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AI is not careful: approach to the stock market and preference for AI advisor

International Journal of Bank Marketing

Jieun Koo
Pukyong National University, Busan, South Korea

Received 23 October 2023
Revised 28 April 2024
17 June 2024
Accepted 23 June 2024

Abstract

Purpose – Financial institutions actively seek to leverage the capabilities of artificial intelligence (AI) across diverse operations in the field. Especially, the adoption of AI advisors has a significant impact on trading and investing in the stock market. The purpose of this paper is to test whether AI advisors are less preferred compared to human advisors for investing and whether this algorithm aversion diminishes for trading.

Design/methodology/approach – The four hypotheses regarding the direct and indirect relationships between variables are tested in five experiments that collect data from Prolific.

Findings – The results of the five experiments reveal that, for investing, consumers are less likely to use AI advisors in comparison to human advisors. However, this reluctance to AI advisors decreases for trading. The author identifies the perceived importance of careful decision-making for investing and trading as the psychological mechanism. Specifically, the greater emphasis on careful decision-making in investing, as compared to trading, leads to consumers' tendency to avoid AI advisors.

Originality/value – This research is the first to investigate whether algorithm aversion varies based on whether one's approach to the stock market is investing or trading. Furthermore, it contributes to the literature on carefulness by exploring the interaction between a stock market approach and the lay belief that algorithms lack the capability to deliberate carefully.

Keywords Artificial intelligence, Algorithm aversion, Carefulness, Effort heuristic, Investing, Trading

Paper type Research paper

1. Introduction

Artificial intelligence (AI) has radically revolutionized industries and enhanced everyday experiences. With its ability to process vast amounts of data, recognize patterns and make informed decisions, AI has become a center of dramatic innovation. As of a forecast update in 2023, the adoption of AI has shown impressive growth: the global AI market was projected to reach $1.8 trillion by 2030, with an annual growth rate of 34.5% from 2021 to 2030 (Statistia, 2023). Industries ranging from healthcare, retail and entertainment to manufacturing, transportation and education have integrated AI to optimize operations, develop predictive analytics and create personalized user experiences. AI's influence continues to expand, making it an indispensable tool shaping the present and future of various sectors.

The financial sector is one of the salient domains where AI has garnered remarkable traction. The global market size of AI in banking is projected to reach $64.03 billion by 2030 (Allied Market Research, 2021), and algorithmic trading accounts for about 70% of the comprehensive trading volume in the USA stock market (Treleaven *et al.*, 2013). A compelling example of AI adoption in the fintech realm is the proliferation of robo-advisors. These AI-powered financial assistants offer personalized investment recommendations tailored to individual preferences and financial goals. Also, by automating the investment advisory process, robo-advisors significantly cut down on human resource costs and administrative overhead. Consequently, the fintech industry is experiencing a disruptive change wherein AI-driven solutions are not just delivering substantial cost efficiencies but also improving customer satisfaction.

This work was supported by a Research Grant of Pukyong National University (2023).

International Journal of Bank Marketing

0265-2323
DOI 10.1108/IJBM-10-2023-0568

Responding to the rapid growth of AI advisors in the financial market, prior literature around AI has sought insights about when and why consumers show an aversion to or appreciation of AI. Based on technology acceptance models, research has shown that perceived usefulness and trust (Belanche *et al.*, 2019; Eren, 2021), perceived risk and ease of use (Atwal and Bryson, 2021) and technological optimism and insecurity (Flavián *et al.*, 2022) affect the attitude about AI advisors. Other research has reported the effects of psychological characteristics that consumers have. For instance, fear of investment fraud (Brenner and Meyll, 2020), trust in people (Tubadji *et al.*, 2021), involvement level (Northey *et al.*, 2022), overconfidence in one's financial knowledge (Piehlmaier, 2022) and political ideology (Riedel *et al.*, 2022) determine the likelihood of adopting AI financial advisors.

