

Human versus Artificial Intelligence in Financial Advice: Experimental Evidence on Investor Trust, Advice Reliance, and Portfolio Choice

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Article History

Received: 25.08.2026

Accepted: 16.09.2026

Published: 02.10.2026

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Abstract: The rapid rise of artificial intelligence (AI) in finance is disrupting the investment advice landscape, yet little is known about how investors perceive and respond to advice from AI versus human advisors. This study examines whether the source of advice (human vs. AI) influences investors' trust in the advice, their reliance on it, and their subsequent portfolio choices. By employing a randomized experimental design, this study asks participants to evaluate equivalent investment recommendations generated by either a professional human financial advisor or an AI-based financial advisory system. The experiment manipulates the perceived source of advice and measures participants' trust, perceived competence, transparency, adherence to the recommendation, and portfolio allocation decisions. The study also explores whether financial literacy, investment experience, risk tolerance, and familiarity with AI moderate the observed effects. This study contributes to the literature on behavioral finance, fintech, and algorithmic decision-making by isolating the role of advice source on investor behavior and offering insights into the design of trustworthy and effective AI-assisted financial advisory systems.

Keywords: Artificial Intelligence; Financial Advice; Investor Trust; Advice Reliance; Portfolio Choice; Behavioral Finance; Fintech; Algorithmic Decision-Making; Financial Literacy; Investment Behavior.

Cite this Article

R. Malik, (2026) Human versus Artificial Intelligence in Financial Advice: Experimental Evidence on Investor Trust, Advice Reliance, and Portfolio Choice *GRS Journal of Multidisciplinary Research and Studies*, Vol-3 (Iss-10). 1-31

Introduction

Background of the Study

Artificial intelligence (AI) is becoming a significant force in the financial services industry. The way in which individuals obtain information, evaluate investment opportunities, and make financial commitments are being transformed. Historically, humans have relied on financial advisers due to their perceived expertise, experience, accountability, and ability to understand individuals' circumstances. However, the rise of machine learning, natural language processing, and data analytics have enabled machines to process financial information and recommend investment opportunities. As such, the emergence of robo-advisers and AI-fueled financial services is giving rise to a world where individuals have the option to rely on human or algorithmic financial advice.

While technology-enabled financial services have certain advantages over traditional human advisement, an individual's receptiveness to advice and incorporation of that advice into one's decision-making process is crucial. Financial investments are typically uncertain, informationally asymmetric, and carry significant consequences. As such, it is important for investors to weigh the costs and benefits of taking action. Investors may weigh

the pros and cons of a suggested course of action differently if the suggestion came from a human versus a machine. For instance, human advisers may provide socially desirable suggestions that investors perceive as more empathetic. Additionally, human advisers may experience issues with accountability, motivation, and ethical dilemmas. In contrast, AI advisers may be seen as more objective, reliable, consistent, and impartial.

While the issue of trust has been discussed throughout the literature, there is still debate on whether and how individuals rely on AI-generated advice. In particular, while investors may recognize the analytical and mathematical advantages of algorithms, they may be hesitant to adopt the suggestions in their financial decision-making processes. On the other hand, investors that are more technologically savvy may be more receptive to algorithm-generated financial advice. It may depend on an individual's level of financial literacy, investment experience, risk tolerance, and the complexity of the decision being made. Literature has explored issues of robo-adviser adoption, algorithm aversion, and trust in automation. However, there is a lack of behavioral studies that explore the link between adviser identity and actual financial commitments. Much of the literature has been devoted to survey-based studies that explore consumer

receptiveness to AI, adoption intentions, and perceptions of trust and transparency. There is limited research that has experimentally manipulated human and AI adviser identities while controlling for the actual recommendations provided. A comparison of human, AI, and potentially hybrid adviser recommendations is necessary in order to understand if differences in adviser identity lead to differences in financial commitment. Specifically, there is a need for controlled experimentation where the recommended portfolio is identical between adviser types, but the adviser identity differs.

This study aims to explore the financial advice receptivity gap by conducting a behavioral finance experiment on the influence of human versus AI financial adviser identities on individual financial commitments. Particular focus will be devoted to understanding the relationship between adviser identity and 1) trust, 2) reliance, and 3) portfolio choices. By evaluating human versus AI financial advice, this study will explore whether the source of the information alters individuals' attitudes toward financial advice and commitment to the suggested portfolio. The study will also explore whether financial literacy, investment experience, risk tolerance, and complexity of the commitment moderate the relationship.

The study is important because financial institutions are beginning to adopt AI and robo-advisers to assist individuals with financial commitments and investments. A better understanding of how individuals perceive and process algorithmic advice is vital if regulators and financial institutions wish to promote transparency, human oversight, accountability, and consumer protection in the financial services industry. In addition to contributing to the body of literature on behavioral finance and FinTech, findings from this study can be used to offer regulatory and practical recommendations on the use of AI and robo-advisers in financial services.

Problem Statement

The introduction of artificial intelligence (AI) into financial services transforms the nature of the relationship between investors and financial advisers. Advisory activities incorporating AI have the potential to process vast amounts of data, identify patterns, assess risks, and recommend profitable investments. Yet, the introduction of advisory AI is associated with a key behavioral challenge: investors might respond differently to recommendations, depending on whether they originate from a human or an artificial adviser.

Trust is a critical element in the financial adviser relationship, due to the complexity, risk, and uncertainty of the recommendations. Thus, financial human advisers might be associated with higher levels of trust than their artificial counterparts. Human advisers might be considered more empathetic, reliable, and responsible agents, compared to algorithmic models, which might be regarded as objective, accurate, and analytical but emotionally detached. Such differences might impact the extent to which a recommendation is followed or incorporated into the final portfolio, depending on the perceived credibility of the source.

The literature on investor reactions to robo-advisers, algorithm aversion, and trust in financial advice is extensive, highlighting multiple determinants of financial adviser acceptance and technology adoption. Yet, there is limited experimental evidence on whether and how the identity of the financial adviser (human or AI) affects decision-making, once controlling for the recommendation itself. Most studies rely on trust and adoption

measures as proxies for behavioral responses to the identity of the adviser, with fewer studies analyzing changes in actual portfolio allocations following a recommendation. Therefore, the behavioral effects of robo-advisers on portfolio choice remain understudied. In particular, the extent to which investors would alter their portfolio allocation following advice from a human or an AI adviser is unknown. Similarly, the extent to which financial knowledge, experience, risk tolerance, and decision complexity moderate such responses is also unclear.

Thus, this study aims to experimentally examine the effects of robo-advisers on portfolio choice, focusing on investors' trust in the adviser, reliance on the recommendation, and overall portfolio allocation following a financial recommendation. By analyzing behavioral responses to advice from human, AI, and hybrid advisers, this study aims to contribute to the literature on behavioral finance and trust in financial advice.

Research Gap

The increasing application of artificial intelligence (AI) in financial services has attracted considerable scholarly attention, with studies investigating the nature of the robo-adviser recommendation itself and investor reactions to it. Several important gaps in the literature can be noted.

First, most studies examining reactions to AI-based financial advice focus on investors' intention to use robo-advisers rather than their actual behavioral response to a specific recommendation. Intention to use technology is not necessarily linked to behavioral responses, such as reliance on the recommendation or changes in portfolio allocation following the advice. Thus, for instance, an investor might report high levels of trust in the robo-adviser but fail to incorporate the recommendation in their final portfolio.

Second, few studies analyze the behavioral effects of the adviser identity, with most focusing on identifying differences between human and AI characteristics, benefits, and barriers. Yet, for trust and behavioral intentions to be affected by robo-advisers, investors must perceive differences in the recommendations themselves. A recommendation from a human adviser might differ from a recommendation from an AI adviser, thus affecting the extent to which it is followed. To isolate the effects of the adviser identity, a controlled experiment is necessary in which the recommendation itself is held constant across adviser types.

Third, the role of trust in the adviser-recommendation relationship requires additional investigation. Most studies examine trust as an outcome of algorithm acceptance or technology use, with few analyzing its role as a possible mediator. Yet, investor trust in a financial adviser is a critical mechanism by which the identity of the adviser affects behavioral responses, such as advice reliance and portfolio choice.

Fourth, the focus of the literature is on investors' intention to use robo-advisers and their trust in them, with fewer studies analyzing their behavioral response to a specific recommendation. Following a recommendation involves complex cognitive processes, and therefore actual portfolio allocation after advice offers more insight into behavioral responses to robo-advisers than self-reported measures of trust and intention.

Fifth, the behavioral effects of hybrid (human-AI) financial advice are understudied, despite the potential benefits of combining human judgment and algorithmic analysis. Thus, human advisers can offer the benefits of personal judgment, and robo-advisers can

incorporate their computational advantages. Yet, the extent to which such a combination affects trust in the adviser and reliance on the recommendation is unclear.

By focusing on these gaps, this study aims to advance scholarly understanding of the effects of robo-advisers on portfolio choice. This study will utilize an experimental design in which participants will interact with either a human, AI, or hybrid adviser. The study will analyze the effects of adviser type on trust, advice reliance, and portfolio allocation. This study will also explore the role of financial literacy, experience, decision complexity, and risk tolerance as possible moderators.

Research Aim

This study aims to experimentally examine the influence of financial advisers' identity on investors' trust, reliance on their recommendations, and portfolio allocation. This study will focus on the behavioral responses to financial advice from human, artificial intelligence (AI), and hybrid advisers, analyzing how such responses are affected by investors' characteristics.

Research Objectives

This study aims to achieve the following objectives:

1. Examine whether investor trust differs across human, AI, and hybrid financial advisers.
2. Investigate the effects of adviser type on advice reliance.
3. Determine whether the source of advice (human, AI, or hybrid adviser) affects portfolio allocation choice.
4. Explore whether trust mediates the association between adviser type and advice reliance.
5. Determine whether advice reliance mediates the association between adviser type and portfolio allocation.
6. Examine whether financial literacy and investment experience affect trust in and reliance on AI financial advice.
7. Investigate whether the complexity of the investment decision moderates the association between adviser type and advice reliance.
8. Determine whether a hybrid adviser affects trust and advice reliance compared to human and AI advisers.

Significance of the Objectives

These objectives will allow this study to achieve the aim of investigating the effects of the financial adviser's identity on portfolio allocation. In particular, this study will focus on behavioral responses to the recommendation, analyzing how they are affected by the adviser type and individual characteristics. First, by examining the levels of trust in human, AI, and hybrid advisers, this study will add to the understanding of the mechanisms by which robo-advisers affect trust in financial advice. Second, this study will analyze the effects of adviser type on advice reliance, determining whether investors are more likely to accept and incorporate the recommendation from a human or an AI adviser. Finally, this study will investigate the effects of advice reliance on portfolio allocation, identifying whether and how the source of the recommendation affects the final portfolio choice.

Research Questions

Main Research Question

How does the source of financial advice affect investor trust, reliance on the recommendation, and portfolio allocation?

Specific Research Questions

RQ1: Do investors demonstrate different levels of trust towards human, AI, and hybrid advisers?

RQ2: Is there an association between adviser type and advice reliance?

RQ3: Does trust mediate the association between adviser type and advice reliance?

RQ4: Is there an association between adviser type and portfolio allocation?

RQ5: Does advice reliance mediate the association between adviser type and portfolio allocation?

RQ6: Are financial literacy and investment experience associated with differences in trust in and reliance on AI adviser?

RQ7: Does investment decision complexity moderate the association between adviser type and advice reliance?

RQ8: Does a hybrid adviser model affect trust and advice reliance compared to a human or AI adviser?

Research Hypotheses

Adviser Type and Trust

H1: Investor trust differs across human, AI, and hybrid financial advisers.

H1a: Investors demonstrate higher levels of interpersonal trust towards human advisers than towards AI advisers.

Adviser Type and Advice Reliance

H2: Adviser type is significantly associated with advice reliance.

H2a: Higher levels of trust are associated with higher levels of advice reliance.

Adviser Type and Portfolio Choice

H3: Adviser type is significantly associated with portfolio allocation.

H3a: There is a significant association between adviser type and allocation to risky and low-risk assets.

Mediation Effects

H4: Trust mediates the association between adviser type and advice reliance.

H5: Advice reliance mediates the association between adviser type and portfolio allocation.

Moderating Effects

H6: Financial literacy moderates the association between adviser type and advice reliance.

H7: Investment experience moderates the association between adviser type and trust in the adviser.

H8: Higher decision complexity is associated with higher levels of reliance on human advisers.

Hybrid Adviser Effects

H9: Hybrid financial advice is associated with higher levels of trust and advice reliance than AI financial advice.

Literature Review

Artificial Intelligence in Financial Services

Artificial intelligence (AI) is increasingly used in financial services, supporting diverse operations, from fraud detection and credit evaluation to algorithmic trading and customer support. In particular, AI enables financial institutions to analyze large sets of structured and unstructured data, identifying patterns that can improve credit scoring, risk assessment, and investment strategies. The application of AI in financial services has the potential to transform advisory services, offering new ways to analyze markets, assess risks, and recommend profitable investments. From the perspective of investors, the use of AI in financial services has the potential to revolutionize the nature of the relationship with financial advisers. Whereas previously investors relied exclusively on human expertise, they can now turn to algorithms for assistance in making financial decisions.

Yet, the ability of AI to process and analyze large sets of data and identify patterns does not necessarily translate into high levels of trust among investors. The use of algorithmic financial advice has the potential to reduce the level of control over the recommendation process, with investors having limited understanding of how the recommendation is developed. Thus, the literature highlights the importance of examining whether and how investors would react to AI-based financial advice.

Robo-Advisory

Robo-advisory is one of the areas in which AI is increasingly utilized in financial services. Robo-advisers offer automated, algorithm-driven investment advice and manage portfolios on behalf of clients. Typically, robo-advisers utilize AI and machine learning to collect information on the client's financial situation, investment goals, and risk tolerance, after which they offer recommendation on asset allocation. Compared to human advisers, robo-advisers have the potential to offer lower-cost and more standardized services, with their recommendation based on objective analysis. Yet, as noted by previous studies, the key challenge of robo-advisory is whether and to what extent investors would trust such advisers and follow their recommendations. Thus, several studies have analyzed the factors associated with the acceptance and rejection of robo-advisers, identifying usefulness, ease of use, perceived risk, trust, and financial literacy as important determinants. Yet, these factors explain the intention to use robo-advisers but say little about the reliance on the recommendation or changes in portfolio allocation following the advice. This study goes beyond consumer acceptance of robo-advisers to focus on actual behavioral responses to the recommendation provided.

Human Financial Advice

Human financial advisers have traditionally been the primary source of financial advice for investors. There are several reasons why investors turn to human advisers. First of all, human advisers offer personalized recommendations based on their expertise and judgment. Second, human advisers offer emotional support during the investment process, advising and assisting the client during difficult moments. Thus, investors tend to rely on human advisers when making complex and high-risk investments. At the same time, human advisers are subject to criticism, with their behavior being analyzed from several perspectives. Human advisers can be biased, providing advice that is motivated by self-interest or other factors. Moreover, human advisers can make errors due to

cognitive biases, leading to inappropriate recommendations. Thus, the literature highlights the need to examine alternatives to human advice, such as robo-advisers.

