AI advisor's reasoning because it indicates that the analysis is humanly understandable, not merely computationally solvable. This placement

treats financial literacy as a measured individual-difference boundary on source-to-self inference, not as a manipulated moderator or as a general moderator of risk preference.

Method

Study 2 used data collected from 300 U.S.-based participants recruited through Prolific (*M*age = 35.44 years, *SD* = 11.64; 153 females).

The study used the same advisor-source manipulation logic and process measures as Study 1, but placed the advice in a different financial decision context. Participants imagined using a retirement-account planning service, contributing $5,000 to a retirement account, and reading an advisor analysis comparing a stable income fund with a diversified growth fund. The primary dependent variable was relative preference for the diversified growth fund on a 1–7 scale, with higher values indicating greater willingness to choose the risk-bearing retirement option. The new focal variable was financial literacy. Financial literacy was measured with the three standard financial literacy questions summarized by Lusardi and Mitchell (2014), covering compound interest, inflation, and risk diversification. Each correct answer was coded as 1, and each incorrect or "do not know" answer was 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. Advisor source was coded 0 = AI advisor and 1 = human advisor. Financial literacy was mean-centered before constructing the advisor source × financial literacy interaction term. The focal conditional-process model tested whether financial literacy moderated the effect of advisor source on perceived attainability of advisor reasoning and whether this first-stage moderation carried forward through financial self-efficacy to financial risk-taking propensity.

Results

The perceived-source check indicated the intended advisor-source perception, with lower scores in the AI-advisor condition ($M = 1.67$, $SD = 0.83$) and higher scores in the human-advisor condition ($M = 6.11$, $SD = 0.91$). The relative risk 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 ($\alpha = .93$) and financial self-efficacy ($\alpha = .89$).

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. $M = 3.68$, $SD = 1.48$). Financial literacy scores were $M = 1.64$ ($SD = 0.96$) in the human-advisor condition and $M = 1.44$ ($SD = 0.99$) in the AI-advisor condition.

Consistent with H3, measured financial literacy qualified the effect of advisor source on perceived attainability of advisor reasoning. Advisor source was coded 0 = AI advisor and 1 = human advisor. Financial literacy was treated as a measured continuous moderator and was mean-centered before constructing the interaction term. 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 ($b = -0.17$, $SE = 0.29$, $t = -0.58$, $p = .562$).

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 ($b = 0.64$, $p < .001$), and financial self-efficacy positively predicted financial risk-taking propensity controlling for condition, perceived attainability of advisor reasoning, and financial literacy ($b = 0.46$, $p < .001$).

We then tested the theorized first-stage conditional serial indirect effect using PROCESS Model 83 with 5,000 bootstrap samples. 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. Because financial literacy was measured rather than manipulated, the interaction should be interpreted as an individual-difference pattern, not as evidence that experimentally changing financial literacy would causally alter the advisor-source effect. The advisor-source 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 is consistent with the claim that consumers with fewer measured financial knowledge anchors rely more heavily on advisor source when judging whether financial reasoning is personally manageable. For these consumers, a human advisor appears to provide a more accessible cue that the reasoning is humanly understandable and therefore personally attainable.

Importantly, this boundary pattern should not be interpreted as evidence that lower-literacy consumers are less intelligent or generally less capable. Nor should it be read as a

causal test of financial-literacy change. Rather, the findings indicate that measured objective financial knowledge is associated with how much consumers rely on advisor source as a model for their own financial reasoning.

Figure 3 summarizes the Johnson-Neyman analysis from Study 2.

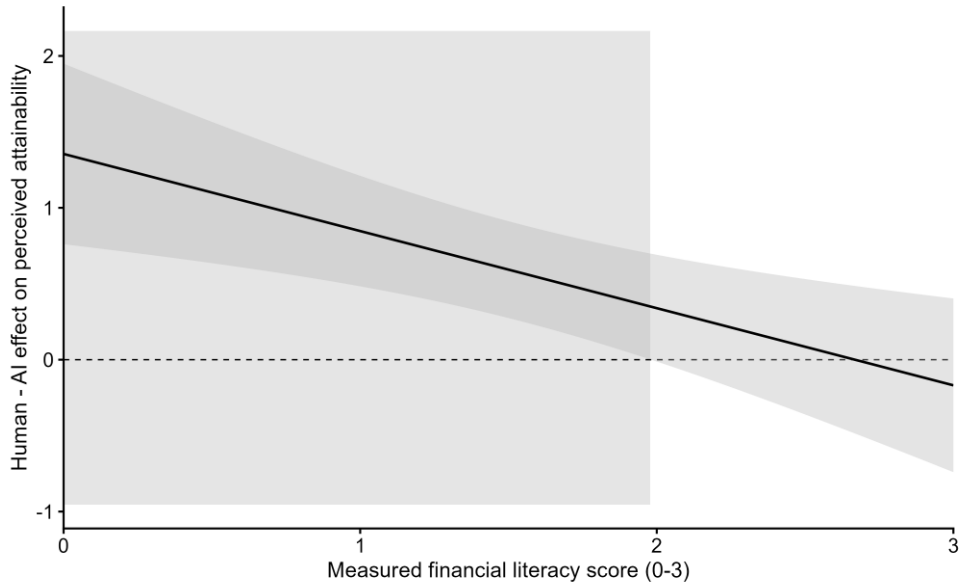


Figure 3. Study 2 Johnson-Neyman analysis. The figure displays the estimated Human - AI effect on perceived attainability of advisor reasoning across the measured financial literacy score (0-3). The ribbon represents the 95% CI, and the shaded region indicates where the 95% CI excludes zero in the positive direction. Financial literacy was measured, not manipulated.