Despite the previous findings that have identified explanatory factors, little attention has been given to the question of whether an approach to the stock market can influence the preferences for AI advisors. This study aims to address this gap by investigating whether consumers' reactions to AI financial advisors differ depending on the approach of attempting to profit in the stock market, specifically investing versus trading. Investing pursues gains by holding an asset for years, whereas trading is a strategy that captures short-term gains for days or weeks. These two approaches are the main methods of generating wealth in the stock market (Aaziznia, 2020), and AI advisors are ubiquitous tools in investing and trading. Given that customers participating in the financial industry hardly avoid encountering AI, companies must improve and innovate their algorithm-based services in a way that aligns with customer expectations and preferences. To help create more effective and user-friendly AI advisory solutions, it is necessary to understand how individuals respond to AI advisors used in investing and trading.

The current research proposes that AI advisors are less preferred than human advisors for investing, but the difference in preference diminishes for trading. The five empirical studies support our contention. Studies 1A and 1B show that participants' responses to AI advisors are less favorable than to human advisors for investing, but this effect attenuated for trading. Studies 2 and 3 reveal the underlying mechanism for these findings. This effect occurs because people believe that, investing, compared to trading, places greater importance on careful deliberation, but AI advisors are perceived to have less capacity for careful deliberation when compared to human advisors. Finally, Study 4 suggests that human's intervention with AI advisors helps to overcome AI aversion for investing.

The current research makes three fundamental contributions. First, it contributes to the literature on AI advisors in financial services. Indeed, while prior research mainly focused on the influence of consumer-sided characteristics (e.g. perceived trust, involvement), our research investigates the role of a stock market approach in consumers' acceptance of AI. Second, our research extends the literature on why algorithm aversion occurs. Although numerous reasons have been reported, such as uniqueness neglect (Longoni *et al.*, 2019) and lack of emotional abilities (Castelo *et al.*, 2019), to the best of our knowledge, this work is the first attempt to show the notion that AI cannot deliberate carefully contributes to algorithm aversion in financial contexts. Third, the current research advances the understanding of the effort heuristic. Adding to the literature that people strongly associate value with effort in service or product evaluations (Kruger *et al.*, 2004), I show that the heuristic also influences consumers' responses to AI versus humans.

The remainder of this paper is structured as follows. I begin by reviewing the relevant literature on AI aversion and appreciation, carefulness and effort, followed by the development of hypotheses. Then five experiments lend support for the proposed effect of a stock market approach on the preference for AI and human advisors. Lastly, I elaborate on theoretical and practical implications along with a suggestion for future research.

2. Literature review

2.1 Algorithm aversion versus appreciation in finance

Germann and Merkle (2022) refer to algorithm aversion as "the tendency of humans to shy away from using algorithms even when algorithms observably outperform their human counterparts." Despite many pieces of evidence showing the algorithm's superior performance (e.g. Buczynski *et al.*, 2021) in the financial domain, people consistently reject algorithms and rely more on human advisors. For instance, when making forecasts for stock prices, people severely discount advice from statistical methods and make decisions in favor of human experts (Filiz *et al.*, 2021; Önkal *et al.*, 2009). Similarly, investors are reluctant to allocate their investment budget to a robo-advisory algorithm, and the budget share delegated to the algorithm remains below 50% even if financial education increases the share (Litterschedit and Streich, 2020). Algorithm aversion also manifests in the decision of whether to exclude controversial stocks from an investment portfolio. People perceive human fund managers as more appropriate decision-makers than computer algorithms regarding controversial stocks (Niszczota and Kaszás, 2020). Cohering with these findings, people are less likely to use an algorithm in uncertain decision domains (Dietvorst and Bharti, 2020) and for tasks that are complex (Xu *et al.*, 2020) and require a high level of involvement (Northey *et al.*, 2022). Since financial decisions are considered inherently unpredictable, complicated and important, the disadvantages of using AI advisors are salient to investors, resulting in algorithm aversion.