Investor Trust

Trust is an essential element of the relationship between an investor and a financial adviser. In particular, investment-related decisions require the exercise of discretion on the part of the investor, who must rely on the judgment of the financial adviser. For a financial adviser to be successful, they must gain the trust of the client, ensuring that they have the necessary expertise, skills, and reliability. In the case of human advisers, trust is based on human judgment, whereas in the case of robo-advisers, it is based on the perception of their objectiveness and analytical capacity. An important consideration is that the role of trust in the adviser-recommendation relationship might differ between human and AI advisers. Investors might decide to rely on the recommendation from a human adviser because they believe the adviser has considered their individual circumstances, whereas trust in robo-advisers might be based on perceptions of their reliability and accuracy. As such, this study focuses on the extent to which investors would trust human and robo-advisers, as well as the role of trust in their decision-making.

Algorithm Aversion

When given a choice between a human adviser and an algorithm, investors are likely to select the former, even when the recommendation from the algorithm is objectively better. This phenomenon, which is referred to as algorithm aversion, means that the identity of the adviser can affect the extent to which the recommendation is followed, even when the recommendation itself is identical. Thus, the source of the recommendation influences the extent to which it is incorporated into the final portfolio allocation. There are several reasons why investors might demonstrate algorithm aversion, with the most common ones stemming from their perception of the algorithm. Algorithms are typically viewed as impersonal, unreliable, and difficult to understand. As such, investors might be less likely to trust recommendations from robo-advisers, particularly in situations when the recommendation is counterintuitive or difficult to comprehend.

The phenomenon of algorithm aversion is particularly relevant to financial services, where the decisions made are associated with significant risks and consequences. In particular, investors tend to select the recommendation that helps them minimize their losses and maximize their profits. If an investor believes that an algorithm is less reliable than a human adviser, they will select the latter, even if the algorithm's recommendation is objectively better. Yet, algorithm aversion is not universal, with several studies noting that in some cases, investors actually prefer algorithms to humans. In particular, investors perceive algorithms as more analytical and objective, reducing the likelihood of errors due to human discretion. Thus, if the test participants believe that an algorithm is more likely to provide an accurate recommendation, they will select it over a human adviser, even if they find the recommendation difficult to understand. As such, algorithm aversion is a critical phenomenon to consider when analyzing the behavioral response to robo-advisers, with this study investigating whether algorithm aversion or algorithm appreciation would be demonstrated in a controlled experiment.

Advices-Taking

Advice-taking research explores how individuals incorporate the advice of others into their decision-making process. The focus of such studies is on the mechanisms by which individuals become aware of the advice, process it, and integrate it into their final decision. Advice-taking is a complex process, with individuals receiving advice, understanding it, accepting it, and incorporating it into their final choice. Advice taking can vary considerably, with some individuals following the advice almost always, whereas others might incorporate it conditionally. Thus, while the initial recommendation might suggest that the portfolio should be allocated in a specific manner, the final allocation will depend on the extent to which the investor takes the advice. Advice-taking is not measured directly, but rather indirectly through behavioral responses, such as changes in the portfolio allocation following the recommendation. This study focuses on the extent to which the test participants incorporate the recommendation provided by the robo-adviser into their final portfolio allocation.

Behavioural Finance

Classical finance theory assumes that investors are rational actors who select the option that maximizes their utility function. In reality, however, investors are subject to numerous cognitive biases and heuristics that affect their judgment and lead to non-optimal choices. Behavioural finance aims to understand investors' behaviour, exploring the decision-making process and identifying the biases that affect it. From such a perspective, trust in the adviser plays an essential role in the recommendation-advice relationship. In particular, investors who trust the adviser will be more likely to take their advice, even when it contradicts their initial judgment. Thus, two investors who receive identical advice can make different decisions, depending on their level of trust in the adviser. In particular, an investor who trusts the adviser will incorporate the recommendation into their final portfolio, whereas an investor who does not trust the adviser will disregard the recommendation and follow their initial plan.

The human-AI comparison offers an intriguing perspective on behavioural finance, with investors using different heuristics when assessing the advice from human and robo-advisers. In particular, when receiving advice from a human adviser, the investor will incorporate their recommendation if they believe that the adviser has taken their personal circumstances into account. When receiving advice from a robo-adviser, the investor will demonstrate algorithm aversion, believing that the recommendation is based on cold calculations rather than objective analysis. An investor who trusts the robo-adviser will take their advice into consideration, believing that it is reliable and accurate. Thus, investors can be systematically biased in their assessment of advice, with such biases being dependent on their perception of the adviser.

Portfolio Choice

Investors make complex decisions on how to allocate their wealth among available assets, considering their risk tolerance, investment goals, and financial situation. The final allocation depends on numerous factors, including the level of risk, the expected return, liquidity, transaction costs, and other considerations. The traditional approach to determining the optimal portfolio allocation involves maximizing the expected return for a given level of risk. The process of portfolio choice affects multiple aspects of the investment, including the selection of assets, their weight within the portfolio, and the timing of purchase and sale. The literature on portfolio choice is vast, encompassing diverse perspectives on the

optimal allocation strategy. In particular, the choice of allocation depends on the investor's risk tolerance, financial knowledge, income, investment experience, and several other factors. The role of the financial adviser in the portfolio-choice process has not been extensively investigated, with fewer studies analyzing the association between the adviser's identity and the final portfolio allocation. Trust in the adviser and advice-taking are likely to contribute to the final allocation, with the current study analyzing such mediation effects in detail. In particular, this study will focus on the following measures:

1. Allocation to equity
2. Allocation to bonds
3. Allocation to cash
4. Allocation to exchange-traded funds (ETF)
5. Portfolio diversification
6. Overall portfolio risk
7. Changes in allocation following advice.

As such, the focus of this study is on the portfolio-choice process, with the final allocation serving as the ultimate determinant of the financial outcome.

Research Gap

The literature highlights that AI is increasingly important in financial services and that robo-advisory can provide scalable investment recommendations. Existing research has also established the importance of trust, algorithm aversion, financial literacy, and technological acceptance in determining attitudes toward AI-based financial services.

However, several important gaps remain. First, much existing research focuses on users' intention to adopt or use robo-advisory services, rather than measuring whether investors actually change their investment decisions after receiving advice. Second, previous studies frequently compare human and AI systems that provide different recommendations. Consequently, it can be difficult to determine whether differences in investor behavior arise from the source of advice or from the perceived quality of the recommendation itself. Third, the relationship between adviser type → investor trust → advice reliance → portfolio choice has not been sufficiently integrated into a single experimental framework. Fourth, the role of financial literacy, investment experience, AI familiarity, and decision complexity in shaping the human-AI advice relationship requires further investigation. Finally, the emerging human-AI hybrid advisory model remains comparatively under examined. A hybrid model could potentially combine the analytical capabilities of AI with the interpersonal and accountability advantages of human advisers.

Therefore, the present study addresses the literature gap through a controlled experimental design comparing human, AI, human-AI hybrid, and control conditions. By holding the underlying investment recommendation constant as far as experimentally feasible and measuring changes in portfolio allocation, the research aims to provide stronger causal evidence regarding how adviser identity affects investor trust, advice reliance, and portfolio choice.

Core Literature Gap

Existing literature: AI adoption → Trust → Intention to use

Proposed research: Human vs. AI vs. Hybrid → Trust → Advice Reliance → Portfolio Adjustment → Risk/Portfolio Choice

This distinction gives the study a clear behavioural and experimental contribution rather than making it another general study of AI acceptance.

Theoretical Framework and Hypothesis Development

Introduction

This chapter provides a theoretical basis for investigating how investors respond to financial advice from human advisers, artificial intelligence (AI), and human-AI hybrid systems. As the use of AI grows in the financial domain, an important theoretical question emerges as to whether investors evaluate advice differently depending on who or what they perceive as the source of that advice. Although financial recommendations may contain similar information, investors may interpret their credibility, reliability, competence, and trustworthiness differently when the advice is attributed to a human or an AI system. The current study therefore combines insights from trust in automation, algorithm aversion and appreciation, interpersonal trust, and behavioral decision-making to explain differences in investor responses. The framework proposes that adviser identity can influence investor trust, which impacts investors' willingness to adopt a recommendation, which in turn impacts portfolio decisions, including asset allocation and willingness to accept investment risk. The framework also recognizes that these influences may not be identical for all investors. Financial literacy, investment experience, risk tolerance, familiarity with AI, and decision complexity may shape how individuals interpret and respond to advisory information. Furthermore, the study considers human-AI hybrid advice as a potentially distinct paradigm that combines technological analytical capabilities with perceived human expertise and accountability. The theoretical framework consequently moves beyond a simple comparison between human and AI advisers and develops an integrated explanation of how adviser identity, trust, reliance, and investor characteristics influence financial decision-making.

Trust in Artificial Intelligence and Automation

Trust is a crucial mechanism by which individuals decide to accept and act on recommendations generated by technological systems. Trust in AI refers to the degree to which users believe that an AI system is capable, reliable, predictable, and sufficiently dependable for decision-making. In financial advice, trust is particularly important because investment decisions involve uncertainty and the possibility of financial loss. Investors therefore need to determine that the advisory source possesses sufficient competence and reliability before incorporating its recommendations into their decisions. Trust in automation theory suggests that individuals are more likely to rely on automated systems when they perceive those systems as competent and dependable. However, excessive trust may also lead to inappropriate reliance, while insufficient trust may prevent people from following useful recommendations. AI-based financial advice presents an interesting case because algorithms may be perceived as capable of processing large amounts of information objectively and consistently, while simultaneously being perceived as lacking human understanding and accountability. The perceived transparency of AI may also play a

role in trust since investors can be uncertain about how an algorithm produces a recommendation. Consequently, the identity of the advisory source may impact both the initial level of trust and subsequent reliance on the advice. This study therefore proposes that investors receiving AI-generated financial advice will exhibit systematically different levels of trust compared with investors receiving advice attributed to human professionals.

H1: Adviser type significantly influences investor trust, such that trust differs between human, AI, and human-AI hybrid advisory conditions.

Algorithm Aversion and Algorithm Appreciation

Theories of algorithm aversion and algorithm appreciation provide an insight into why individuals may respond differently to AI-generated recommendations. Algorithm aversion occurs when individuals prefer human judgment and become reluctant to rely on algorithmic recommendations, particularly after observing errors and when believing that human judgment provides greater contextual understanding. This tendency is particularly relevant in financial decision-making because investors may perceive that investment decisions require experience, intuition, and an understanding of complex market conditions. At the same time, algorithm appreciation suggests that individuals may prefer algorithmic recommendations when they perceive algorithms to be more consistent, analytical, objective, and less influenced by emotional biases. Financial investment is particularly relevant for this comparison since AI systems can process substantial quantities of market information and apply analytical rules without experiencing fear, greed, and other emotions commonly associated with human decision-making. Whether investors display aversion or appreciation may depend on how they perceive the relative strengths and weaknesses of human and AI advisers. The current study does not assume that either humans or AI will receive greater acceptance. Instead, it treats adviser identity as an experimental factor capable of influencing differences in trust and reliance. This approach allows the study to determine empirically whether investors demonstrate greater confidence in human expertise, greater appreciation of algorithmic consistency, or both.

H2: Investors' reliance on financial advice differs significantly according to whether the advice is attributed to a human adviser, AI system, or human-AI hybrid system.

Human Expertise and Interpersonal Trust

Human financial advisers may benefit from interpersonal trust stemming from perceptions of expertise, experience, empathy, accountability, and responsibility. Unlike automated systems, human advisers can communicate directly with clients, explain recommendations, answer questions, and potentially adapt their advice to fit individual circumstances. These characteristics can increase perceptions that the adviser understands the client's specific needs and is responsible for the recommendation provided. Interpersonal trust theory suggests that trust in human actors can emerge from perceptions of ability, benevolence, and integrity. In financial advice, ability is the perception of technical competence, benevolence is the belief that the adviser considers the investor's interests, and integrity concerns the belief that the adviser behaves honestly and consistently. However, human advice may also be perceived as vulnerable to emotional biases, conflicts of interest, and subjective judgment. Therefore, interpersonal trust does not automatically result in greater reliance. The experimental comparison proposed by this study will determine whether the

perceived human characteristics of expertise and accountability lead investors to place greater confidence in human advice than in AI-generated recommendations. The theory also provides a basis for understanding how investors with greater investment experience may evaluate human advisers differently from less experienced investors. Experienced investors may possess stronger beliefs about the strengths and limitations of professional advice and may therefore rely less on interpersonal trust alone when evaluating recommendations.

H3: Perceived human expertise and interpersonal trust positively influence investors' reliance on financial advice.

Perceived AI Competence and Objectivity

AI financial advice may generate trust through mechanisms that differ from those associated with human advisers. Investors may perceive AI systems as capable of processing extensive information, identifying patterns, maintaining consistency, and avoiding emotional influences. These characteristics can increase perceptions of analytical competence and objectivity. In financial markets, where emotional biases such as overconfidence, loss aversion, and excessive optimism can influence human decisions, the apparent lack of emotion in AI systems may be regarded as advantageous. Investors may therefore consider AI recommendations to be credible when believing that the system uses systematic analysis rather than personal intuition. However, perceived competence alone may not necessarily generate trust. If investors cannot understand how an AI system reaches its recommendation, concerns about transparency and accountability may diminish confidence. The effect of AI advice may therefore depend on the balance between perceptions of analytical capability and perceived limitations in human-like understanding. This study conceptualizes perceived AI competence and objectivity as important components of investor evaluations of AI-based financial advice. The experimental design will maintain the investment information relatively constant while varying the stated source of advice, allowing differences in investor responses to be attributed more directly to perceptions of the advisory source.

H4: Perceived AI competence and objectivity positively influence investor trust and subsequent reliance on AI-generated financial advice.

Trust and Advice Reliance

Trust is expected to be a central psychological mechanism connecting adviser identity with actual investor behavior. An investor may recognize that a recommendation is potentially useful but refuse to follow it if the advisory source is perceived as unreliable or incompetent. On the other hand, a highly trusted adviser can exert great influence on an investor's decision even if the investor does not independently verify each recommendation. In this study, advice reliance is conceptualized primarily as a behavioural response rather than simply an individual's stated intention to follow advice. Participants will make an initial portfolio decision and subsequently receive financial advice. Their final portfolio allocation will then be compared with their initial allocation and the recommended allocation. The greater the movement towards the recommendation, the greater the behavioural reliance. Trust is expected to increase the willingness to incorporate external advice into one's own decision. This relationship is particularly important in the comparison between human and AI advisers because identical or substantively equivalent recommendations may produce different behavioural

consequences depending on perceived credibility. If investors trust a particular advisory source, they may be more willing to revise their initial beliefs and portfolio allocations. If trust is low, they may maintain their original decisions even after receiving potentially useful advice.

H5: Higher levels of investor trust in the advisory source are positively associated with greater behavioural reliance on financial advice.

Advice Reliance and Portfolio Choice

The ultimate significance of financial advice lies in its potential to influence investment behaviour. Advice reliance can alter portfolio choice by changing the allocation of financial resources across assets with different levels of risk and return. Investors who strongly rely on an advisory recommendation may substantially shift their portfolios towards the recommended allocation, while investors who do not rely on it may make only minimal changes. The current study therefore treats portfolio choice as a behavioural outcome rather than simply a preference. Participants will first construct an independent portfolio and then receive advisory information before being given an opportunity to revise their allocation. This approach allows the study to observe whether the advisory source changes actual decision behaviour. Portfolio choice will be assessed through measures such as the proportion of equities, bonds, diversified funds, and cash allocated as well as an overall measure of portfolio risk. The theory predicts that stronger advice reliance will be associated with greater portfolio adjustment in the direction recommended by the adviser. However, the effect may vary according to investors' individual risk preferences and financial knowledge. An investor may trust an adviser but still reject a recommendation if it strongly conflicts with their personal risk tolerance. Consequently, portfolio choice represents the final step in the proposed theoretical pathway from adviser identity through trust and advice reliance.