Study 3: Financial-Ability Mindset as a Boundary Condition

Study 3 tests a second first-stage boundary condition: whether the human-advisor source effect depends on consumers' financial-ability mindset. If human advisors operate as attainable models for the self, then this effect should be stronger when financial-ability mindset is framed as developable rather than fixed. Under a growth mindset, a human advisor's reasoning should invite assimilation: a person can learn to reason this way, so the task may be personally manageable. Under a fixed financial-ability mindset, the same human reasoning may be less likely to feel attainable because it can imply a stable ability gap.

Method

Study 3 used data collected from 400 U.S.-based participants recruited through Prolific (*M*age = 34.84 years, *SD* = 11.49; 204 females).

Before the advisor-source manipulation, participants completed a short 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 indicating which statement best summarized the article before proceeding to the advisor-source manipulation in a savings-allocation context. Participants imagined using a banking or savings app allocation service and read an advisor analysis comparing a guaranteed account with a diversified mutual fund. The primary 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. The perceived attainability of advisor reasoning and financial self-efficacy measures matched the prior studies.

The mindset manipulation check adapted implicit self-theory check items used in prior research (Levy et al., 1998; Rai & Lin, 2019; Montford et al., 2019) to the financial-ability mindset domain. It included four items assessing whether financial reasoning can improve, with one fixed-ability item reverse-coded and averaged into a composite.

The focal conditional-process model treated mindset as a manipulated moderator of the advisor-source effect on perceived attainability of advisor reasoning and tested 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. Mindset was coded 0 = fixed mindset and 1 = growth mindset.

Results

The perceived-source check indicated the intended advisor-source perception, with low scores in the AI-advisor cells (fixed mindset: $M = 1.65$, $SD = 0.86$; growth mindset: $M = 1.78$, $SD = 0.91$) and high scores in the human-advisor cells (fixed mindset: $M = 6.08$, $SD = 0.97$; growth mindset: $M = 6.22$, $SD = 0.89$). The relative risk 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 ($\alpha = .88$), financial self-efficacy ($\alpha = .90$), and the financial-ability mindset check ($\alpha = .93$). The mindset manipulation check was successful: participants in the growth financial-ability mindset condition agreed more strongly that financial-ability mindset 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 showed the expected source-by-mindset pattern. In the fixed financial-ability mindset condition, means were 4.46 ($SD = 1.48$) for human advisors and 4.12 ($SD = 1.33$) for AI advisors. In the growth financial-ability mindset condition, means were 5.19 ($SD = 1.40$) for human advisors and 4.21 ($SD = 1.52$) for AI advisors.

Financial self-efficacy showed the same directional pattern: fixed/human $M = 4.02$, $SD = 1.41$; fixed/AI $M = 3.72$, $SD = 1.35$; growth/human $M = 4.61$, $SD = 1.47$; growth/AI $M = 3.93$, $SD = 1.52$. Financial risk-taking propensity also followed the same pattern: fixed/human $M = 3.93$, $SD = 1.49$; fixed/AI $M = 3.61$, $SD = 1.38$; growth/human $M = 4.39$, $SD = 1.44$; growth/AI $M = 3.82$, $SD = 1.26$.

The financial-ability mindset check was higher in the growth financial-ability mindset cells (growth/AI: $M = 4.49$, $SD = 1.08$; growth/human: $M = 4.63$, $SD = 1.27$) than in the fixed financial-ability mindset cells (fixed/AI: $M = 3.18$, $SD = 1.16$; fixed/human: $M = 3.29$, $SD = 1.24$).

Consistent with H4, mindset moderated the effect of advisor source on perceived attainability of advisor reasoning. Advisor source was coded 0 = AI advisor and 1 = human advisor. Mindset was coded 0 = fixed mindset and 1 = growth mindset. 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 × 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 growth financial-ability mindset. The implied human-advisor effect under growth financial-ability mindset was 0.98 scale points ($SE = 0.20$, $t = 4.84$, $p < .001$). This pattern supports the first-stage claim that human advisor reasoning feels most attainable when consumers construe financial-ability mindset as learnable.

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 mindset ($b = 0.56$, $p < .001$), and financial self-efficacy positively predicted financial risk-taking propensity controlling for condition, mindset, and perceived attainability of advisor reasoning ($b = 0.51$, $p < .001$).

We then tested the theorized first-stage conditional serial indirect effect using PROCESS Model 83 with 5,000 bootstrap samples and seed 123456. 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 growth financial-ability mindset than under 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 extends the boundary-condition evidence by experimentally manipulating beliefs about the malleability of financial-ability mindset. The human-advisor source increased perceived attainability of advisor reasoning more strongly under a growth mindset than Under a fixed financial-ability mindset, and this first-stage moderation carried forward through financial self-efficacy to financial risk-taking propensity.

This pattern suggests that human advisors become more self-diagnostic when the relevant ability is construed as learnable. Under a growth mindset, participants can assimilate the advisor's reasoning to the self: if another person can reason in this way, the reasoning may also be personally learnable. Under a fixed financial-ability mindset, the same human reasoning is less readily assimilated because it may instead signal a stable ability gap.

Together with Study 2, this result shows that the human-advisor effect is not uniform across consumers or contexts. It is stronger among consumers with lower measured financial literacy and when consumers are encouraged to view financial-ability mindset as developable. These boundary patterns sharpen the proposed mechanism by showing when human advisor reasoning is most likely to be perceived as attainable and translated into financial self-efficacy.

Figure 4 summarizes the descriptive means from Study 3.