On the other hand, a stream of research has documented the results suggesting that consumers may prefer advice from algorithms to advice from humans, a phenomenon referred to as algorithm appreciation (Logg *et al.*, 2019). People exhibit algorithm appreciation in domains where tasks involve numeric estimation or are perceived as objective (Morewedge, 2022). For example, numeric judgments such as weight estimates, song rank forecasts and student performance predictions rely more on algorithm advice than human forecasts (Dietvorst *et al.*, 2015; Logg *et al.*, 2019). When the task's objectivity is high compared to low (e.g. financial vs dating advice) and consumption involves utilitarian considerations compared to hedonic considerations (e.g. useful versus enjoyable), AI recommenders are either more effective than or at least as effective as humans (Castelo *et al.*, 2019; Longoni and Cian, 2022; Wien and Peluso, 2021). Considering that financial decisions require processing numeric information, have concrete criteria such as return rate, and possess utilitarian benefits of increasing financial assets, people would give greater weight to AI advisors' recommendations than human advisors in the realm of finance.

Although the two groups of literature suggest conflicting perspectives, I propose that introducing approaches to the stock market can reconcile them. Specifically, algorithm aversion or appreciation depends on whether a stock market approach is investing or trading. In the following, I review the literature suggesting that the perceived importance of carefulness in each stock market approach explains how individuals respond to AI or human advisors for investing or trading.

2.2 Approach to the stock market and association with carefulness

Investing and trading are two distinct approaches to participating in financial markets (Aaziznia, 2020). Investing typically has a long-term focus, with investors aiming to accumulate wealth over an extended period, often 5–10 years. They buy and hold a portfolio of stocks, mutual funds, bonds and other investment instruments for years and adjust the portfolio infrequently. In contrast, trading is usually short-term in nature, involving the buying and selling of financial instruments over relatively brief time periods, ranging from minutes to weeks or months. Traders execute frequent transactions to profit from short-term price fluctuations. Trading generally falls into two categories: Day trading buys and sells financial instruments within as little as a few seconds or the same day, whereas swing trading holds assets from days to weeks.

Previous research has suggested that a long-term perspective, compared to a short-term perspective, is associated with carefulness. Using functional magnetic resonance imaging, McClure *et al.* (2004) found that when people choose rewards in the more distant future over immediate rewards, the fronto-parietal region, the area associated with higher cognitive functions, shows greater activity. This suggests that patience with a long-term perspective involves cognitively careful and deliberative work of the brain. Making accurate predictions for the future also requires careful processing of past experiences, such as assessing their relevance and deciding whether to integrate them into the predictions. Peetz and Buehler (2012) showed that when predicting spending in the distant future, people tend to examine past experiences more carefully than in the near future, resulting in better predictions. Further, a long-term perspective leads to careful behaviors, such as planning behavior or responsible financial behavior. Future time perspective refers to a trait that visualizes a distant future and values a long-term perspective. When future time perspective is strong, financial planning behavior (Tomar *et al.*, 2021) and retirement saving practices increase (Jacobs-Lawson and Hershey, 2005). Healthy eating and condom use are also cautious and deliberative actions, and these behaviors are more valued in a far-sighted condition (Lutchyn and Yzer, 2011). Sternberg and Ruzgis (1994) also proposed that prudence is associated with the pursuit of long-term goals and is therefore resistant to impulsive behavior. Taken together, these studies suggest that a perspective that looks beyond the present moment and considers distant consequences entails carefulness.

However, research has yet to apply the link between a long-term perspective and carefulness to investing and trading in the stock market. To fill this gap, the current research suggests that, as a consequence of the association, individuals place different weight on carefulness for each approach to the stock market. Specifically, individuals may perceive carefulness as more crucial in investing compared to trading.

2.3 Carefulness and effort

Carefulness demands putting in effort. Carefulness means giving cautious attention, being thorough and painstaking in action to avoid possible danger or harm (Banawan and Rodrigo, 2019; Castelao-Huerta, 2023). Similarly, it is defined as the tendency to think and plan cautiously before acting or speaking (ACT WorkKeys, 2022). One of the facets of conscientiousness is also carefulness (also called caution), measured by statements such as “I avoid mistakes,” “I choose my words with care,” “I think before I speak,” and so on (MacCann *et al.*, 2009; Rikoon *et al.*, 2016). These definitions share a common element that achieving a high level of carefulness requires exerting effort. Prior findings supported the tight link between carefulness and effort. For example, as developing scientific products typically goes through careful deliberation and meticulous experiments, people believe that scientific products are the outcome of effort rather than insight, in contrast to artistic products (Miceli *et al.*, 2020). In caregiving situations, people perceive themselves to be better caregivers when investing more effort in the task than using effort-reducing products (Garcia-Rada *et al.*, 2022). When observing a robot transporting an object for a longer duration, which typically indicates investing a greater effort, human observers perceive that interactions with the object require a high level of carefulness (Lastrico *et al.*, 2022). Online shopping contexts where consumers expect to spend less effort reduce the systematic processing of information and promote heuristic-based decisions. This suggests that priming for low effort hinders careful thoughts and decisions (Niza Braga and Jacinto, 2022). As such, effort is an essential component in achieving the desired level of carefulness.