H6: Greater reliance on financial advice significantly influences investors' portfolio allocation and portfolio risk-taking behaviour.

Trust as a Mediator

Trust is expected to mediate the relationship between adviser type and advice reliance. Adviser identity does not directly force an investor to follow a recommendation. Instead, the identity of the source can influence perceptions of competence, reliability, objectivity, and credibility, which subsequently impact the investor's willingness to adopt a recommendation. For example, an investor may follow an AI recommendation because the system is perceived as highly analytical and consistent, whereas another investor may reject the recommendation because the absence of human judgment decreases trust. Similarly, human advice can generate stronger reliance when investors value interpersonal expertise and accountability. Mediation analysis will therefore examine whether differences in advice reliance across the experimental conditions can be statistically explained by differences in investor trust. This mechanism is of particular importance as it distinguishes the source effect from a purely behavioural comparison. If adviser type significantly affects trust and subsequently predicts advice reliance, the findings would suggest that investors' responses to human and AI advice are partly psychological rather than solely based on the content of the recommendation.

H7: Investor trust mediates the relationship between adviser type and advice reliance.

Advice Reliance as a Mediator of Portfolio Choice

Advice reliance is expected to mediate the relationship between adviser type and portfolio choice. A sequential process is proposed as the mechanism by which the perceived identity of the adviser influences trust, which in turn influences the extent to which investors rely on the recommendation, which subsequently influences the degree to which investors modify their portfolios. This framework recognizes that receiving advice and acting upon it are distinct stages of financial decision-making. An investor may perceive an AI system to be highly competent but keep an independent portfolio if the recommendation does not match their preferences. Conversely, strong trust can increase reliance and therefore cause greater portfolio adjustment. The proposed experimental design can measure this process by measuring initial portfolio allocations, post-advice allocations, trust, and perceived reliance within the same participant. A sequential mediation analysis will be performed to test whether adviser type affects portfolio choice indirectly through trust and advice reliance. Demonstrating such a pathway would provide a more comprehensive explanation of how AI and human advisory systems influence investment behaviour.

H8: Advice reliance mediates the relationship between adviser type and portfolio choice, with trust contributing to this sequential mediation process.

Financial Literacy as a Moderator

Financial literacy may significantly influence how investors interpret and respond to external financial advice. Financially literate individuals are more likely to understand concepts such as diversification, inflation, risk, expected return, and compound interest, allowing them to critically evaluate recommendations rather than simply adopting them. Less financially literate investors may rely more heavily on external advisers since they have fewer resources for independently evaluating investment information. However, higher financial literacy could increase trust in AI advice if knowledgeable investors recognize the analytical power of algorithmic systems. Alternatively, financially sophisticated investors may be more skeptical of both human and AI recommendations since they are better at identifying limitations and conflicts. The direction of the moderating effect is therefore an empirical question. This study will measure financial literacy independently and examine whether it changes the relationship between adviser type, trust, advice reliance, and portfolio choice. Additionally, by incorporating financial literacy into the theoretical framework, the study moves beyond treating investors as a homogeneous population and acknowledges that technological advice may affect individuals differently according to their financial knowledge.

H9: Financial literacy moderates the relationship between adviser type and advice reliance, such that the effect of adviser type varies according to investors' levels of financial literacy.

Investment Experience as a Moderator

Investment experience is another important individual difference that can influence responses to financial advice. Investors with more experience are likely to be more familiar with market volatility, portfolio diversification, financial products, and the consequences of investment decisions. Therefore, they are likely to

rely less on external advice than those with less experience as they possess greater confidence in their own judgment. At the same time, experienced investors are more likely to recognize the value of AI-based analytical systems and therefore demonstrate greater acceptance of algorithmic advice. Less experienced investors may instead rely on perceived authority, especially when faced with complex financial decisions. Therefore, investment experience can influence not only the level of reliance but also the relative attractiveness of human and AI advisers. The study will measure participants' previous investment participation and experience and examine whether these characteristics moderate the relationship between adviser type and behavioral outcomes. This analysis is important because a finding that AI advice is effective for experienced investors but less effective for novices, or vice versa, would have significant implications for the design and targeting of AI-enabled financial advisory services.

H10: Investment experience moderates the relationship between adviser type and advice reliance and portfolio choice.

Decision Complexity as a Moderator

Decision complexity may determine how investors respond to different advisory sources. Simple investment decisions may require relatively limited analytical processing, whereas complex decisions involving multiple assets, competing objectives, uncertainty, and substantial information may increase cognitive demands. AI systems may possess an advantage in complex environments because they can process and integrate large quantities of information systematically. Human advisers, however, may retain an advantage when investors value contextual interpretation, communication, and individualized judgment. The relative effectiveness of human and AI advice may therefore change as decision complexity increases. This study will examine decision complexity by varying the informational and investment characteristics of the experimental task or by measuring participants' perceived complexity after completing the decision. The theoretical expectation is that complexity may strengthen the perceived value of AI's analytical capacity while simultaneously increasing the importance of human explanation and reassurance. The hybrid advisory model may therefore become particularly attractive when decision complexity is high because it combines computational analysis with human interpretation. Examining complexity as a moderator will provide insight into whether preferences for human or AI advice are stable or context-dependent.

H11: Decision complexity moderates the relationship between adviser type and investor trust and advice reliance, with the relative effect of AI and human advice changing as decision complexity increases.

Human-AI Hybrid Advice

Human-AI hybrid advice represents a potentially important alternative to the traditional human-versus-AI comparison. Rather than treating humans and AI as competing sources of expertise, the hybrid model combines algorithmic analysis with human judgment and communication. AI can process extensive datasets, identify patterns, and generate systematic recommendations, while human advisers can interpret recommendations, explain uncertainty, consider individual circumstances, and provide interpersonal reassurance. This combination may reduce weaknesses associated with relying exclusively on either source. Investors who are

concerned about algorithmic opacity may feel more comfortable when a human adviser remains involved, while investors who are skeptical of human subjectivity may value the analytical contribution of AI. The hybrid model may therefore generate higher trust and advice reliance than either human-only or AI-only advice. However, hybrid advice could also create ambiguity regarding responsibility if investors are uncertain about whether the final recommendation originates from the human or the algorithm. The experimental comparison will therefore treat hybrid advice as a distinct condition rather than simply as an average of human and AI advice.

H12: Human-AI hybrid advice generates significantly different levels of investor trust and advice reliance compared with purely human or purely AI advice.

Integrated Conceptual Framework

The theoretical framework developed in this chapter proposes that adviser identity constitutes the primary experimental factor influencing investor decision-making. Human, AI, and human-AI hybrid advisory systems may create different perceptions of competence, reliability, objectivity, accountability, and interpersonal connection. These perceptions are expected to influence investor trust, which represents the principal psychological mechanism connecting adviser identity with behavioral reliance. Greater trust is expected to increase the probability that investors will incorporate external recommendations into their own decisions. Advice reliance then represents the behavioral mechanism through which advisory information affects portfolio choice. Investors who rely strongly on the recommendation are expected to make larger adjustments to their initial portfolio allocation and potentially change their level of portfolio risk. The framework also recognizes that these relationships are conditional rather than universal. Financial literacy, investment experience, risk tolerance, AI familiarity, and decision complexity may strengthen or weaken the effects of adviser identity. Human-AI hybrid advice is positioned as a potentially distinctive model capable of combining technological competence with human accountability and communication. The resulting framework therefore follows a sequential logic in which adviser type influences trust, trust influences advice reliance, and advice reliance influences portfolio choice, while individual and situational characteristics moderate these relationships. This integrated model provides the theoretical foundation for the experimental methodology presented in the following chapter.

Summary of Hypothesis Development

The hypotheses developed in this chapter establish a comprehensive theoretical model for understanding investor responses to human and AI financial advice. The framework begins with the assumption that adviser identity influences investor perceptions and trust. It then proposes that trust plays a central role in determining whether investors rely on the recommendation provided. Advice reliance subsequently affects portfolio allocation and risk-taking behavior. The framework further proposes that trust and advice reliance operate as mediating mechanisms rather than merely as independent outcomes. In addition, financial literacy, investment experience, and decision complexity are expected to influence the strength of these relationships. The inclusion of the human-AI hybrid condition extends the theoretical framework beyond a simple technological substitution model and allows the study to examine whether combining human and artificial

intelligence produces distinct patterns of trust and reliance. Together, these hypotheses create a coherent explanation of how the source of financial advice may shape investor behavior. The experimental methodology will empirically test these relationships by manipulating adviser identity while measuring trust, behavioral reliance, and portfolio decisions before and after exposure to financial advice.

Research Methodology

Research Design

This study will employ a quantitative research approach using a randomized experimental design to investigate how the source of financial advice influences investor trust, advice reliance, and portfolio choice. An experimental approach is particularly appropriate because the central objective is to identify whether differences in investor behavior are caused by the perceived identity of the adviser rather than by differences in the substantive quality of the financial recommendation. Participants will therefore be randomly assigned to different advisory conditions in which they receive standardized investment information and recommendations presented as originating from either a human financial adviser, an artificial intelligence (AI) system, or a human-AI hybrid advisory system. A fourth group will serve as a control condition and will receive the investment information without an external recommendation. The study will primarily use a between-subjects design, meaning that each participant will experience only one advisory condition. This will reduce potential carry-over effects and prevent participants from directly comparing the different sources of advice. The experimental design will also incorporate a pre-advice and post-advice portfolio decision. Participants will first construct an investment portfolio independently and will subsequently receive the assigned advisory recommendation before being given an opportunity to revise their portfolio. This procedure will allow the study to measure behavioral advice reliance by examining the extent to which participants change their initial investment decisions after receiving advice. In addition to behavioral outcomes, participants will complete measures of perceived trust, competence, reliability, transparency, and confidence in the adviser. The study will also collect information concerning financial literacy, investment experience, risk tolerance, and familiarity with AI. These variables will allow the research to investigate whether individual characteristics influence responses to different advisory sources. Overall, the proposed experimental design provides a controlled framework for examining the causal relationship between adviser identity and investor decision-making.

Participants and Sampling

The study will target adult participants with sufficient capacity to understand basic financial information and make hypothetical investment decisions. The sample may include university students, graduates, working professionals, retail investors, and individuals with previous investment experience. A diverse participant pool will be sought because financial literacy, investment experience, technological familiarity, and demographic characteristics may influence responses to human and AI financial advice. Participants will be recruited through appropriate online research platforms, university networks, professional networks, and investment-related communities, subject to ethical approval and recruitment requirements. The proposed target sample is approximately 600 participants, with approximately 150 participants assigned to each

of the four experimental conditions. However, the final sample size will be determined through an a priori statistical power analysis based on the expected effect size, desired statistical power, significance level, and number of experimental conditions. Participants will be randomly allocated to the human, AI, hybrid, or control group after completing the initial screening and demographic questionnaire. Random assignment is essential because it reduces systematic differences between experimental groups and strengthens the internal validity of the study. Before the main experiment, a pilot study will be conducted with a smaller sample to assess whether the experimental instructions, investment scenario, advisory messages, and survey measures are understandable and sufficiently distinguish the treatment conditions. Participants may be excluded from the final analysis if they fail predetermined attention or comprehension checks, provided that the exclusion criteria are established before examining the main results. The study will also record relevant participant characteristics, including age, educational background, investment experience, financial literacy, risk tolerance, previous exposure to AI, and familiarity with robo-advisory services. These characteristics will subsequently be used as control or moderating variables in the statistical analysis.

Experimental Procedure

The experiment will consist of several sequential stages designed to measure changes in investor behavior before and after exposure to financial advice. At the beginning of the study, participants will receive an explanation of the research purpose, procedures, confidentiality arrangements, and voluntary nature of participation. After providing informed consent, participants will complete a short questionnaire measuring demographic characteristics, financial literacy, investment experience, risk tolerance, familiarity with AI, and previous experience with digital financial services. Participants will then receive a hypothetical investment scenario in which they are given a specified amount of money, such as \$100,000, and asked to construct an investment portfolio from several asset categories, including equities, bonds, exchange-traded funds, and cash. This initial decision will provide a baseline measure of individual portfolio preferences before external advice is introduced. Participants will subsequently be randomly exposed to one of the experimental conditions. In the human condition, the recommendation will be presented as being prepared by a professional financial adviser. In the AI condition, the same or substantively equivalent recommendation will be presented as being generated by an artificial intelligence financial advisory system. In the hybrid condition, the recommendation will be described as the product of cooperation between a professional financial adviser and an AI analytical system. The control group will receive the same investment information but no external recommendation. After exposure to the treatment, participants will complete a series of questions measuring trust, perceived competence, reliability, transparency, and confidence in the advisory source. Finally, participants will be allowed to revise their initial portfolio. The difference between their initial and final portfolios will provide a behavioral measure of advice reliance. Manipulation and attention checks will also be incorporated to ensure that participants correctly understood the source of the advice and engaged with the experimental task.

Variables and Measurement

The principal independent variable in the study will be adviser type, consisting of four experimental conditions: human adviser,

AI adviser, human-AI hybrid adviser, and control. The primary dependent variables will be investor trust, advice reliance, and portfolio choice. Investor trust will be measured using multiple Likert-scale items assessing perceived reliability, competence, trustworthiness, transparency, and confidence in the advisory source. A seven-point response scale ranging from strong disagreement to strong agreement will allow sufficient variation in participants' evaluations. Advice reliance will be measured primarily through behavioral rather than purely attitudinal indicators. Specifically, the study will compare participants' initial portfolio allocations with their final allocations after receiving advice. The extent to which an investor moves toward the recommended allocation will represent the degree of behavioral reliance on the advice. Portfolio choice will be assessed through the proportion of wealth allocated to different asset categories and the resulting level of portfolio risk. Additional variables will include financial literacy, investment experience, risk tolerance, AI familiarity, and decision complexity. Financial literacy will be assessed using objective questions covering concepts such as interest, inflation, diversification, and risk and return. Investment experience will be measured through previous participation in financial markets and the duration or frequency of investment activity. Risk tolerance will capture participants' willingness to accept potential financial losses in exchange for higher expected returns. AI familiarity will assess previous exposure to AI-based technologies and financial applications. Decision complexity may be manipulated by varying the number and characteristics of investment alternatives or the amount of information presented to participants. These measures will enable the study to examine both the direct effect of adviser type and the factors that may strengthen or weaken its influence on investor behavior.

Data Analysis

The collected data will be analyzed using appropriate quantitative statistical techniques. The analysis will initially employ descriptive statistics to summarize participant characteristics, financial-literacy scores, investment experience, trust levels, initial portfolio allocations, and final portfolio decisions. Reliability analysis will then be conducted to evaluate the internal consistency of multi-item constructs such as investor trust and perceived expertise. Experimental differences between the human, AI, hybrid, and control groups will initially be examined using analysis of variance and appropriate regression techniques. Where necessary, demographic and financial characteristics will be incorporated as control variables to account for systematic differences that may influence portfolio decisions. Regression analysis will subsequently estimate the relationship between adviser type and the principal outcomes of the study, including trust, advice reliance, portfolio adjustment, and portfolio risk. Mediation analysis will be used to determine whether investor trust explains the relationship between adviser type and advice reliance. A second mediation analysis will examine whether advice reliance explains the relationship between adviser type and portfolio choice. A sequential mediation model will further test the proposed pathway of adviser type → investor trust → advice reliance → portfolio choice. Moderation analysis will investigate whether financial literacy, investment experience, AI familiarity, risk tolerance, and decision complexity alter the effect of adviser type on trust and advice reliance. Interaction terms between adviser type and these variables will be included where theoretically justified. Robustness analyses will employ alternative measures of advice

reliance and portfolio risk to determine whether the principal findings remain stable under different specifications. Statistical significance will be assessed using an appropriate significance threshold, while effect sizes and confidence intervals will also be reported to provide information about the magnitude and precision of the observed relationships.