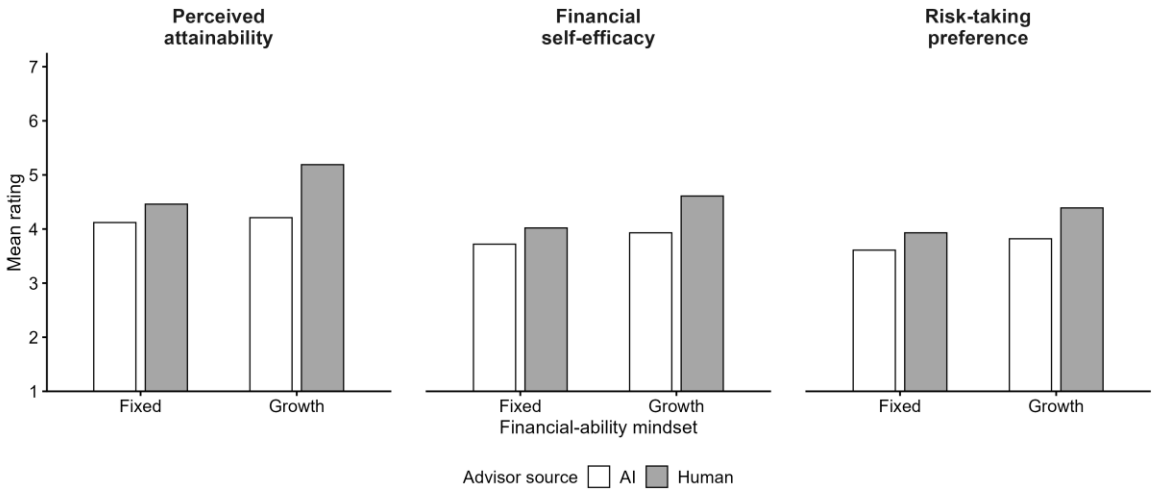


Figure 4. Study 3 descriptive means. Bars display observed means for perceived attainability of advisor reasoning, financial self-efficacy, and financial risk-taking propensity across fixed versus growth financial-ability mindset and AI versus human advisor source.

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: whether the source of financial advice changes consumers' perceived capability to understand and handle financial decisions themselves. Across three experiments, we develop and test an attainability-based self-efficacy account. We find that human financial advisors, relative to AI advisors, can increase consumers' perceived attainability of advisor reasoning. This perception increases financial self-efficacy, which subsequently increases financial risk-taking propensity.

The central insight is that advisor source matters not only because consumers evaluate advisors differently, but also because consumers evaluate themselves differently. A human advisor can function as an attainable model of financial reasoning. When consumers observe financial analysis attributed to another person, they may interpret the reasoning as more understandable, learnable, and personally reproducible. By contrast, the same analysis attributed to AI may still appear competent, accurate, or useful, but that competence may be

attributed to computational capacity rather than to a form of reasoning that consumers can map onto their own possible capability. The relevant psychological shift is therefore not from low advice quality to high advice quality. It is from externally located competence to self-relevant capability.

This distinction is important for understanding financial advice as part of the consumer service experience. Financial advice is not merely an informational input that consumers accept or reject. It can also serve as a model of how financial reasoning is performed. In advisory journeys involving robo-advisors, digital investment platforms, automated advisory tools, and human professionals, the source of advice may shape whether consumers feel capable of understanding the product, evaluating risk, and taking an active role in the decision. In this sense, advisor source becomes a service-design cue that shapes consumer agency and willingness to engage with financial risk.

Study 1 provided initial evidence for the proposed serial process. Participants exposed to a human financial advisor, compared with an AI financial advisor, perceived the advisor's reasoning as more attainable, reported higher financial self-efficacy, and showed greater financial risk-taking propensity. The serial mediation evidence supported the path 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 suggested that this process was not reducible to the measured perceived advice quality, general advisor attitude, or stable risk averseness.

Studies 2 and 3 clarified when this process is stronger while moving beyond the initial stock-analysis paradigm. Study 2 provided measured-moderator evidence consistent with financial literacy as a first-stage boundary condition in a retirement-fund allocation context. The human-advisor advantage on perceived attainability of advisor reasoning was stronger

among participants with lower measured financial literacy, consistent with the idea that consumers with fewer domain-specific knowledge anchors may find advisor source more diagnostic when judging whether financial reasoning is personally attainable. Study 3 then provided manipulated boundary evidence in a guaranteed-account versus mutual-fund context. The human-advisor advantage was stronger under a growth financial-ability mindset rather than fixed, suggesting that human advisors become more self-diagnostic when consumers believe that financial reasoning can be learned. Together, these studies specify not only whether human advisors can increase financial self-efficacy, but also for whom and under what psychological conditions this effect is most likely to emerge.

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 advice acceptance from consumer self-evaluation. Chang et al. (2026) show that trust in AI financial services can support vicarious learning, financial self-efficacy, and adoption. The present research asks a different question: does advisor source affect what consumers believe they themselves can do when the financial reasoning is otherwise identical? This distinction is theoretically important because advisor competence, trust, and consumer self-efficacy are separable constructs. Consumers may evaluate an AI system favorably without feeling personally capable, just as they may perceive a human advisor as fallible while still finding the advisor's reasoning more self-relevant and learnable. Thus, advisor source can shape self-directed inference even when advice content is held constant.

Second, the research extends self-efficacy, social comparison, and role-modeling perspectives by specifying when financial advice becomes vicarious information for the self. Chang et al. (2026) already show that trust in AI financial services can support vicarious learning and financial self-efficacy. Reich and Teeny (2026) further show that AI can raise

self-confidence in domains where it is perceived as a lower social referent. The present account identifies a different trigger and boundary condition: perceived attainability of advisor reasoning in a fact-based financial-analysis context. Human advisors can serve as attainable models of financial reasoning when their reasoning appears understandable, learnable, and relevant to consumers' own possible competence. AI advisors may still appear competent, but their reasoning is less likely to be self-diagnostic when it is attributed to external computational capacity. This contribution is especially relevant to financial service encounters because advisors do not only provide recommendations. They may also shape whether consumers view the financial decision as something that people like themselves can understand, evaluate, and manage.