According to previous literature, AI, as opposed to humans, is not perceived as capable of making efforts. It is common sense that robots and AI systems are typically designed to minimize the effort and labor required by humans. Humans have consciousness, intentions, or the ability to exert effort and work hard, whereas algorithms just calculate and operate on programming and data. Moreover, this understanding that humans exert "sweat" while algorithms do not devalues AI's intervention because effort is often used as a cue for assessing quality, an effect known as the effort heuristic (Kruger *et al.*, 2004). Prior research has provided supporting evidence. For instance, perceived effort in relationship maintenance diminished when the relationship partner used AI assistance compared to the condition with no aid, leading to reduced relationship satisfaction and increased partner uncertainty (Liu *et al.*, 2024). The evaluation of service robots' performance (vs human employees) is degraded because robots just perform on predetermined and standardized instructions, which negatively influences the perceived effort of robots (Nie and Huang, 2023). Robots were perceived as less courageous than humans when providing assistance in disaster response (Chen and Huang, 2023). This effect may stem from the fact that robots simply follow programmed commands rather than exert their best effort to save lives at the potential cost of self-sacrifice. Consequently, robot's helping behaviors are undervalued. A similar pattern was observed even in the domain of art. Perceived effort and estimated time to create artwork were rated lower when labeled as "AI-created" than "human-created" (Bellaiche *et al.*, 2023). Similarly, AI-created artworks were perceived as having less aesthetic value than human-made artworks (Chamberlain *et al.*, 2018). However, when participants were exposed to videos depicting robots physically crafting art, their negative judgments toward AI-created artworks diminished. This result implies that people might consider the level of artistic endeavor exerted by the creator as a crucial indicator of the artwork's quality. Buell and Norton (2011) reported consistent results, referred to as the labor illusion. When technology-mediated services such as online travel websites show how they work (e.g. the travel website presents a changing list of sites under searching), there is an increase in perceived effort and consequently higher perceived value of the service. In sum, due to AI or robots' nature to operate on predetermined instructions and algorithms, people perceive that they do not exert physical or mental effort in the way humans do.

Taken together, the perceived lack of effort of AI may render it incapable of making careful decisions, and this biased perception may influence the choice of advisors for investing and trading. In the next section, I provide the conceptual framework to address these research questions and present the hypotheses.

3. Conceptual framework and hypotheses

3.1 Approach to the stock market and perceived importance of carefulness (H1)

I propose that careful judgments are perceived as more important for investing than trading. As explained above, investing typically takes a long-term perspective, often holding assets for years or even decades whereas trading often occurs within compressed time frames such as seconds and weeks (Aaziznia, 2020). As a long-term focus is associated with higher levels of carefulness (McClure *et al.*, 2004; Tomar *et al.*, 2021), investing may make the concept of carefulness more accessible, and therefore people are primed to focus on this dimension. According to Yi (1990), a concept that is contextually activated attracts people's attention. In contrast, trading does not prime carefulness as much as investing because a short-term focus does not have a clear association with carefulness. Therefore, people give more weight to carefulness in investing compared to trading and perceive that investing requires more thoroughness and prudence to make the right decisions.