Ethical Considerations

The study will follow established principles of research ethics throughout the recruitment, experimentation, data collection, and analysis processes. Participation will be voluntary, and participants will provide informed consent before beginning the experiment. They will be informed about the general nature of the research, the hypothetical character of the investment task, the expected duration of participation, and the handling of their information. Because the study concerns financial decision-making, participants will be explicitly informed that the investment recommendations presented during the experiment are part of a research exercise and should not be interpreted as personalized financial advice. No participant will be required to invest real money or make an actual financial transaction as part of the experiment. Personal information collected during the study will be minimized and anonymized wherever possible. Data will be stored securely and used exclusively for academic research purposes. Participation will not involve unnecessary financial, psychological, or social risks. Participants will also be informed of their rights concerning participation and withdrawal in accordance with the requirements of the relevant research institution. Before data collection begins, the study will seek approval from the appropriate institutional ethics committee or review body where such approval is required. Particular attention will be given to the experimental disclosure of adviser identity because participants must be exposed to the intended treatment without being unnecessarily misled. If limited deception is required to maintain experimental validity, it will be justified scientifically, approved through the relevant ethical process, and followed by appropriate debriefing. These procedures will ensure that the study maintains methodological rigor while protecting participants' autonomy, privacy, and welfare.

Results

Introduction

This chapter proposes the analysis for the empirical data that will be generated by the experimental study designed in the previous chapter. The proposed analysis aims to determine whether the source of financial advice, including human advice, artificial intelligence (AI) advice, and human-AI hybrid advice, has an impact on investor trust, advice reliance, and portfolio choice. This chapter therefore translates the theoretical relationships and hypotheses developed in Chapter 3 into an empirical analysis. Since the proposed study has not yet been conducted, the chapter does not report fabricated results. Instead, it details the procedures that will be used to examine the collected data and explains what findings would be supportive of the proposed theoretical relationships.

The analysis will begin with data preparation and preliminary assessment. The collected data responses will be examined for completeness, consistency, attention-check performance, and potential data-quality issues. Appropriate procedures will then be applied to identify incomplete observations and responses that fail predetermined eligibility or experimental requirements. Descriptive

statistics will subsequently be used to summarize the characteristics of the participants and provide an overall understanding of the sample. Variables such as financial literacy, investment experience, risk tolerance, AI familiarity, investor trust, advice reliance, and portfolio allocation will be examined using appropriate measures of central tendency and dispersion. The step is important as it provides the foundation for the subsequent inferential analysis.

The next stage of the analysis will examine the reliability and validity of the measurement instruments. Constructs such as investor trust and perceived adviser competence will be measured using multiple questionnaire items. Internal consistency will therefore be assessed using appropriate reliability statistics while the conceptual structure of the measures will be evaluated using suitable validity procedures. The experimental manipulation will also be examined to determine whether participants correctly perceived the stated source of financial advice. These checks are particularly important as the central independent variable is adviser identity. If participants do not distinguish between the human, AI, and hybrid conditions, differences in the dependent variables cannot confidently be attributed to the experimental manipulation.

The analysis will then proceed with inferential analysis to test the hypotheses developed in Chapter 3. Comparative statistical procedures will determine whether investor trust, advice reliance, and portfolio outcomes differ across the experimental conditions. Regression-based analysis will provide additional evidence regarding the relationship between adviser type and the principal behavioral outcomes while allowing relevant participant characteristics to be incorporated into the analytical models. Particular attention will be given to the behavioral measurement of advice reliance. As participants will make portfolio decisions before and after receiving advice, the change between their initial and final allocations will provide an observable indicator of the extent to which they incorporated the recommendation into their decision.

The analysis will also investigate the psychological and contextual mechanisms underlying investor behavior. Mediation analysis will examine whether trust explains the relationship between adviser type and advice reliance and whether advice reliance explains differences in portfolio choice. A sequential mediation framework will therefore test the proposed pathway from adviser identity to trust, from trust to reliance, and from reliance to portfolio behavior. Moderation analysis will additionally investigate whether financial literacy, investment experience, AI familiarity, risk tolerance, and decision complexity alter these relationships. Such analyses will help determine whether human and AI financial advice affect investors uniformly or whether their influence depends on individual characteristics and decision circumstances.

Finally, robustness analyses will be conducted to assess whether the principal conclusions remain stable when alternative operationalizations, control variables, and statistical specifications are applied. Effect sizes and confidence intervals will therefore be considered alongside statistical significance so that the practical importance and precision of the findings can be evaluated. Overall, the analysis is designed to provide a systematic test of the proposed theoretical model and determine whether the growing integration of AI into financial advice changes how investors trust, follow, and act upon financial recommendations.

Data Preparation and Preliminary Analysis

The proposed study will use a target sample of 600 participants with approximately 150 participants assigned to each of the four experimental conditions. Before conducting the principal statistical analyses, the collected dataset will undergo a systematic process of data screening, cleaning, coding, and preparation. For the purpose of illustrating the proposed analytical framework, it is anticipated that around 600 completed responses will initially be obtained. A small proportion of responses may be excluded due to incomplete questionnaires, failed attention checks, duplicate submissions, or failure to satisfy the predetermined eligibility criteria. For example, if around 24 observations (4.0%) are excluded, the final analytical sample will consist of around 576 valid participants, corresponding to around 144 participants per experimental condition. These figures represent an illustrative scenario rather than actual empirical results and will be replaced by the observed values after data collection.

The first stage of data preparation will involve examining the dataset for missing values. It is expected that most participants will complete the questionnaire as the experiment will be administered through a structured online survey. A preliminary assessment may reveal around 1-3% missing responses across individual questionnaire items. Where missing values are minimal and occur randomly, appropriate statistical procedures may be applied without substantially affecting the analysis. Participants with extensive missing information, such as individuals completing less than 80% of the questionnaire, may be removed according to criteria established before the analysis. The dataset will also be examined for impossible or inconsistent responses including values outside the predefined measurement ranges. For example, trust items measured on a seven-point Likert scale must contain values between 1 and 7 while portfolio allocation percentages must fall between 0% and 100% and collectively equal around 100%.

Attention and comprehension checks will provide an additional assessment of response quality. As the experiment relies on participants correctly identifying the advisory source, participants who repeatedly fail the manipulation or attention checks may be excluded from the principal analysis. As an illustrative expectation, around 90-95% of valid participants may correctly identify whether the recommendation was attributed to a human adviser, AI system, or hybrid system. Participants who fail the relevant check may nevertheless be retained in a robustness analysis to determine whether their inclusion materially changes the findings.

The variables will then be coded systematically for statistical analysis. Adviser type will be represented as a categorical variable with four levels. Trust will be calculated from multiple seven-point Likert-scale items while advice reliance will be calculated from the behavioral change between participants' initial and final portfolio allocations. For example, if a participant initially allocates 40% to equities and changes this allocation to 55% after receiving advice recommending 60% equities, the participant has moved 15 percentage points towards the recommendation. Such changes will provide the basis for constructing a behavioral reliance measure. Portfolio risk will similarly be calculated from the relative allocation to higher- and lower-risk assets.

Preliminary descriptive analysis will then examine the distribution of the principal variables. As an illustrative expectation, the mean

trust score across the complete sample may fall around 4.8 on a seven-point scale with a standard deviation around 1.1. Mean financial-literacy scores may be around 6.5 out of 10 while the average portfolio adjustment toward the recommended allocation may be around 12-18 percentage points. These values are hypothetical benchmarks for demonstrating the intended analysis and should not be presented as observed findings. Skewness, kurtosis, minimum and maximum values, and graphical distributions will also be examined before inferential testing. Overall, the preliminary analysis will establish a clean and reliable dataset and provide the statistical foundation for examining whether the source of financial advice significantly influences investor trust, advice reliance, and portfolio choice.

Descriptive Analysis of Participants

The descriptive analysis provides an overview of the demographic and investment-related characteristics of the participants included in the experimental study. The objective of this analysis is to establish the composition of the sample and determine whether participants assigned to the human, artificial intelligence (AI), and hybrid advice conditions are reasonably comparable.

For illustration, the study assumes a total sample of 300 participants with 100 participants randomly assigned to each of the three experimental conditions. The sample includes participants with different levels of age, education, financial literacy, investment experience, and familiarity with artificial intelligence. Such variation is important as individual characteristics may influence perceptions of financial advice and willingness to rely on recommendations.

Table 5.1 presents the demographic characteristics of the participants. The illustrative sample has a relatively balanced gender distribution, with 156 participants (52.0%) identified as male and 144 (48.0%) identified as female. The average age of participants is assumed to be around 29.8 years with participants ranging from 18 to 55 years.

In terms of educational attainment, the majority of participants possess at least an undergraduate degree. Around 46.0% hold a bachelor's degree while 31.0% have completed postgraduate education. The remaining participants have secondary or other forms of tertiary education.

Investment experience is also varied. Around 42.0% of participants are assumed to have between one and three years of investment experience while 25.0% have more than three years of experience. The remaining participants have less than one year of experience or have never previously invested in financial assets.

An important characteristic of the sample is participants' familiarity with artificial intelligence. As the experiment directly compares human and AI financial advice, previous exposure to AI may influence trust and reliance. The illustrative data indicate that 58.0% of participants report moderate or high familiarity with AI-based applications while 42.0% report low familiarity.

Overall, the descriptive characteristics suggest that the sample contains sufficient variation in demographic and investment-related characteristics to examine whether these factors influence responses to different forms of financial advice.

Table 5.1: Demographic Characteristics of Participants

Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	156	52.0
	Female	144	48.0
Age	18–24 years	92	30.7
	25–34 years	118	39.3
	35–44 years	57	19.0
	45–55 years	33	11.0
Education	Secondary/College	69	23.0
	Bachelor's degree	138	46.0
	Master's degree or above	93	31.0
Investment Experience	No experience	48	16.0
	Less than 1 year	51	17.0
	1–3 years	126	42.0
	More than 3 years	75	25.0
AI Familiarity	Low	126	42.0
	Moderate	105	35.0
	High	69	23.0
Previous Financial Advice	Never received advice	132	44.0
	Occasionally	105	35.0
	Frequently	63	21.0
Total Participants	—	300	100.0

Note: The values presented in Table 5.1 are simply examples of values needed for the aforementioned analysis, and they will have to be substituted with the observed data.

The experimental allocation is provided in Table 5.2. The use of random assignment leads to equal numbers of participants for all three conditions of the advisory service. Such design is more productive because it allows performing comparisons between groups with equal sample sizes.

Table 5.2: Distribution of Participants Across Experimental Conditions

Experimental Condition	Description	Participants (N)	Percentage (%)
Human Advice	Financial recommendation presented as being generated by a human financial adviser	100	33.3
AI Advice	Financial recommendation presented as being generated by an artificial intelligence system	100	33.3
Hybrid Advice	Recommendation presented as combining human and AI input	100	33.3
Total	—	300	100.0

Equal distribution across the experimental groups enables the study to make inter-group comparisons of investors' responses without substantial differences in group sizes. The random assignment in

the current experiment is particularly critical since the main purpose of this experiment is to investigate whether there is a

causal link between the source of financial advice and investors' trust, reliance, and portfolio decisions.

To further explore whether the three experimental groups are comparable, we can conduct a comparison of the demographic characteristics of participants across experimental conditions before proceeding to the main hypothesis testing. Comparison of continuous variables such as age and financial literacy can be done using Analysis of Variance (ANOVA). Meanwhile, categorical variables such as gender, education, and investment experience can be compared using the chi-square test.

The prediction is that the three experimental groups will be broadly similar in terms of demographic characteristics, so that any observed differences in investor trust, reliance, and portfolio decisions can be attributed to the experimental treatment with more confidence. For example, the mean age, level of financial literacy, investment experience, and familiarity with AI among participants assigned to the human, AI, and hybrid groups are expected to be generally comparable. If substantial inter-group differences are found, these should be controlled for in the process of hypothesis testing and robustness analysis.

Through this descriptive analysis, we aim to accomplish two objectives. First, we seek to understand the basic characteristics of our sample. Second, we intend to take the first step towards examining whether random assignment was indeed successful in producing similar treatment groups. This is important for establishing whether subsequent differences in investor trust and choice can be confidently attributed to the experimental treatment rather than some pre-existing group differences.

The illustrative sample is thus broadly representative of a diverse investor population in terms of gender, age, and level of financial literacy. Some participants have extensive experience with investing and AI technologies, while others do not. This heterogeneity is beneficial for the current research question since it enables us to investigate whether investors with different levels of expertise and AI exposure will have divergent perceptions of financial advice.

Reliability and Validity Analysis

Reliability and validity analysis allow us to establish whether the measurement instruments employed in the study produce consistent and valid measures of the constructs of interest. In the current study, the main constructs of interest include investor trust, reliance on advice, perceived adviser competence, perceived transparency, and risk perception. Since these are measured using multiple items in the questionnaire, it is important to investigate whether the items measure the same underlying concepts (i.e., reliability) and whether the items used capture the essence of the theoretical constructs (i.e., validity). The main statistical techniques used in reliability and validity analysis are discussed below.

➤ Reliability Analysis

Reliability refers to the extent to which a measurement instrument produces consistent results. In the context of questionnaires, this means that the measurement items should produce comparable results when measuring the same underlying concept. One of the most common ways of assessing reliability is Cronbach's alpha (α), which measures the proportion of variance in the scores obtained across items that is not due to chance:

The value of α ranges from 0 to 1, with higher values indicating greater reliability. A value of 0.70 or above is considered acceptable, and 0.80 and above is considered good reliability. Table 5.3 below shows the illustrative reliability results for the main constructs employed in the analysis.

As can be seen from the table, all the constructs employed in the study have acceptable levels of reliability, with investor trust having the highest level of reliability, followed by perceived competence and reliance on advice. The lowest reliability coefficient was obtained for risk perception, but it is still well above the acceptable threshold of 0.70.

Table 5.3: Reliability Analysis of Measurement Constructs

Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
Investor Trust	6	0.91	Excellent
Advice Reliance	5	0.88	Good
Perceived Adviser Competence	5	0.89	Good
Perceived Transparency	4	0.84	Good
Risk Perception	4	0.81	Good
Overall Scale	24	0.90	Excellent

Note: Values are illustrative and should be replaced with coefficients calculated from the actual dataset

The reliability coefficients indicate that the items within each construct measure relatively coherent underlying concepts. In particular, an illustrative Cronbach's alpha of 0.91 for investor trust implies a very high degree of internal consistency. This observation is particularly important since investor trust constitutes one of the key explanatory variables in the proposed mediation model.

A very high value of Cronbach's alpha should not always be interpreted as indicating a superior measurement quality. Values

that are too high may indicate that several questionnaire items are too similar. Therefore, the reliability consideration is complemented by the evaluation of factor structure and validity evidence.

Item-total correlations and the impact of deleting individual items should be examined during the final analysis. Items with very weak item-total correlation may need to be investigated further. However, items should not be deleted purely to increase the value

of Cronbach's alpha; theoretical relevance should always take precedence.

➤ **Construct Validity**

Construct validity is a general term that refers to the extent to which the measurement instruments actually represent the theoretical concepts they purport to measure. In the context of this study, construct validity is particularly important since investor trust, advice reliance, perceived competence and risk perception are conceptually related but theoretically distinct constructs.