This contribution also introduces perceived attainability of advisor reasoning as a process variable that explains when advisor source becomes self-diagnostic. A human advisor does not automatically increase consumer capability beliefs. The advisor's reasoning must be experienced as sufficiently attainable and relevant to the self. This specification helps reconcile why human financial reasoning may sometimes empower consumers but may also intimidate them when it appears distant, expert-only, or inaccessible. In the present framework, human advisors increase financial self-efficacy when their reasoning invites assimilation rather than contrast.

Third, the research contributes to consumer risk-taking and welfare theory by moving the endpoint from AI-service adoption to financial risk-taking propensity. The results suggest that financial self-efficacy can increase willingness to allocate money to a higher-risk option because the decision feels more understandable and manageable. However, greater financial risk-taking is not necessarily better financial behavior. This distinction is central to consumer welfare. A service interface that increases perceived capability may help consumers engage with suitable financial products, but it may also increase 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 can alter consumers' psychological readiness to engage with financial risk.

Practical Implications

The findings have implications for the design of financial advisory services that combine human and AI-based advice. The results should not be interpreted as suggesting that firms should simply increase consumers' financial risk-taking propensity. In consumer-finance contexts, greater risk-taking is not inherently desirable. A more appropriate practical objective is to help consumers understand financial reasoning while ensuring that their confidence remains aligned with their goals, liquidity needs, time horizon, risk tolerance, and loss capacity.

This perspective is relevant for firms developing robo-advisory platforms, hybrid advisory services, and digitally mediated wealth-management interfaces. AI advisors may be well suited to scalable analysis, standardized portfolio recommendations, risk profiling, rebalancing, and automated monitoring. Human advisors, however, may provide distinct value when they make financial reasoning feel understandable, personally relevant, and learnable. The human element in financial advice should therefore not be viewed only as emotional reassurance, trust repair, or premium service. It may also help consumers translate advice into a stronger sense of personal financial capability.

A first design implication is that advisory interfaces should make reasoning attainable, not merely recommendations available. Consumers may receive a recommendation without understanding how to evaluate it or how it relates to their own financial situation. Human advisors, and human-supported digital interfaces, can increase perceived attainability of advisor reasoning by explaining the logic behind a recommendation, clarifying tradeoffs, and showing how risk, return, time horizon, and loss capacity are connected. The goal is not to

turn consumers into professional advisors. It is to help them see the reasoning process as understandable and personally usable.

A second implication is that advisory support should account for consumer financial literacy. Study 2's measured pattern suggests that consumers with lower financial literacy may be especially responsive to human explanations because they have fewer domain-specific knowledge anchors for judging whether financial reasoning is personally attainable. For these consumers, human advisors may be particularly useful when they explain the reasoning behind a recommendation, clarify downside risks, and connect the recommendation to the consumer's goals and constraints. Consumers with higher financial literacy may require less self-efficacy support from advisor source alone and may place greater value on efficiency, analytical depth, customization, transparent assumptions, or access to detailed scenario analysis.

A third implication concerns how advisory interfaces frame financial-ability mindset. Study 3 suggests that human advisor reasoning is more likely to increase perceived attainability of advisor reasoning when consumers view financial-ability mindset as developable. This implies that advisory systems may benefit from explaining not only what recommendation is being made, but also how consumers can learn to understand the reasoning process. Platforms can provide step-by-step explanations, plain-language risk comparisons, interactive examples, and educational prompts that frame financial reasoning as learnable rather than reserved for experts.

A fourth implication concerns safeguards. If human advisor cues increase financial self-efficacy and thereby increase willingness to choose risk-bearing options, firms should ensure that heightened confidence does not become overconfidence. Advisory systems may therefore need to incorporate comprehension checks, suitability assessments, risk-disclosure prompts, portfolio stress tests, and opportunities for consumers to reconsider high-risk

choices. These design features are not merely compliance tools. They help ensure that increased consumer agency remains calibrated to actual understanding and appropriate risk exposure.

Hybrid advisory models are especially relevant in this regard. The present findings do not imply that human advisors are uniformly superior to AI advisors, nor that AI advice should be minimized. Rather, they suggest that human and AI components may provide different forms of value. AI systems may provide scalable analysis and consistent portfolio construction, whereas human advisors or human-like explanations may help consumers interpret the reasoning and assess its relevance to their own financial capability. Hybrid disclosure also matters: augmented human agents can produce positive engagement while activating machine-related heuristics, with communication style shaping the balance of these responses (Kissoon et al., 2026). Effective hybrid design should therefore combine analytical accuracy, perceived attainability of advisor reasoning, and suitability safeguards.

Limitations and Future Research

This research has several limitations that suggest directions for future work. First, the studies use controlled experimental scenarios rather than naturally occurring advisory interactions. This design is useful for isolating advisor source while holding advice content constant, but it abstracts from the complexity of actual financial service encounters. In real-world settings, human and AI advisors may differ not only in source labels but also in interaction style, responsiveness, disclosure format, emotional tone, personalization, and regulatory positioning. Future research could examine whether the same mechanism holds in interactive settings, such as chatbot-based investment guidance, video consultations, hybrid robo-advisory platforms, or branch-based advisory interactions.

Second, the outcome measure captures financial risk-taking propensity through a hypothetical portfolio-allocation task. This measure is appropriate for testing the proposed

psychological process, but it does not establish whether consumers make better or worse financial decisions. Future research should examine consequential choices, longitudinal investment behavior, portfolio suitability, learning outcomes, and post-decision satisfaction. A particularly important direction is to test whether increased financial self-efficacy remains aligned with actual understanding over time or whether it contributes to overconfidence, excessive trading, or unsuitable product adoption, outcomes that have long been central to household-investing research (Barber & Odean, 2001; Seru et al., 2010).

Third, the current research focuses on a human versus AI advisor-source distinction. However, AI systems increasingly vary in anthropomorphism, transparency, explainability, autonomy, and human-in-the-loop review. Some AI advisors may become more human-like, while some human advisors may deliver standardized, opaque, or scripted recommendations. Future research should therefore move beyond a binary source distinction and examine which specific features make advice feel attainable. 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 a recommendation is generated by AI.

Fourth, the present framework examines financial literacy and financial-ability mindset as boundary conditions. Other consumer characteristics may also shape the process. Numeracy, financial experience, risk tolerance, technology readiness, algorithm aversion, age, income uncertainty, and prior experiences with financial institutions may all influence whether human or AI advice becomes self-diagnostic. Future research could also examine cultural differences, since social comparison, authority perception, and attitudes toward financial expertise may vary across markets.

Fifth, future work should examine consumer welfare more directly. The present account treats financial risk-taking propensity as a behavioral outcome, not as a welfare criterion. A stronger welfare test would assess whether advisor-source design improves

consumers' ability to choose products that match their goals, constraints, liquidity needs, and loss capacity. Such work could distinguish empowering financial self-efficacy from uncalibrated confidence and would be especially valuable for regulators and service providers seeking to design responsible AI-enabled financial advice.

Finally, future research could examine how human and AI advice can be combined most effectively. The present findings suggest that human advisor source can provide a distinctive self-evaluative cue under certain conditions, but they do not imply that human advice is always preferable. Hybrid advisory models may be especially promising if AI systems provide scalable analysis while human advisors or human-like explanations help consumers understand the reasoning and assess its relevance to their own financial situation. Understanding how to combine analytical accuracy, perceived attainability of advisor reasoning, and suitability safeguards is an important direction for future research.

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

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Appendix: Study Stimulus Materials and Measures

Study 1 Stock-Analysis Stimulus

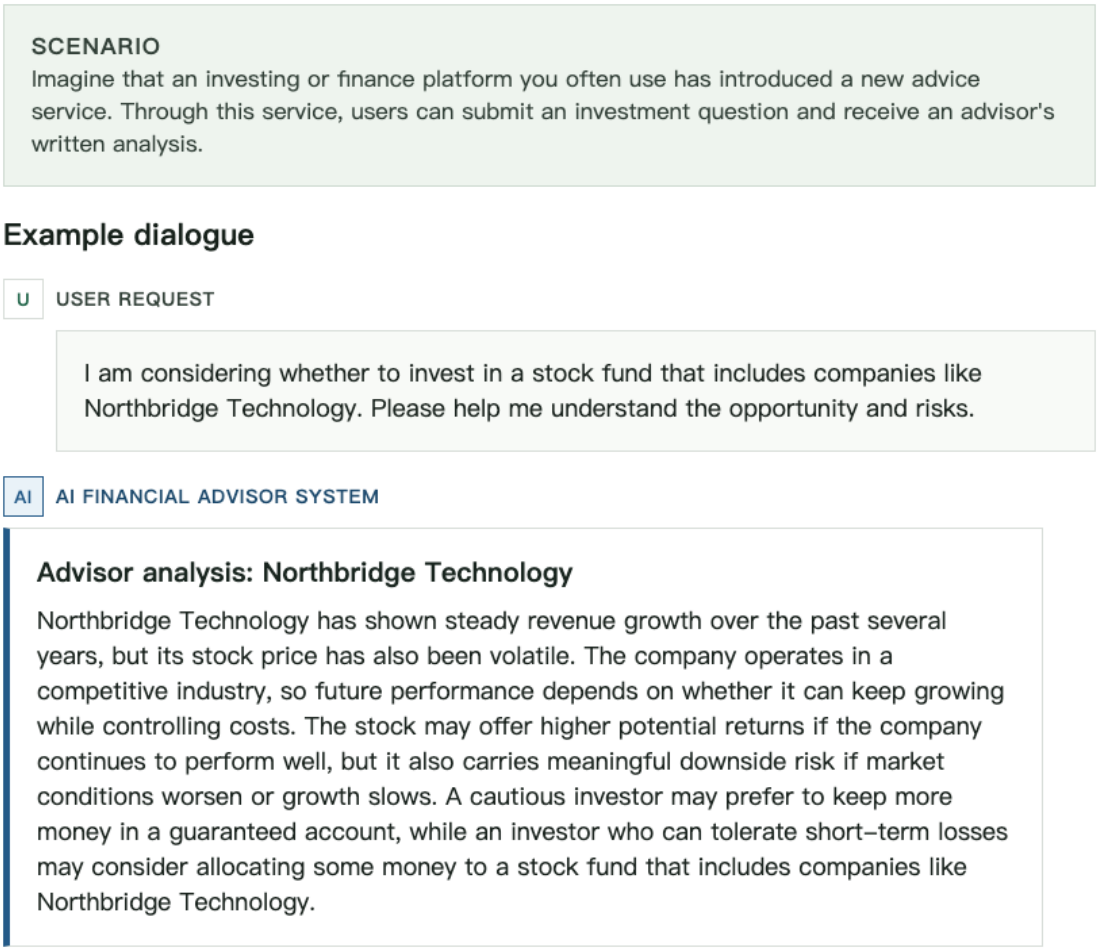


Figure A1. Study 1 AI-advisor HTML dialogue stimulus.