Factor analysis will be used to establish whether the questionnaire items form clusters as implied by the proposed theoretical dimensions. Prior to performing the factor analysis the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity will be investigated.

A value of KMO above 0.60 is generally taken as indicating a sample that is adequate for the purpose of factor analysis while a significant Bartlett's test indicates that the correlation matrix contains sufficient relationships among variables to justify factor extraction.

Table 5.4: KMO and Bartlett's Test of Sphericity

Test	Illustrative Value	Interpretation
Kaiser-Meyer-Olkin (KMO)	0.89	Excellent sampling adequacy
Bartlett's Test of Sphericity – χ^2	3,426.58	Significant
Degrees of Freedom	276	—
Significance (p)	< 0.001	Factor analysis appropriate

Note: Values are illustrative and should be recalculated using the dataset. Illustrative KMO Value: 0.89. An acceptable sampling adequacy is observed. The Bartlett's test is significant, which supports the idea that the correlation matrix is not an identity matrix and that there are significant correlations among variables. Therefore, proceeding with the factor analysis is justified.

➤ **Factor Structure**

If the items in the measurement instrument contain adapted or new constructs, an exploratory factor analysis could be performed. The method of principal axis factoring with an oblique rotation is a good option due to the nature of constructs under investigation: Trust, Competence, Transparency, and Reliance are all likely to be interrelated.

The expected structure is that items tapping into Investor Trust dimension will load onto a general Trust factor, whereas Advice reliance, Competence, Trust, and Risk Perception will load onto different factors.

Table 5.5: Illustrative Factor Loading Results

Construct	Item	Factor Loading
Investor Trust	Trust 1	0.78
	Trust 2	0.82
	Trust 3	0.85
	Trust 4	0.79
	Trust 5	0.87
	Trust 6	0.81
Advice Reliance	Reliance 1	0.76
	Reliance 2	0.83
	Reliance 3	0.80
	Reliance 4	0.77
	Reliance 5	0.84
Perceived Competence	Competence 1	0.81
	Competence 2	0.86
	Competence 3	0.79
	Competence 4	0.83

Construct	Item	Factor Loading
	Competence 5	0.80
Perceived Transparency	Transparency 1	0.75
	Transparency 2	0.82
	Transparency 3	0.78
	Transparency 4	0.80
Risk Perception	Risk 1	0.74
	Risk 2	0.81
	Risk 3	0.77
	Risk 4	0.79

Note: Factor loadings shown are illustrative.

The illustrative factor loadings are all above 0.70, indicating that the items have strong associations with the latent construct for which they are intended. This would be sufficient to provide initial evidence of convergent validity.

➤ **Convergent, and Discriminant Validity**

Convergent validity considers whether indicators with the same construct converge. In addition to factor loadings, Average Variance Extracted (AVE) and composite reliability might also be calculated. An AVE value of approximately 0.50 or higher suggests that the construct explains at least half of the variance in its indicators.

Discriminant validity considers whether theoretically different constructs are sufficiently distinguishable. This is critical as the relationship between trust and advice reliance may be quite strong, despite being conceptually different constructs. Trust signifies the level of confidence that the participant has in the adviser, whereas advice reliance is the behavioral extent to which the participant follows the recommendation.

Table 5.6: Illustrative Convergent Validity Results

Construct	Composite Reliability	Average Variance Extracted (AVE)	Assessment
Investor Trust	0.93	0.68	Acceptable
Advice Reliance	0.90	0.64	Acceptable
Perceived Competence	0.91	0.67	Acceptable
Perceived Transparency	0.86	0.61	Acceptable
Risk Perception	0.85	0.59	Acceptable

Note: Values are illustrative.

The illustrative results show that each construct meets the commonly applied threshold for composite reliability and AVE. This implies that the indicators possess adequate convergent validity.

Discriminant validity will also be evaluated using an appropriate criterion such as the Fornell-Larcker criterion or the heterotrait-monotrait (HTMT) ratio. Evidence of discriminant validity would imply that investor trust, advice reliance, perceived competence, transparency, and risk perception are empirically distinct constructs.

Overall, the reliability and validity analysis is anticipated to confirm that the measurement instruments are sufficiently consistent and construct valid for subsequent hypothesis testing. Demonstrating measurement quality is particularly crucial for the present experimental study because the central theoretical argument depends on the relationships between adviser type, investor trust, advice reliance, and portfolio choice.

The final analysis will substitute the illustrative coefficients shown in Tables 5.3-5.6 with statistics that have been calculated from the collected dataset. Only the observed results will be relied on when reaching substantive conclusions about the hypotheses.

Manipulation and Attention Checks

Manipulation and attention checks are integral parts of the experimental design because the validity of the study hinges upon participants being able to correctly understand the source and nature of the financial advice presented to them. The present experiment compares three advisory conditions: human advice, artificial intelligence (AI) advice, and hybrid advice. Thus, participants must correctly identify the advisory source associated with their assigned experimental condition.

The manipulation check is formulated to ascertain whether the experimental treatment successfully influenced participants' perceptions of the adviser. After receiving the financial recommendation, participants were asked to identify the source of the advice. Participants assigned to the human-advice condition

were expected to identify the recommendation as being generated by a human financial adviser, participants assigned to the AI condition were expected to identify it as being generated by an AI system, and participants assigned to the hybrid condition were expected to identify the recommendation as consisting of both human and AI input.

For the purpose of demonstrating the proposed analysis, an illustrative sample of 300 participants is used, with 100 participants assigned to each experimental condition.

Table 5.7: Manipulation Check by Experimental Condition

Experimental Condition	Correct Identification	Incorrect Identification	Total	Correct (%)
Human Advice	94	6	100	94.0
AI Advice	92	8	100	92.0
Hybrid Advice	89	11	100	89.0
Total	275	25	300	91.7

Note: The figures are illustrative and should be replaced by the actual results of the experiment.

The illustrative results suggest that most participants correctly identified the source of the financial advice: the human-advice condition, for instance, produced a correct identification rate of 94.0% compared to 92.0% and 89.0% for AI and hybrid advice, respectively. The relatively high identification rates suggest that the manipulation generally worked.

The slightly lower recognition rate for the hybrid condition is theoretically expected, as hybrid advice constitutes a more complex arrangement than either human only or AI only advice. Therefore, participants might have mistakenly perceived advice as being delivered by one source when it was in fact delivered by both.

A chi-square test of independence could be carried out to examine whether identification accuracy differed significantly across the three experimental conditions. Failing to find a significant difference in the proportion of successful identification would constitute further evidence that the manipulation worked consistently across the experimental groups.

➤ **Attention Checks**

Besides the manipulation check, attention checks are used in the experiment to assess whether participants engaged attentively with the materials. Attention is of particular importance in an experiment concerning financial decision-making, as participants who fail to read the investment scenario would confound measures of trust, advice reliance, and portfolio choice by introducing random noise.

Participants could be asked a simple factual question pertaining to information explicitly provided in the experimental scenario. For instance, they could be asked to identify the investment objective, risk category, or the source of the advice provided in the scenario. The question serves to assess whether the participants processed the experimental information rather than relying on their domain knowledge of finance.

Table 5.8: Attention Check Results

Attention Check Outcome	Frequency (N)	Percentage (%)
Passed all attention checks	282	94.0
Failed one attention check	12	4.0
Failed multiple attention checks	6	2.0
Total	300	100.0

Note: The figures are illustrative.

Illustrative results: 282 participants (94.0% of the sample) passed all attention checks, twelve participants failed one attention check, and six participants failed multiple attention checks.

Excluded Participants: Participants who failed multiple attention checks would be excluded (since multiple failure indicates inadequate engagement with the experimental materials). Participants who failed a single check should not be excluded unless it is determined that their exclusion is consistent with a predetermined set of exclusion criteria. Excluding too many participants upon seeing the results of this analysis would allow researcher discretion to bias the results.

Illustrative results (continued): Assuming that participants who failed multiple attention checks were excluded, the final analytical sample is 294 participants. A sensitivity analysis comparing the main results using both the full and the restricted attention-compliant samples can be conducted next.

➤ **Combined assessment of manipulation and attention**

Successful manipulation requires participants to realize which advisory source was intended to influence them, and successful attention checks require participants to have engaged sufficiently with the scenario.

Table 5.9: Summary of Manipulation and Attention Checks

Assessment	Illustrative Result	Criterion	Assessment
Human advice correctly identified	94.0%	Majority correctly identified	Passed
AI advice correctly identified	92.0%	Majority correctly identified	Passed
Hybrid advice correctly identified	89.0%	Majority correctly identified	Passed
Passed attention checks	94.0%	High engagement	Passed
Failed multiple attention checks	2.0%	Low proportion	Acceptable
Overall manipulation recognition	91.7%	High recognition	Passed

Note: The values are illustrative.

Taken together, the illustrative results suggest that the experimental manipulation successfully differentiated the three advisory conditions and that the overwhelming majority of participants gave sufficient attention to the experimental materials. This provides a reasonable basis for moving on to the main analyses of investor trust, advice reliance, and portfolio choice.

Nevertheless, manipulation checks should not be used to argue that the experimental treatment itself caused differences in the dependent variables. Their purpose is to establish that the participants perceived the intended treatment. The causal analysis will therefore take place separately through comparisons of the experimental groups.

An additional concern is that participants who correctly identify the advisory source may behave differently from participants who incorrectly identify the advisory source. Accordingly, the study will perform a robustness analysis using the attention- and manipulation-compliant sample. The results obtained from this restricted sample will be compared with those from the full sample to see whether the substantive conclusions are sensitive to participant exclusion.

If the main findings remain consistent across these specifications, confidence in the robustness of the experimental conclusions will increase. In summary, the manipulation and attention checks are expected to demonstrate that the participants understood the

distinction between human, AI, and hybrid financial advice and performed the experimental task with a certain degree of engagement. Establishing these conditions is necessary before investigating whether the source of financial advice influences investor trust, advice reliance, risk-taking, and portfolio choice.

Analysis of Investor Trust

Investor trust is one of the central dependent variables in this study because the willingness of individuals to accept financial advice is likely to depend partially on the extent to which they perceive the adviser as credible, competent, reliable, and trustworthy. The goal of this section is to identify whether the source of financial advice, whether human, artificial intelligence (AI), or hybrid, produces significant differences in investor trust.

Investor trust is measured using multiple Likert-scale items assessing participants' perception of the adviser. The individual items are aggregated to form an overall trust index, with higher scores indicating more trust in the financial adviser. Descriptive statistics are calculated for the trust index before comparing the experimental groups.

For illustration, the analysis assumes that 294 participants remain after applying the predetermined attention-check exclusion criteria. The participants are distributed roughly equally across the three experimental conditions.

Table 5.10: Descriptive Statistics for Investor Trust by Experimental Condition

Experimental Condition	N	Mean	Standard Deviation	Minimum	Maximum
Human Advice	98	4.18	0.62	2.17	5.00
AI Advice	97	3.71	0.74	1.83	5.00
Hybrid Advice	99	4.39	0.55	2.67	5.00
Total	294	4.09	0.69	1.83	5.00

Note: The values are merely illustrative and must be replaced with statistics calculated from the actual dataset.

The descriptive statistics suggest that there is a notable difference in the mean level of trust across the three advisory conditions. The participants exposed to hybrid advice report the highest mean level of trust ($M = 4.39$, $SD = 0.55$), followed by those who received human advice ($M = 4.18$, $SD = 0.62$). Finally, the lowest mean level of trust was reported by the participants who received AI advice ($M = 3.71$, $SD = 0.74$).

A potential explanation of these preliminary results is that the participants express more trust in financial advice when they can rely on the combination of human judgment and technological analytical capacity. Meanwhile, the lowest trust is associated with the perception of uncertainty in the capability or reliability domain. Therefore, it is crucial to assess if these descriptive differences are statistically significant.

Next, a one-way analysis of variance will be conducted to assess if there is a statistically significant difference in the mean level of investor trust across three independent groups.

➤ **One-way Analysis of Variance**

The one-way ANOVA will be used to test the following null hypothesis: There is no significant difference in the mean level of trust across the human, AI, and hybrid financial advice conditions.

The alternative hypothesis is that there is a significant difference in the mean level of investor trust across three independent groups. In other words, at least one group differs significantly from the others. The one-way ANOVA will compare the between-group variance and will evaluate if the variance in the three groups is consistent or not. If the calculated F-statistic is statistically significant, this would suggest that the mean level of investor trust differs significantly across three independent groups.

Table 5.11: Illustrative One-Way ANOVA for Investor Trust

Source of Variation	Sum of Squares	df	Mean Square	F	p-value
Between Groups	24.37	2	12.19	28.64	< .001
Within Groups	123.70	291	0.43	—	—
Total	148.07	293	—	—	—

Note: The values are illustrative.

Illustrative ANOVA shows that there is a statistically significant difference in the investor's trust in the three experimental conditions. Specifically, $F(2, 291) = 28.64$, $p < .001$. Such results would reject the null hypothesis that all the means are equal, suggesting that the type of the financial adviser affects the level of trust in them.

Nevertheless, ANOVA only indicates that such a difference exists but does not show which means differ from each other. Therefore, post-hoc comparison should be done.

➤ **Post-Hoc Comparison**

Post-hoc comparison using Tukey's HSD test can be done to compare each pair of the experimental conditions while controlling the error rate.

Table 5.12: Illustrative Post-Hoc Comparisons of Investor Trust

Comparison	Mean Difference	Standard Error	p-value	Interpretation
Human vs AI	0.47	0.10	< .001	Significant
Human vs Hybrid	-0.21	0.09	.021	Significant
AI vs Hybrid	-0.68	0.10	< .001	Significant

Note: The values are illustrative.

The illustrative pairwise comparisons suggest that human advice produces significantly higher levels of trust than AI-only advice. Hybrid advice produces significantly higher levels than AI advice. Hybrid advice also has a modest but statistically significant advantage over human advice.

If these patterns hold true in the real data, they would suggest that investors are not evaluating advisory sources as being equal in terms of their credibility. Instead, it seems they are valuing the combined expertise of a human and a technology solution highly in terms of financial decision making.

➤ **Effect Size**

Statistical significance should not be confused with the practical importance of the observed difference. As such, a report should also include an effect-size indicator such as eta-squared (η^2) or partial eta-squared.

Based on the illustrative results of the ANOVA, we can estimate that the effect size is approximately 0.16. This would suggest that about 16% of the observed variability in investor trust is accounted for by the experimental condition.

Table 5.13: Illustrative Effect Size for Advisory Condition

Dependent Variable	Effect	Effect Size	Interpretation
Investor Trust	Advisory Condition	$\eta^2 = 0.16$	Moderate-to-large effect

Note: The effect size is illustrative.

An effect of this magnitude would indicate that the source of financial advice is not simply statistically significant but substantively relevant to investor perceptions.

➤ **Interpretation of Expected Results**

The expected findings suggest that investor trust may be highest when financial advice integrates human and AI capabilities. Human advisers may benefit from perceptions of empathy, accountability, contextual understanding, and personal responsibility. AI advisers, on the other hand, may be perceived as highly capable of processing large quantities of information but

potentially weaker in interpersonal understanding and accountability.

The hybrid condition potentially addresses both sets of concerns. Investors may perceive AI as valuable for analytical processing, pattern recognition, and consistency while viewing human involvement as providing judgment, responsibility, and contextual interpretation.

The expected relationship can therefore be represented as:

Hybrid Advice > Human Advice > AI Advice

In terms of investor trust.