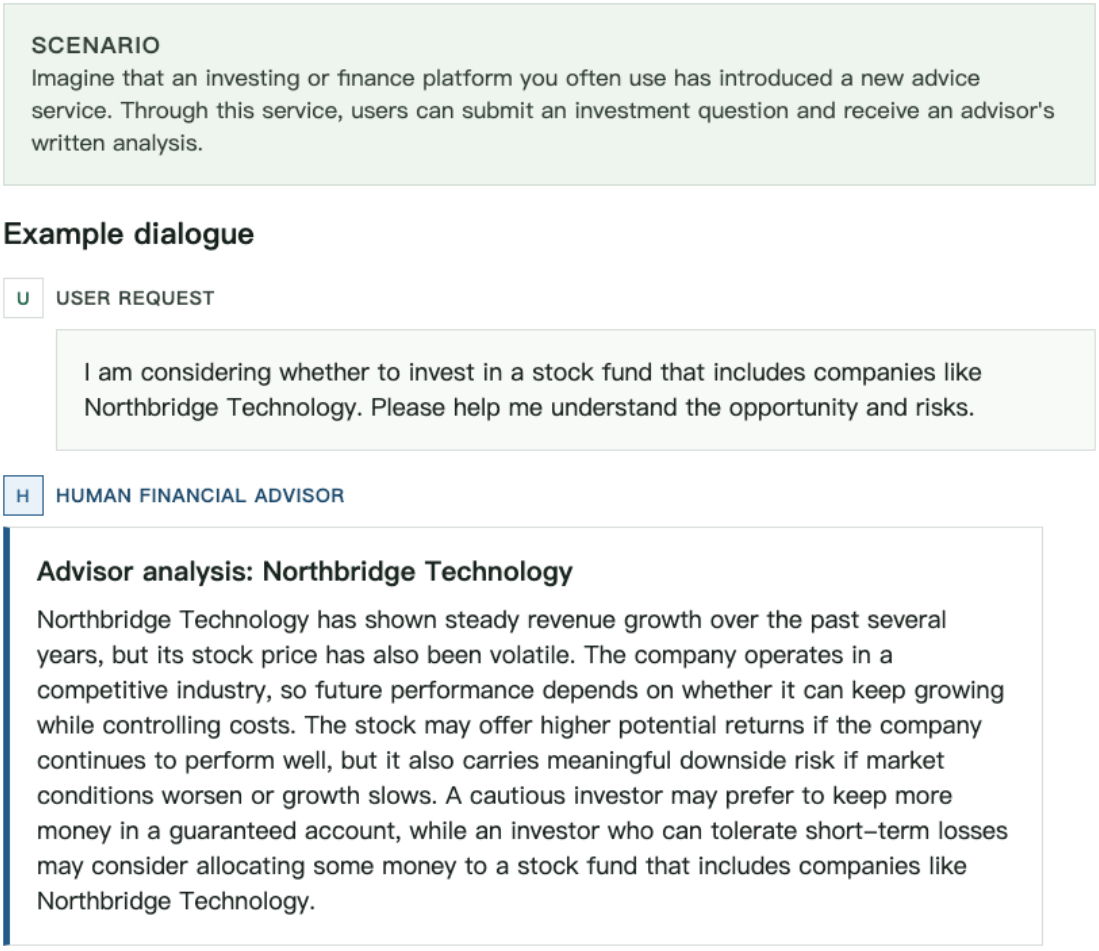


Figure A2. Study 1 human-advisor HTML dialogue stimulus.

Study 2 Retirement-Fund Stimulus

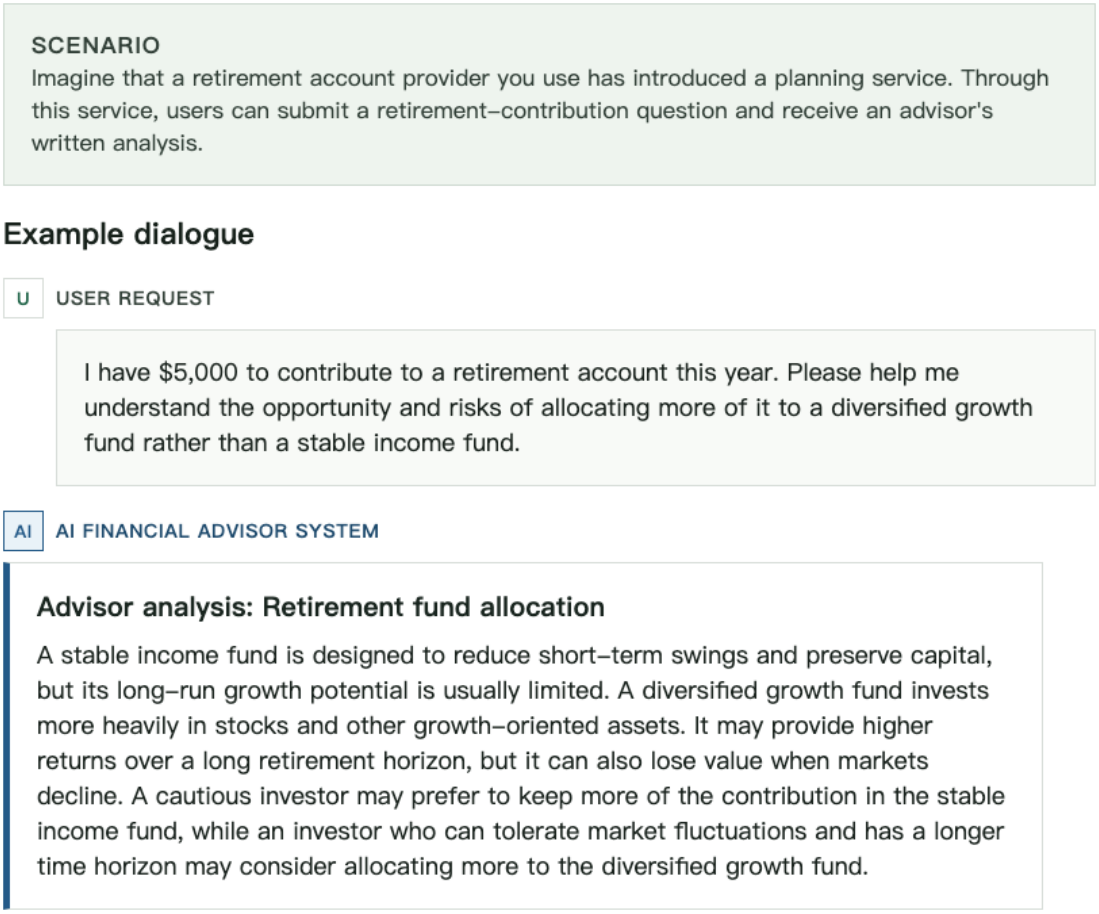


Figure A3. Study 2 AI-advisor HTML dialogue stimulus.

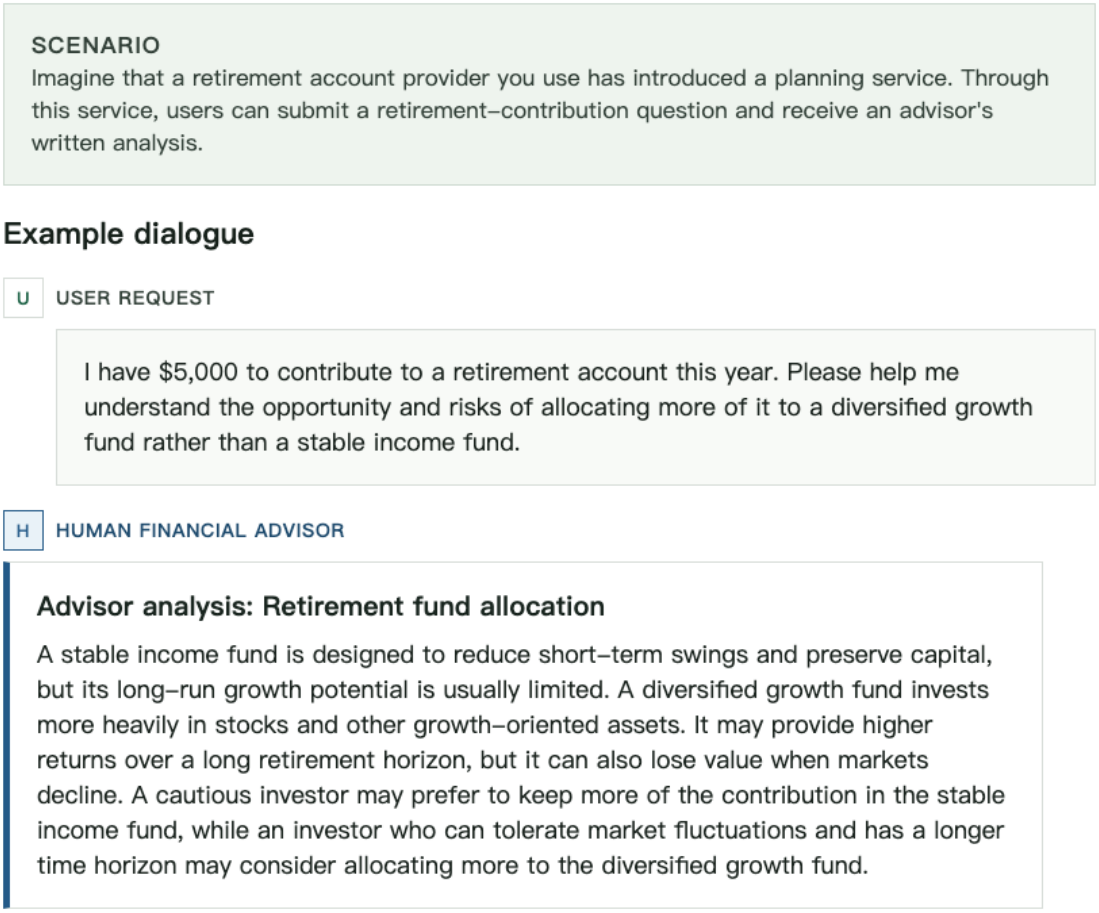


Figure A4. Study 2 human-advisor HTML dialogue stimulus.

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."