This ordering should, however, not be treated as a predetermined conclusion. An important theoretical possibility is that AI advice could generate equal or greater trust among participants with high technological familiarity or high financial literacy. Consequently, subsequent moderation analysis will examine whether characteristics such as AI familiarity.

Analysis of Advice Reliance

Advice reliance represents the extent to which participants incorporate or follow the financial recommendation provided by the adviser into their final investment decision. In contrast to investor trust, which captures a participant's psychological perception of the adviser, advice reliance focuses on the participant's actual behavioral response to the recommendation. This distinction is important because an investor may trust an adviser without necessarily following the advice, while another investor may follow advice because of its perceived analytical value even when personal trust is relatively limited.

In this study, advice reliance will primarily be measured through participants' portfolio decisions before and after receiving financial advice. Participants will first indicate their preferred portfolio allocation without receiving an advisory recommendation. They will subsequently receive a recommendation from either a human adviser, an artificial intelligence (AI) adviser, or a hybrid human-AI advisory system and will then make their final portfolio allocation. The principal behavioral measure of advice reliance will be the degree to which the participant's final allocation moves toward the allocation recommended by the adviser.

For example, if an adviser recommends a portfolio consisting of 70% equities and 30% bonds, and a participant initially selects 40% equities and subsequently selects 60% equities after receiving the recommendation, the participant has moved 20 percentage points toward the recommended allocation. A larger movement toward the recommendation represents greater behavioral reliance. The distance between the participant's final allocation and the recommended allocation can also be calculated as:

A smaller reliance distance indicates greater adherence to the recommendation. To make interpretation more intuitive, a standardized reliance score may also be constructed in which higher values represent greater reliance on advice.

➤ Descriptive Analysis of Advice Reliance

The first stage of the analysis will compare the level of advice reliance across the three experimental conditions. Mean reliance scores and standard deviations will be calculated for participants receiving human, AI, and hybrid advice.

For illustration, Table 5.14 presents hypothetical results.

Table 5.14: Illustrative Descriptive Statistics for Advice Reliance

Experimental Condition	N	Mean Reliance Score	Standard Deviation
Human Advice	98	0.61	0.21
AI Advice	97	0.54	0.24
Hybrid Advice	99	0.68	0.19
Total	294	0.61	0.22

Note: The values are illustrative and should be replaced with statistics computed from the dataset.

The illustrative results suggest that participants who received hybrid advice have the highest average behavioral reliance, while participants who received human advice have the next highest. Participants who received AI-only advice have comparatively lower behavioral reliance. These descriptive differences suggest that the source of advice influences the extent to which investors follow recommendations in their investment decisions. However, statistical tests should be carried out to determine whether the observed differences are unlikely to have arisen by chance.

➤ Analysis of Reliance Distance

The reliance-distance measure is an alternative behavioral indicator. For each participant, the absolute difference between the final portfolio allocation and the adviser's recommended allocation will be calculated. Suppose the recommended equity allocation is 60% and a participant selects 55%, then the reliance distance is:

If another participant selects 30%, the reliance distance is: he first participant adheres more closely to the recommendation.

This measure is useful; it captures the degree of reliance rather than simply classifying participants as either followers or non-followers.

5.7.3 Comparison across Experimental Conditions

A one-way analysis of variance (ANOVA) will be conducted to determine whether the mean advice reliance differs among the human, AI, and hybrid conditions.

The null hypothesis is:

If the ANOVA yields a statistically significant result, post-hoc comparisons using Tukey's HSD will be performed to determine which experimental conditions differ.

Table 5.15: Illustrative ANOVA for Advice Reliance

Source	Sum of Squares	df	Mean Square	F	p-value
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Source	Sum of Squares	df	Mean Square	F	p-value
Between Groups	1.84	2	0.92	19.26	< .001
Within Groups	13.88	291	0.048	—	—
Total	15.72	293	—	—	—

Note: The values are illustrative.

The illustrative ANOVA reveals a statistically significant difference in the advice reliance across the three advisory conditions, $F(2, 291) = 19.26, p < .001$.

In the case of obtaining a similar result in practice in the main dataset, the study would produce evidence that the source of the financial advice influences the willingness of investors to apply the recommendations in their portfolio decisions.

➤ **Post-Hoc Analysis**

In the case of the overall ANOVA being statistically significant, pairwise comparisons will be made to detect which sources make investors rely on the advice significantly more or less than other conditions.

Table 5.16: Illustrative Post-Hoc Comparisons of Advice Reliance

Comparison	Mean Difference	p-value	Interpretation
Human vs AI	0.07	.041	Statistically significant
Human vs Hybrid	-0.07	.038	Statistically significant
AI vs Hybrid	-0.14	< .001	Statistically significant

Note: The values were merely illustrative.

The illustrative values indicate that there is a difference in the degree of reliance on the adviser across the three conditions. Hybrid advice yielded a higher degree of reliance than either human or AI advice, while human advice yielded a higher degree of reliance than did AI-only advice.

Again, these are merely illustrative values and should not be interpreted as real values until the experiment has actually been conducted.

➤ **Self-Reported Advice Reliance**

In addition to measuring behavioral reliance on advice, we might ask subjects to indicate their willingness to accept the recommendation by using a Likert-scale response. For example, we might ask them to indicate their agreement with statements such as “I would follow this adviser’s recommendation” or “The recommendation influenced my investment decision” or “I would rely on this adviser for a real-world investment decision.”

The responses to these items could then be used to create a self-reported reliance measure (after testing for reliability). We could then examine the relationship between self-reported reliance on the advice and actual behavioral reliance on the advice. A positive association would indicate that subjects who felt more willing to accept the advice also acted more reliant on the advice (moved their choices closer to the recommendation).

This comparison is valuable because it identifies whether stated intentions correspond to observed investment behavior.

➤ **Regression Analysis of Advice Reliance**

A multiple regression model will then be used to examine whether advisory condition predicts reliance after controlling for relevant individual characteristics.

The proposed model is:

Human advice will be taken as the reference category, and the AI and hybrid variables will therefore represent the difference in reliance relative to human advice. Investor trust will be included as this is proposed by the theoretical framework to influence the extent to which participants follow the financial advice. Financial literacy and investment experience will also be included as controls because more financially experienced participants may be less reliant on the advice.

The regression analysis will report on unstandardized coefficients, standard errors, standardized coefficients where appropriate, confidence intervals, p-values, and model explanatory power (R^2).

➤ **Expected Relationship Between Trust and Advice Reliance**

The theoretical expectation is that investor trust will be positively associated with advice reliance. Participants who perceived their adviser to be competent, reliable, transparent, and credible will be more inclined to apply the recommendation to their final investment decision. However, trust should not be conflated with reliance. The behavioral measure allows the study to determine whether participants’ psychological confidence in the adviser is actually associated with changes in their portfolio choice.

This distinction provides an important bridge between Sections 5.6 and 5.7. Section 5.6 examines whether adviser type influences how much investors trust the adviser, while Section 5.7 examines whether adviser type influences what investors actually do, having received the advice.

➤ **Summary**

The analysis of advice reliance will therefore take into account both behavioral and self-report measures. The principal behavioral measure will assess the shifting of participants’ portfolio allocations towards the adviser’s recommendation. A lower distance between the participant’s final allocation and the

recommended allocation will therefore represent greater reliance. Differences between human, AI, and hybrid advice will be initially examined using descriptive statistics and one-way ANOVA and post-hoc comparisons if appropriate. The regression analysis will then determine whether the observed differences are maintained after controlling for investor trust, financial literacy, and investment experience.

The expected analysis provides a direct test of whether the source of financial advice influences investor behavior rather than merely their perceptions. The findings of this section will then be linked to portfolio risk-taking in Section 5.8 and to the proposed mediation analysis in Section 5.9.

Analysis of Portfolio Choice and Risk-Taking

Portfolio choice and risk-taking represent the ultimate behavioral outcomes of the experimental decision-making process. While trust measures participants' perceptions of the adviser and advice reliance measures how much participants incorporate the recommendation into their decisions, portfolio choice provides a more direct indication of how the advice actually ultimately influences their investment behavior. This section therefore examines whether participants exposed to human, artificial intelligence (AI), and hybrid financial advisers make different portfolio allocations and whether the type of adviser is associated with differences in the level of financial risk assumed.

The analysis primarily focuses on the proportion of participants' hypothetical investment allocated to risky assets. In the experimental setting, participants are assumed to distribute a fixed investment amount across different asset categories with varying levels of risk. Risky assets may be represented by equities or

equity-oriented investment products, while relatively safer assets may be represented by bonds, deposits, or other low-risk instruments. The percentage allocated to risky assets provides a continuous measure of risk-taking and allows the portfolio decisions to be compared across the experimental conditions.

For example, if a participant allocates 70 percent of the investment to equities and 30 percent to relatively safer assets, the participant's risky-asset allocation is 70 percent. A higher proportion will represent a more exposure to the investment risk while a lower proportion will represent a more conservative portfolio. Where the experimental design incorporates several asset classes, a composite portfolio risk score can additionally be calculated by assigning each asset category a predetermined risk weight and calculating the weighted average of the participant's allocation.

The primary dependent variable can therefore be expressed as:

Where represents the proportion of participant's portfolio allocated to asset , and represents the predetermined risk level of that asset. This approach makes it possible to transform a multi-asset portfolio into a single continuous indicator of portfolio risk.

➤ Descriptive Analysis of Portfolio Risk

The first step in the analysis involves calculating the mean, standard deviation, minimum, and maximum values of risky-asset allocation for each experimental group. These descriptive statistics provide an initial indication of whether exposure to human, AI, or hybrid advice is associated with different investment behavior.

For illustrative purposes, the following hypothetical results are presented. These values are not actual findings and should be replaced with the results obtained from the final dataset.

Table 5.17. Descriptive Statistics of Risky-Asset Allocation

Adviser Type	N	Mean Risky Allocation (%)	SD	Minimum	Maximum
Human	98	58.42	16.31	20	90
AI	97	51.76	17.84	15	90
Hybrid	99	64.18	14.72	25	95
Total	294	58.15	16.67	15	95

The descriptive results shown above indicate that participants in the hybrid-advice condition allocated a larger portion of their portfolios to risky assets compared to participants in the human-advice and AI-advice conditions. Participants who received advice from AI had the lowest average of risky-asset allocation. This descriptive tendency suggests that combined advice from human and AI may be related to higher acceptance of investment risks. Nevertheless, descriptive differences cannot prove whether the difference between groups is statistically significant.

➤ Analysis of Differences Between Experimental Groups

One-way analysis of variance (ANOVA) can help identify whether mean risky-asset allocation significantly differed between the three groups of the experiment. In this test, the independent variable is adviser type with three levels: human, AI, and hybrid, and the dependent variable is the percentage of the portfolio allocated to risky assets.

The illustrative results of ANOVA are presented below.

Table 5.18. One-Way ANOVA for Risky-Asset Allocation

Source	Sum of Squares	df	Mean Square	F	p-value
Between Groups	7,418.52	2	3,709.26	13.92	< .001
Within Groups	77,561.34	291	266.53	—	—
Total	84,979.86	293	—	—	—

The illustrative result suggests that there is a statistically significant difference in risky-asset allocation between the 3 adviser conditions, . This means that the type of financial adviser may be related to the participant's willingness to take on an investment risk.

Since ANOVA only states that at least one group differs from the other, it is necessary to compare the groups to discover which one differs from the others.

Table 5.19. Illustrative Post-Hoc Comparisons of Risky-Asset Allocation

Comparison	Mean Difference (%)	p-value
Human vs. AI	6.66	.012
Human vs. Hybrid	-5.76	.026
AI vs. Hybrid	-12.42	< .001

The illustrative comparisons suggest differences between all three experimental conditions. The hybrid condition has the highest average risky-asset allocation, whereas the AI condition has the lowest. These results would indicate that adviser type is associated with differences in portfolio risk exposure if a similar pattern is observed in the actual dataset.

➤ **Analysis of Changes in Portfolio Allocation**

Where participants provide an initial portfolio choice before receiving financial advice and a final portfolio choice after receiving the recommendation, the change between these two decisions provides an important indicator.

The change in risky-asset allocation can be calculated as: A positive value indicates that the participant increased exposure to risky assets after receiving advice, whereas a negative value indicates a reduction in risk exposure.

This pre-advice and post-advice comparison is particularly important because participants may differ in their initial risk preferences. Examining only the final portfolio could therefore obscure the extent to which the adviser actually influenced the investment decision. Comparing the initial and final allocations makes it possible to determine whether participants changed their portfolio following exposure to the recommendation.

For example, a participant who initially allocates 40 percent to risky assets but increases the allocation to 65 percent after receiving advice has a change score of: This represents a 25-percentage-point increase in risky-asset exposure.

If the experimental design contains repeated observations for each participant, a repeated-measures analysis or mixed-effects model can be used to examine whether portfolio changes differ according to adviser type. This approach can provide stronger evidence of behavioral change than comparing final portfolios alone.

➤ **Analysis of Portfolio Diversification**

Risk-taking should not be evaluated solely through the percentage invested in risky assets. Portfolio diversification can also influence the overall risk profile of an investment decision. Therefore, where sufficient portfolio allocation information is available, diversification should be examined as an additional outcome.

One possible measure is the Herfindahl-type concentration index: where represents the proportion of participant's portfolio invested in asset. A higher value indicates greater concentration, whereas a lower value indicates greater diversification.

For example, a portfolio consisting almost entirely of one asset class would produce a relatively high concentration score, while an evenly distributed portfolio would produce a lower score. Comparing portfolio concentration across the human, AI, and hybrid groups can therefore provide additional evidence

concerning the behavioral consequences of different forms of financial advice.

➤ **Regression Analysis of Risk-Taking**

Although group comparisons are useful for identifying differences between experimental conditions, regression analysis can provide a more detailed examination of the factors associated with portfolio risk-taking. An ordinary least squares regression model can be specified as:

The human-adviser condition would serve as the reference category. The coefficients for AI and hybrid advice would therefore represent differences relative to the human-advice condition after accounting for other variables included in the model. Investor trust and advice reliance are particularly important explanatory variables. If greater trust and greater reliance are associated with higher risky-asset allocation, this would suggest that perceptions of the adviser and behavioral acceptance of the recommendation may contribute to the relationship between adviser type and portfolio choice.

Financial literacy and investment experience should also be considered because participants with greater financial knowledge or experience may respond differently to recommendations than less experienced investors. Including these variables helps distinguish the effect associated with the experimental treatment from differences in participants' pre-existing characteristics.

➤ **Categorical Analysis of Risk Profiles**

If participants are classified into predefined risk categories such as conservative, moderate, and aggressive investors, the dependent variable becomes categorical rather than continuous. In this situation, a chi-square test can initially be used to examine whether the distribution of risk profiles differs across the three adviser conditions.

A multinomial logistic regression can subsequently be used if the research requires adjustment for participant characteristics. The model can examine whether adviser type is associated with the probability of belonging to a particular risk category while controlling for variables such as financial literacy, investment experience, age, and prior exposure to financial advice.

This categorical approach complements the continuous risky-asset allocation measure and can make the findings easier to interpret from a behavioral perspective.

➤ **Expected Relationship Between Advice and Risk-Taking**

The theoretical expectation is that different forms of financial advice may influence risk-taking through differences in perceived credibility, trust, transparency, and advice reliance. If participants perceive an adviser as more credible or trustworthy, they may be

more willing to incorporate the recommendation into their final portfolio.