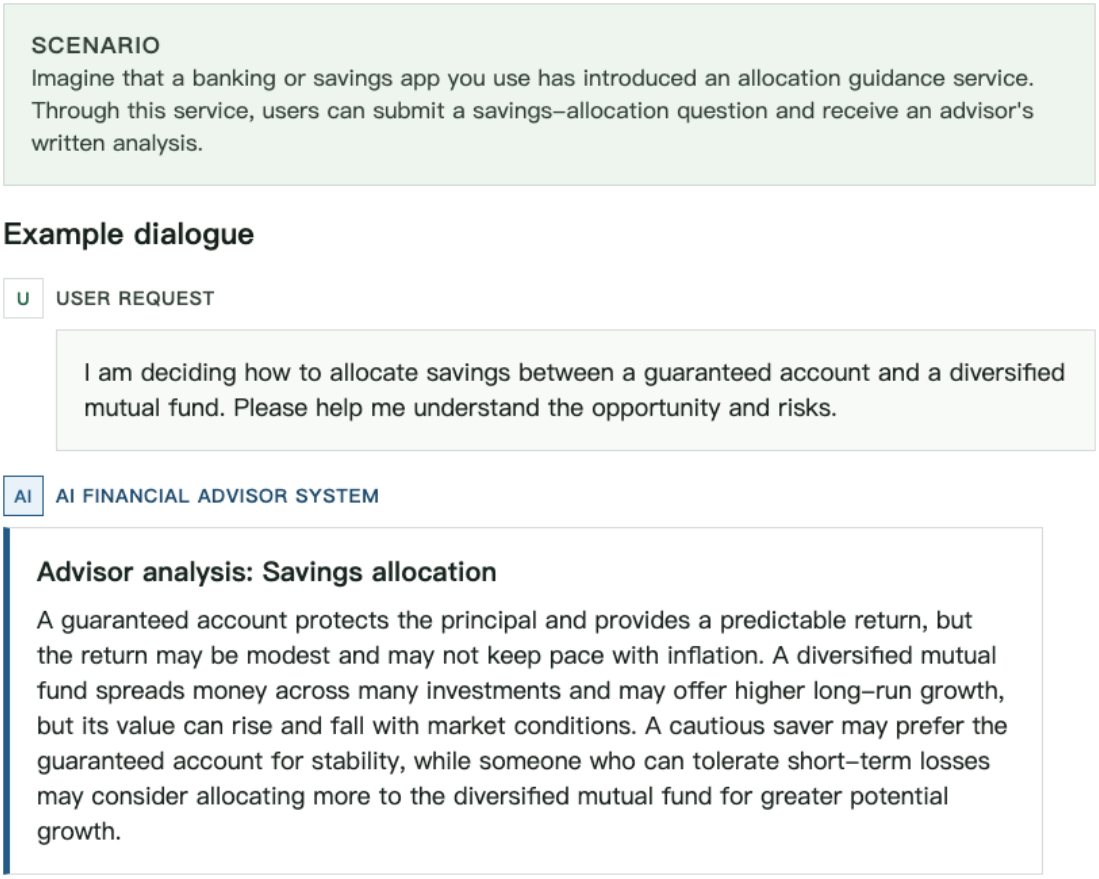


Figure A5. Study 3 AI-advisor HTML dialogue stimulus.

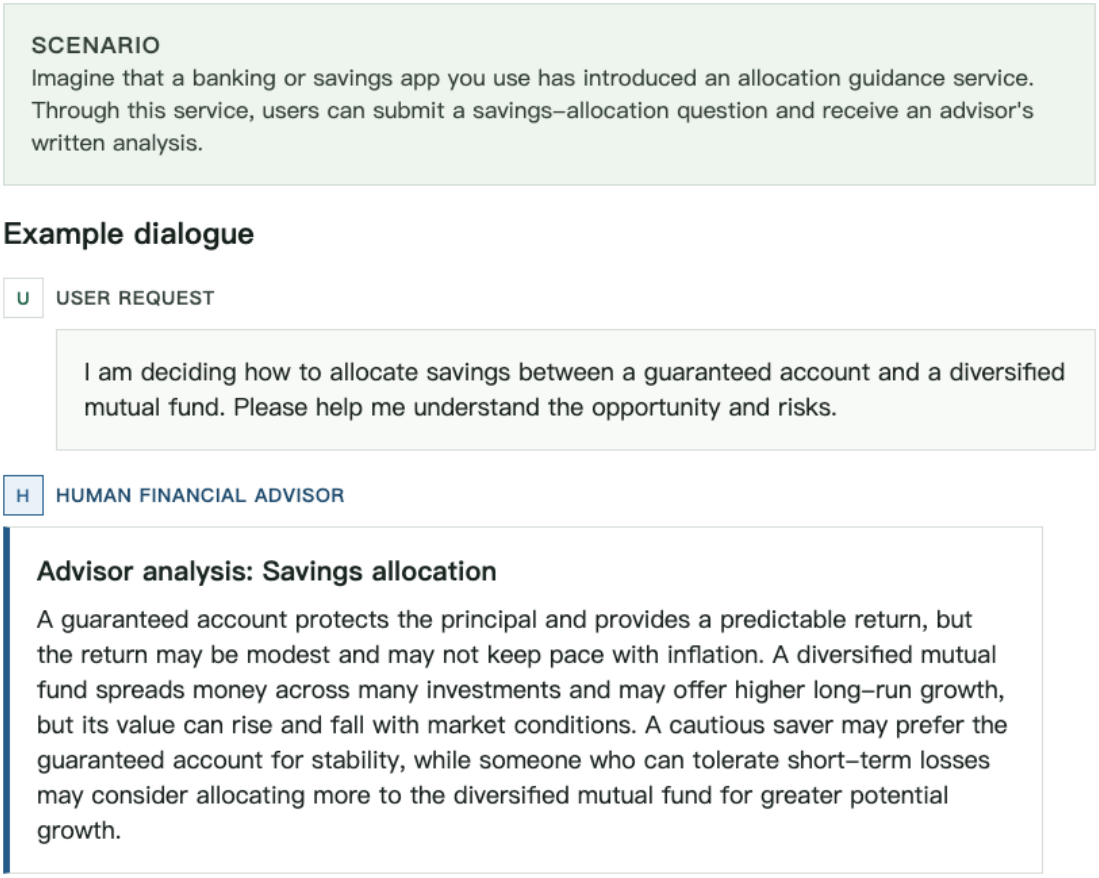


Figure A6. Study 3 human-advisor HTML dialogue stimulus.

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 condition correct answer = A; fixed 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.