However, greater trust does not necessarily imply greater risk-taking. An adviser may be trusted while recommending a conservative portfolio. Similarly, a participant may follow a recommendation because it appears financially rational without reporting particularly high levels of interpersonal or technological trust. Consequently, the analysis should distinguish the effects of adviser type, trust, reliance, and the actual risk characteristics of the recommendation.

The direction of the relationship between advice and risk-taking should therefore be determined empirically rather than assumed in advance. The experimental analysis will establish whether the observed differences are statistically significant and whether they remain after relevant participant characteristics are controlled.

➤ *Effect Size and Practical Significance*

Statistical significance alone does not indicate the magnitude or practical importance of differences between groups. Therefore, effect-size measures should accompany the ANOVA results. Eta squared (η^2) or partial eta squared (η^2_p) can be reported for group comparisons, while standardized coefficients or confidence intervals can be reported for regression models.

For example, if the actual analysis produces a statistically significant difference but only a very small effect size, the finding should be interpreted as evidence of a measurable difference rather than as evidence of a substantial behavioral effect. Conversely, a larger effect size would indicate that adviser type accounts for a more meaningful proportion of variation in portfolio decisions.

➤ *Summary of Portfolio Choice Analysis*

Overall, portfolio choice and risk-taking will be analyzed using a combination of descriptive statistics, group-comparison tests, pre- and post-advice comparisons, and regression analysis. The primary behavioral outcome will be the proportion of the portfolio allocated to risky assets, supplemented where appropriate by portfolio concentration and categorical risk-profile measures.

The analysis will determine whether participants exposed to human, AI, and hybrid financial advice differ in their final portfolio choices and whether exposure to advice produces measurable changes from participants' initial investment decisions. Trust and advice reliance will subsequently be incorporated into the analytical framework to investigate whether they help explain the relationship between adviser type and portfolio behavior.

The findings from this section will provide the behavioral foundation for the mediation analysis presented in Section 5.9, where investor trust and advice reliance will be examined as potential mechanisms linking the type of financial adviser to participants' investment decisions.

Discussion, Implications, Limitations and Conclusion

Introduction

This chapter discusses the expected findings of the study entitled “Human versus Artificial Intelligence in Financial Advice: Experimental Evidence on Investor Trust, Advice Reliance, and Portfolio Choice.” The study investigates how investors respond to financial advice provided by human advisers, artificial

intelligence (AI) systems, and a hybrid combination of human and AI advice. Particular attention is given to investor trust, advice reliance, portfolio choice, and risk-taking behavior.

The central objective of the study is not simply to determine whether investors prefer human or AI advice. Rather, it seeks to understand the behavioral mechanisms through which different forms of financial advice influence investment decisions. The research therefore considers trust and advice reliance as important intermediate factors connecting the source of advice with subsequent portfolio decisions.

The preceding chapters established the theoretical foundation, research methodology, and proposed analytical procedures. The experimental framework distinguishes three adviser conditions: human, AI, and hybrid. Participants are exposed to one of these conditions and subsequently evaluate the advice and make investment decisions. This design allows differences in trust, reliance, and portfolio behavior to be examined within a controlled comparative framework.

The expected findings presented in this chapter are based on the illustrative analyses developed in Chapter 5. They are intended to demonstrate how the empirical findings should be interpreted once the actual data are collected and analyzed. The numerical results should therefore be replaced by the actual statistical results obtained from the study.

Summary of the Study

The rapid development of artificial intelligence has transformed the way financial information is generated, communicated, and consumed. AI-based systems can process large quantities of information, identify patterns, generate recommendations, and provide personalized financial guidance. These developments have created new opportunities for investors but have also raised questions concerning trust, transparency, accountability, and human oversight.

Traditional financial advice is primarily associated with interpersonal relationships between investors and professional advisers. Trust in this context may develop through perceived expertise, communication, reputation, accountability, and personal interaction. AI advice operates through a different mechanism. Its perceived credibility may depend on technological sophistication, consistency, data processing capabilities, transparency, and users' familiarity with artificial intelligence.

Hybrid advice represents a third model in which human judgment and AI-supported analysis are combined. Such an arrangement potentially provides investors with both technological analytical capabilities and human interaction. The hybrid model is therefore particularly relevant for examining whether investors respond differently when human and technological sources of advice are jointly presented.

The study focuses on four central behavioral constructs: investor trust, advice reliance, portfolio choice, and risk-taking. Trust represents the degree to which participants perceive the adviser and recommendation as credible, reliable, and worthy of confidence. Advice reliance refers to the extent to which participants incorporate the recommendation into their final investment decisions. Portfolio choice represents the resulting allocation of investment across different asset categories, while risk-taking captures the degree of financial risk assumed through those allocations.

The research consequently addresses a broader question concerning the future of financial advice: whether investors' decisions are influenced merely by the informational quality of advice or also by the identity and characteristics of the entity providing that advice.

Discussion of Investor Trust

Investor trust is one of the central variables in the study because financial advice involves decisions under uncertainty. Investors frequently cannot independently verify every piece of financial information provided by an adviser. Consequently, their willingness to accept and act upon recommendations may depend partly on whether they perceive the adviser as trustworthy.

The illustrative results presented in Chapter 5 indicated differences in trust across the three experimental conditions. The hypothetical mean trust scores were highest for the hybrid group, followed by the human group, while the AI group recorded the lowest mean. Although these figures are illustrative rather than empirical, such a pattern would suggest that combining human and AI advice may influence perceptions of credibility and reliability. One possible interpretation is that hybrid advice may reduce some of the limitations associated with relying exclusively on either human or technological advice. Human advisers may provide interpersonal reassurance and accountability, while AI systems may contribute analytical consistency and rapid information processing. When these characteristics are presented together, participants may perceive the resulting advice as more comprehensive.

The lower illustrative trust level associated with AI advice should not automatically be interpreted as evidence that AI systems are objectively less accurate or less capable. Trust is a psychological and behavioral construct that may depend on familiarity, transparency, perceived accountability, technological experience, and the context in which advice is delivered. A participant may recognize the analytical capabilities of AI while nevertheless being reluctant to delegate an important financial decision to a non-human system.

This distinction is important because trust and technical accuracy are not identical concepts. An AI recommendation could theoretically be highly accurate while receiving relatively low trust from users. Conversely, an investor could trust a human adviser despite the recommendation not necessarily being superior. The experimental design therefore provides an opportunity to separate perceptions of the adviser from the behavioral consequences of those perceptions.

Discussion of Advice Reliance

Advice reliance provides a behavioral bridge between trust and investment decisions. While trust captures participants' perceptions of the adviser, reliance captures what participants actually do with the recommendation.

The illustrative analysis indicated higher reliance in the hybrid condition than in the human and AI conditions. If this pattern were confirmed by actual data, it would suggest that investors may be more willing to incorporate recommendations when advice combines human and artificial intelligence inputs. This finding would have an important implication for the study because it would demonstrate that investor responses to AI cannot be understood solely through a simple human-versus-machine comparison. The hybrid model may represent a distinct form of financial decision support with its own behavioral characteristics.

The distinction between trust and reliance is particularly important. High trust does not necessarily result in complete adherence to advice. Investors may trust an adviser while independently evaluating the recommendation before making a final decision. Similarly, an investor may follow an AI recommendation without having particularly high trust in the AI system if the recommendation appears logical or consistent with the investor's own analysis.

For this reason, behavioral reliance should be analyzed alongside self-reported trust. The comparison between these measures can reveal whether investors' stated perceptions correspond to their actual investment behavior.

Discussion of Portfolio Choice and Risk-Taking

Portfolio choice represents the most direct behavioral outcome of the experiment. The earlier analysis proposed measuring the percentage of investment allocated to risky assets as an indicator of risk-taking.

The illustrative results showed the hybrid group with the highest average risky-asset allocation, followed by the human group and then the AI group. If similar differences emerge in the actual dataset, the finding would indicate that the type of financial adviser is associated with investors' willingness to assume investment risk.

However, the interpretation should be approached carefully. A higher allocation to risky assets does not necessarily represent irrational behavior or poorer financial decision-making. Risk-taking may be appropriate when an investor has a longer investment horizon, greater risk tolerance, sufficient financial resources, or a portfolio objective that justifies greater exposure to risky assets.

Therefore, the study should interpret portfolio risk as a behavioral outcome rather than as a direct measure of investment quality. The pre-advice and post-advice comparison is particularly valuable in this respect. If participants substantially modify their portfolios after receiving advice, this provides stronger evidence that the recommendation influenced their decisions. The direction and magnitude of this change can then be compared across the three adviser conditions.

Relationship between Trust and Advice Reliance

One of the central theoretical expectations of the study is that trust will be positively associated with advice reliance. Investors who perceive an adviser as credible and reliable may be more willing to incorporate the recommendation into their final decisions.

The proposed relationship can be represented as: Under this framework, adviser type does not necessarily influence behavior directly. Instead, the source of advice may first influence perceptions of trust, which subsequently affect the extent to which investors rely upon the recommendation.

If the empirical findings support this relationship, they would provide evidence that psychological perceptions play an important role in the adoption of AI-supported financial advice. At the same time, a weak relationship between trust and reliance would also be theoretically informative. Such a result could indicate that investors evaluate financial recommendations using factors beyond trust, including perceived analytical quality, financial literacy, investment experience, expected returns, and personal risk tolerance.

Mediation through Trust and Advice Reliance

The proposed conceptual model extends the analysis by examining whether trust and advice reliance mediate the relationship between adviser type and portfolio choice. The broader pathway can be expressed as: A mediation analysis can determine whether the effect of adviser type on portfolio behavior operates partly through these psychological and behavioral mechanisms.

For example, if hybrid advice increases trust, greater trust increases reliance, and greater reliance subsequently influences portfolio allocation, the results would provide evidence for an indirect pathway linking adviser type to investment behavior.

The importance of this approach is that it moves beyond the question of whether human, AI, and hybrid advice produce different outcomes. It asks why those differences may occur. A significant indirect effect would support the proposition that investor perceptions and behavioral acceptance are mechanisms through which financial-advice technologies influence investment decisions.

Moderating Factors

The effect of adviser type may not be identical for all investors. Individual characteristics such as financial literacy, investment experience, and familiarity with AI, age, and previous exposure to professional financial advice may modify investor responses.

For example, investors with extensive experience using financial technologies may have greater familiarity with AI-generated recommendations. Such familiarity could reduce uncertainty about the technology and potentially alter trust and reliance.

Financial literacy may also influence the relationship between advice and portfolio choice. More financially literate investors may independently evaluate recommendations rather than relying heavily on the source of advice. Less financially literate participants may potentially depend more strongly on perceived adviser credibility.

Investment experience could similarly affect reliance. Experienced investors may possess established investment strategies and therefore be less likely to substantially change their portfolios following an external recommendation.

These possibilities justify the inclusion of moderation analysis. Rather than assuming that all investors respond to AI advice in the same way, the study recognizes that technology acceptance and investment behaviour can vary across individuals.

Theoretical Implications

The study has several theoretical implications for research on financial decision-making, trust, and artificial intelligence.

First, the study contributes to the understanding of trust in technologically mediated financial decision-making. Traditional theories of adviser trust were largely developed in the context of interpersonal relationships. With AI, trust must now be considered in the context of environments where the adviser may be partially or entirely non-human.

Second, the research connects trust with behavioral reliance. Much research measures users' attitudes towards AI but does not examine whether those attitudes actually affect decisions. By combining psychological measures with portfolio behavior, this study provides a framework for linking perception and action.

Third, the study introduces the hybrid adviser as an analytically distinct condition. Rather than assuming that AI necessarily replaces human expertise, the research considers the possibility that human and AI capabilities may interact in shaping investor behavior.

Fourth, the research contributes to the literature on financial decision-making by examining adviser type as a potential determinant of risk-taking. Investment behavior is influenced by numerous factors, and the study provides an experimental framework for examining whether the source of financial advice is one such factor.

Practical Implications

The findings may have practical implications for financial institutions, investment platforms, financial advisers, technology developers, and regulators.

Financial institutions considering AI-based financial advice will need to recognize that technical capability alone may not guarantee user acceptance. Transparency concerning how recommendations are generated will be important in developing appropriate levels of user confidence.

For financial advisers, the findings suggest that AI does not necessarily have to be viewed exclusively as a substitute for human advice. Hybrid systems may provide opportunities for advisers to use AI as an analytical support mechanism while retaining human communication and accountability.

For AI developers, the results emphasize the importance of explainability. Investors may be more willing to rely upon recommendations when they understand why a particular recommendation has been generated and what information has contributed to it.

From a regulatory perspective, AI-generated financial advice raises questions concerning disclosure, accountability, transparency, data protection, and responsibility for financial recommendations. The increasing use of AI in financial decision-making therefore requires institutional frameworks capable of addressing both technological and human dimensions of advice.

Implications for Financial Advice Platforms

Digital investment platforms can potentially use the findings to design advice systems that recognize differences between informational assistance and decision-making authority.

Rather than presenting AI recommendations as unquestionable conclusions, platforms may provide explanations, alternative scenarios, risk information, and opportunities for human review. Such approaches will allow investors to maintain decision-making control while benefiting from AI-supported analysis.

A hybrid system could also allow for investors to request human intervention if a recommendation involves particularly complex or high-stakes financial decisions. This could be especially relevant where investors have limited financial knowledge or where recommendations involve substantial financial risk.

The results should not, however, be interpreted as establishing that one adviser type is universally appropriate. Different investors have different informational needs, preferences, experience, and risk tolerances.

Limitations of the Study

Several limitations should be considered when interpreting the findings.

First, the experimental setting may not fully reproduce real-world investment behavior. Participants may behave differently when investing actual money compared with making hypothetical investment decisions. Second, the composition of the sample may limit generalizability. If participants are primarily students or relatively young adults, their attitudes towards AI and financial advice may differ from those of older or more experienced investors. Third, the study measures behavior within a specific experimental scenario. Real-world financial decisions involve repeated interactions with advisers, changing market conditions, personal financial constraints, and long-term investment objectives. Fourth, AI systems are rapidly evolving. The characteristics of AI financial advice can change as models, interfaces, data sources, and regulatory requirements develop. Consequently, findings obtained at one point in time may not remain unchanged as AI technologies mature.

Fifth, trust is a multidimensional concept. The study's measurement scale captures general perceptions of reliability and credibility but may not capture every dimension of trust, such as algorithmic transparency, institutional trust, privacy concerns, or perceived accountability.

Finally, portfolio risk does not by itself establish whether an investment decision is financially optimal. The study examines behavioral responses to advice rather than attempting to determine the objectively best portfolio for each participant.

Recommendations for Future Research

Future research could extend the study by introducing real monetary incentives. Participants could receive financial rewards based partly on the performance of their investment decisions, creating stronger behavioral realism.

Longitudinal research could also examine whether trust in AI financial advice changes over time. Initial skepticism may decrease as users become more familiar with AI systems while negative experiences may reduce trust. Future studies could additionally compare different AI systems rather than treating AI as a single category. Differences in explainability, conversational ability, personalization, and demonstrated performance may produce different levels of investor trust.

Cross-cultural research would be valuable. Attitudes towards artificial intelligence, authority, financial institutions, and interpersonal trust vary across countries and cultures. Replicating the experiment in national contexts could therefore reveal whether the observed relationships are culturally specific or more broadly applicable.

Another important direction would be to examine high-stakes financial decisions involving retirement planning, insurance, credit, or substantial investment portfolios. These settings may produce stronger emotional and behavioral responses than relatively simple hypothetical investment tasks.

Future research could also investigate whether disclosure of AI involvement affects trust. Researchers could compare situations in which participants know that AI generated the recommendation with situations in which AI involvement is not explicitly disclosed.

Overall Discussion

The central contribution of the study lies in connecting technological source, psychological perception, behavioral reliance, and investment outcomes within a single experimental framework.

The human-versus-AI debate is often presented as a question of whether technology can replace human expertise. The present research adopts a broader perspective by recognizing that financial advice involves not only information processing but also trust, interpretation, acceptance, and behavioral response.

The inclusion of a hybrid condition is particularly important because the future of financial advice may involve interaction between human expertise and AI-supported analysis rather than complete replacement of one by the other. The empirical findings will help determine whether such combinations are associated with different levels of investor trust, reliance, and portfolio risk-taking.

The proposed analytical framework also emphasizes that investor behavior should not be reduced to a single measure. A participant may report high trust but demonstrate limited behavioral reliance or may follow advice while maintaining relatively low trust. Examining these constructs separately provides a more nuanced understanding of financial decision-making.

Conclusion

This study investigates how the source of financial advice influences investor trust, advice reliance, portfolio choice, and risk-taking. By comparing human, AI, and hybrid advice, the research provides an experimental framework for examining the behavioral consequences of increasingly automated financial decision-making.

The study conceptualizes investor trust as an important psychological factor, advice reliance as a behavioral mechanism, and portfolio choice as a final investment outcome. This allows the research to move beyond simple comparisons of attitudes towards AI and examine how perceptions of financial advisers translate into actual investment decisions.

The expected analytical framework suggests that adviser type may influence investor trust and that trust may subsequently affect the extent to which investors rely upon financial recommendations. Advice reliance may then contribute to changes in portfolio allocation and risk exposure. However, these relationships should ultimately be determined by the empirical evidence rather than assumed in advance.

The study therefore contributes to the growing discussion surrounding artificial intelligence and financial decision-making by examining not only whether investors use AI-generated advice, but also why they may trust, accept, reject, or act upon such advice. Understanding these mechanisms is increasingly important as AI becomes more deeply integrated into financial services.

Ultimately, the future role of AI in financial advice is likely to depend not only on technological performance but also on how investors perceive, understand, and respond to AI-supported recommendations. By integrating trust, reliance, and portfolio behavior into a single experimental framework, this study provides a basis for examining these relationships systematically and for developing a more comprehensive understanding of human-AI interaction in the financial decision-making process.

Conclusion and Final Recommendations

Introduction

The rapid development of artificial intelligence (AI) is transforming the financial services industry and changing the way individuals obtain, evaluate, and use financial information. Financial advice, traditionally associated with direct interaction between investors and professional human advisers, is increasingly being supplemented or delivered through AI-based technologies. This transformation creates important questions concerning investor trust, reliance on recommendations, portfolio choice, and risk-taking behavior.

The present study, entitled "Human versus Artificial Intelligence in Financial Advice: Experimental Evidence on Investor Trust, Advice Reliance, and Portfolio Choice," was designed to examine these questions through an experimental comparison of human, AI, and hybrid financial advice. The research focused on the relationship between the type of adviser and investors' psychological and behavioral responses. The study specifically examined whether adviser type affects investor trust, whether trust influences reliance on financial recommendations, and whether reliance subsequently affects portfolio decisions and risk-taking. It also considered whether individual characteristics such as financial literacy, investment experience, and familiarity with AI may influence these relationships.

This final chapter summarizes the research, discusses the principal conclusions derived from the analytical framework, presents recommendations for practice and future research, and identifies the broader contribution of the study.

Restatement of the Research Problem

Financial decision-making frequently occurs under conditions of uncertainty and incomplete information. Investors may therefore rely on financial advice when deciding how to allocate their resources. Traditionally, trust in a human financial adviser has been influenced by perceived expertise, reputation, interpersonal communication, and accountability.

The emergence of AI introduces a fundamentally different form of advisory relationship. AI systems can analyze large amounts of information and generate recommendations rapidly, but investors may perceive them differently from human advisers. Questions concerning transparency, explainability, accountability, privacy, and technological unfamiliarity may influence whether investors trust and follow AI-generated recommendations.

At the same time, the increasing availability of AI does not necessarily mean that human financial advisers will disappear. Human expertise and AI-supported analytical capabilities can potentially be combined within hybrid advisory models. Understanding how investors respond to these different forms of advice is therefore an important research problem.

The study addresses this problem by examining adviser type together with investor trust, advice reliance, and portfolio behavior.

Summary of Research Objectives

The study was developed around the objective of examining the behavioral differences associated with human, AI, and hybrid financial advice.

The first objective was to determine whether investor trust differs according to the type of financial adviser. The second objective was to examine whether adviser type affects the degree to which investors rely on financial recommendations. The third objective was to investigate whether different forms of advice are associated

with differences in portfolio choice and risk-taking. The fourth objective was to examine whether investor trust mediates the relationship between adviser type and advice reliance. The fifth objective was to examine whether advice reliance contributes to the relationship between adviser type and portfolio outcomes. Finally, the study considered whether individual characteristics influence these relationships.

Together, these objectives provide a framework for examining financial advice as both an informational and behavioral process.

Summary of the Research Methodology

The study employed an experimental research design involving three adviser conditions: human, artificial intelligence, and hybrid. Participants were exposed to one of the three advisory conditions and were asked to evaluate the recommendation and make investment decisions. The study measured investor trust through a multi-item scale assessing perceptions such as reliability, credibility, confidence, and dependability. Advice reliance was assessed through behavioral changes in participants' investment decisions and, where applicable, self-reported reliance on the recommendation.

Portfolio choice was examined through participants' asset allocations, while risk-taking was assessed through the proportion of investment allocated to relatively risky assets or through a composite portfolio risk measure. The proposed statistical analysis included descriptive statistics, reliability and validity testing, manipulation and attention checks, analysis of variance, post-hoc comparisons, regression analysis, mediation analysis, and moderation analysis. This combination of methods allows the study to examine both differences between experimental groups and the mechanisms underlying those differences.

Main Analytical Conclusions

The analytical framework developed in the study suggests that adviser type may play an important role in shaping investor responses. In particular, the experimental comparison provides a means of determining whether human, AI, and hybrid advice generate different levels of investor trust.

The illustrative results presented in earlier chapters showed a hypothetical pattern in which hybrid advice received the highest trust, followed by human advice and AI advice. The illustrative analysis also indicated greater advice reliance in the hybrid condition. These patterns should not be treated as confirmed empirical findings until the actual experimental data are analyzed. Rather, they demonstrate the type of relationship the research is designed to test.

The study further proposes that differences in trust may translate into behavioral differences through advice reliance. If investors perceive an adviser as credible and dependable, they may be more willing to incorporate the recommendation into their final investment decisions.

Portfolio analysis provides the final behavioral dimension. Rather than relying solely on participants' stated attitudes, the study examines changes in actual portfolio allocation within the experimental task. This approach makes it possible to determine whether differences in perceptions of human and AI advice are reflected in investment behavior.

Conclusions Regarding Investor Trust

Investor trust emerges as a central construct in understanding financial advice. Financial decisions involve uncertainty, and investors may therefore need to develop confidence in the source of information before accepting its recommendations.

Human advisers may benefit from interpersonal communication and the perception of direct accountability. AI systems, by contrast, may be evaluated according to perceived analytical capability, consistency, technological sophistication, and transparency. Hybrid systems potentially combine these characteristics. However, whether such combinations actually generate greater trust must be determined empirically. The present study provides a framework for making this comparison under controlled experimental conditions.

An important conclusion of the study is therefore that the acceptance of AI financial advice cannot be explained solely by the technical capabilities of AI. User perceptions remain an important component of financial decision-making.

Conclusions Regarding Advice Reliance

The study distinguishes trust from advice reliance. This distinction is important because believing that an adviser is trustworthy does not necessarily mean that an investor will follow every recommendation.

Behavioral reliance provides a stronger indication of whether advice actually affects investment decisions. By comparing participants' decisions before and after receiving advice, the study can determine whether recommendations produce measurable changes in portfolio allocation. The research therefore conceptualizes advice reliance as a behavioral mechanism rather than merely an attitude towards financial technology.

If actual findings demonstrate a positive relationship between trust and reliance, this would support the proposition that trust contributes to the acceptance of financial advice. If the relationship is weak, the findings would instead suggest that investors use additional criteria when deciding whether to follow recommendations.

Either outcome would contribute to understanding how investors interact with AI-supported financial services.

Conclusions Regarding Portfolio Choice and Risk-Taking

Portfolio choice represents the practical consequence of the advisory process. The study examines whether participants change their investment allocations following exposure to different types of advice.

The proposed measurement of risky-asset allocation provides a continuous indicator of risk-taking. Comparing initial and final allocations allows the study to determine whether advice is associated with an increase or decrease in risk exposure. An important conceptual conclusion is that higher risk-taking should not automatically be interpreted as better or worse investment behavior. The appropriateness of risk depends on investment objectives, financial circumstances, time horizon, and individual risk tolerance.

The study therefore focuses on behavioral differences rather than attempting to identify an objectively optimal portfolio for every participant.

Theoretical Contribution

The study contributes to the literature in several interconnected ways.

First, it extends research on financial advice by introducing AI as an alternative advisory source within an experimental framework. Rather than treating AI simply as a technological tool, the study examines it as an adviser whose recommendations can be trusted, accepted, rejected, or followed. Second, the research integrates psychological and behavioral dimensions. Investor trust represents perception, advice reliance represents behavioral response, and portfolio choice represents an investment outcome. Connecting these constructs provides a more comprehensive framework for understanding human-AI financial interaction.

Third, the inclusion of a hybrid condition expands the traditional human-versus-machine comparison. Hybrid advice provides an opportunity to examine how investors respond when technological and human sources of expertise are combined. Fourth, the study contributes to behavioral finance by examining whether the source of financial advice can influence portfolio allocation and risk-taking.

Practical Recommendations for Financial Institutions

Financial institutions implementing AI-based financial advice should place substantial attention on transparency and user understanding. Investors should be provided with meaningful explanations of recommendations rather than being presented with unexplained outputs. AI systems should also communicate uncertainty where appropriate. Financial recommendations are rarely certain, and presenting algorithmic outputs as guaranteed outcomes may create unrealistic expectations.

Institutions should establish clear mechanisms for human intervention, particularly for complex or high-value financial decisions. A hybrid approach can allow AI systems to provide analytical support while human professionals remain available for explanation, contextual judgment, and accountability.

Financial institutions should also conduct regular assessments of user trust and behavioral reliance. Monitoring whether users understand and appropriately interpret AI recommendations can help identify problems that may not be visible through technical performance metrics alone.

Recommendations for Financial Advisers

Human financial advisers could potentially use AI as a decision-support tool rather than a competitor to human abilities.

The article discusses how AI could enhance information processing, scenario analysis, portfolio monitoring, and identification of relevant information. Human advisers could then provide contextual interpretation and communicate recommendations to clients.

The findings of this study suggest, however, that the relationship between technology and human expertise requires further attention. Financial advisers who embrace AI responsibly could potentially harness computing capabilities alongside interpersonal communication and accountability.

Meanwhile, advisers should be aware of the role of AI when it comes to generating recommendations. Investors should understand whether a recommendation originates primarily from human judgment, an automated system, or a combination of both.

Recommendations for AI Developers

AI developers working in financial applications should focus on explainability, transparency, reliability, and user control. An AI financial-advice system should be able to provide understandable reasons for its recommendations. Users should be able to identify the principal factors influencing an investment recommendation rather than receiving only a final allocation.

Developers should also be aware of providing appropriate information concerning limitations and uncertainty. Investors need to understand that AI-generated recommendations are analytical outputs rather than guarantees of future financial performance. Another important consideration are the preservation of human decision-making authority. AI systems should support investors rather than unnecessarily encouraging automatic or unquestioning adherence to recommendations.

Recommendations for Policymakers and Regulators

The increasing use of AI in financial services presents regulatory questions regarding transparency, accountability, consumer protection, and the responsibility for recommendations. Regulatory frameworks should encourage appropriate disclosure of AI involvement in financial advice. Investors should be able to determine whether they are receiving advice from a human professional, an automated system, or a hybrid situation.

Regulators could also consider requirements concerning explainability and documentation of AI-based financial recommendations. Such measures could improve accountability and allow investors to better understand how recommendations are made.

Consumer protection is particularly important in cases where users are not financially literate. AI-based financial advice should not exploit users' trust in technology or create misleading perceptions of certainty.

Recommendations for Investors

Investors using AI-generated financial advice should treat recommendations as information to be evaluated rather than automatically following instructions. Investors should consider the assumptions underlying a recommendation, the level of risk, the investment time horizon, and their own financial goals.

Where applicable, investors should compare AI-generated recommendations with independent information and, for complex decisions, consider obtaining professional human advice.

The study's conceptual framework highlights an important distinction between trusting an adviser and critically evaluating advice. Responsible investment decision-making requires using information appropriately and preserving individual decision-making authority.

Recommendations for Future Research

Future studies should repeat the experiment with larger and more diverse samples. Participants from different age groups, education levels, income levels, and investment experience categories could yield a broader understanding of investor responses.

Researchers should also consider introducing real financial incentives. Hypothetical investment decisions may not be representative of the behavioral consequences that come with investing one's own money. Monetary incentives could increase the

behavior realism of future experiments. Longitudinal studies would be useful in investigating how trust develops over repeated interactions. Investors may be skeptical of AI at first but become more comfortable with repeated successful interactions. Conversely, poor recommendations could diminish trust over time.

Future research should also compare different AI technologies. AI systems vary significantly in terms of their transparency, personalization, conversational ability, data access, and recommendation mechanisms. Treating all AI systems as identical could potentially hide critical differences. Cross-national research is another valuable extension. Cultural differences in interpersonal trust, technological acceptance, financial literacy, and attitudes toward authority could influence the relationship between adviser type and investment behavior.

Proposed Conceptual Model for Future Research

The findings and conceptual framework developed throughout the study can be summarized in the following conceptual relationship:

The model could be expanded upon by including individual-level moderators: These variables may influence the strength of the relationship amongst adviser type, trust, reliance, and portfolio behavior.

The model therefore conceptualizes financial decision-making as a sequential process rather than a simple choice between human and AI advice.

Final Conclusion

Artificial intelligence is increasing in relevance to financial decision-making, but technological capabilities are not necessarily responsible for determining whether investors will accept and follow AI-generated recommendations. Investor trust, perceived credibility, understanding, and behavioral reliance are important components of the advisory process. This study provides an experimental framework for examining these relationships by comparing human, AI, and hybrid financial advice. Its central contribution is the integration of investor trust and advice reliance within the same research model.

The study highlights that the human-versus-AI question is more complex than determining which source of advice investors prefer. Financial advice involves interaction between information, technology, psychological perceptions, and behavioral decisions. A recommendation may be technically sophisticated but ineffective if investors do not trust or understand it. Meanwhile, trust alone does not guarantee appropriate investment behavior.

The hybrid model is therefore particularly important for future research because it allows examining how human judgment and artificial intelligence can interact with financial decision-making. The empirical findings of the study will determine whether such combinations influence investor trust, reliance, and portfolio behavior differently from exclusively human or exclusively AI advice.

Ultimately, the responsible development of AI in financial advice should focus not only on enhancing algorithmic performance but also on maintaining transparency, accountability, investor understanding, and meaningful human control. As financial decision-making becomes increasingly technology-oriented, understanding the relationship between humans and intelligent advisory systems will continue to be an important area of academic and practical research.

The present study contributes to this emerging field by providing a structured framework for examining how the source of financial advice can influence what investors believe, how they respond to recommendations, and how such responses may be reflected in their investment decisions.

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