In addition, the lay belief that investing involves less frequent portfolio adjustment than trading may reinforce the association between investing and carefulness. Because investing is the approach of holding assets over a long-time horizon, people tend to believe that portfolio adjustments are infrequent. Consequently, the consequences of a poorly considered investment choice can be enduring and substantial. To mitigate such risks, people may infer that investors need to exercise meticulousness and thoroughness in their initial analyses and portfolio construction. In contrast, traders have the opportunity for more frequent adjustments, which may compensate for less precise initial decisions. Also given that trading often occurs within compressed timeframes, making quick decisions, rather than being careful, becomes crucial for capitalizing on the fast-moving market and promptly adapting to evolving conditions. In sum, investing's extended timeframes drive people to perceive carefulness as more crucial compared to trading with an agile and immediate nature.

H1. Carefulness is perceived as more important for investing than trading.

3.2 Approach to the stock market and algorithm aversion (H2-H3)

I expect that the biased perception regarding the importance of carefulness shapes the different patterns of preference for AI versus human advisors in each stock market approach. Specifically, I propose that consumers tend to avoid algorithm advisors for investing because of the greater emphasis on carefulness in investing. However, this tendency to avoid algorithms diminishes in trading, where there is less emphasis on carefulness. People believe that achieving a high level of carefulness requires putting in effort (Garcia-Rada *et al.*, 2022; Miceli *et al.*, 2020). However, AI is not perceived as exerting effort because it simply operates on programmed codes without any will or intention to achieve a goal (Bellaiche *et al.*, 2023; Nie and Huang, 2023). Consequently, the perception that AI does not make an effort undermines its ability to make cautious and thoughtful decisions. The unfavorable position of AI in terms of carefulness may hurt consumers' attitudes toward algorithms, particularly in investing, where careful considerations and decisions are highly valued. I therefore expect that algorithm aversion occurs in the context of investing. However, the perceived importance of carefulness decreases for trading, which reduces people's sensitivity to AI's lack of carefulness. As a result, I expect algorithm aversion to decrease for trading (see Figure 1 for the conceptual model). Formally,

H2. AI advisors are less preferred to human advisors for investing, but this difference in preference decreases for trading.

H3. The effect of a stock market approach on algorithm aversion is mediated by the perceived importance of carefulness.

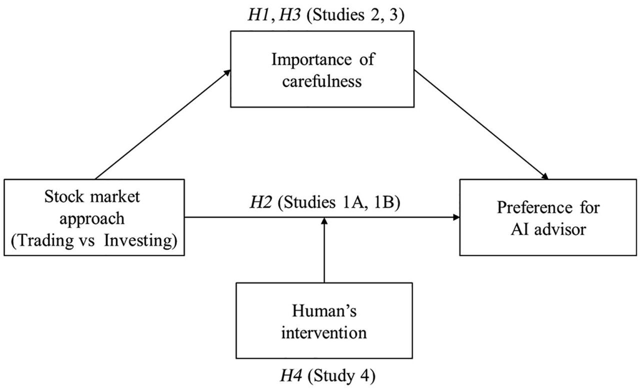

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Figure 1.
Conceptual model

3.3 Human's intervention with AI advisor (H4)
Previous research has shown that adding "human" aspects to AI solves algorithm aversion. For example, consumers are resistant to AI advisors in hedonic consumption, but they become more receptive to AI advisors when humans collaborate with AI (Longoni and Cian, 2022). Similarly, the anthropomorphic design of AI greatly reduces algorithm aversion. Presenting AI advisors with a human-like appearance and name (Wien and Peluso, 2021), using human voice-based communication (Qiu and Benbasat, 2009) and describing AI as understanding people's emotions (Castelo *et al.*, 2019) increase consumer trust and enjoyment, resulting in greater acceptance of AI's recommendations.

Consistent with these studies, I propose that the resistance to AI advisors for investing is reduced by collaboration with human advisors. The current research suggests that the negative response to AI in investing is driven by the preconception that AI lacks carefulness. Thus, a human-AI hybrid advisory system can complement the lack of carefulness of algorithmic advisors. As a result, the negative response to AI in the context of investing is expected to decrease.

H4. Human advisors' intervention with AI advisors reduces the algorithm aversion for investing.

4. Overview of studies
Across five studies, I show that consumers are less likely to choose an AI (vs a human) advisor for investing, but the avoidance of AI diminishes for trading. Note that, in all studies, I referred to investing as "long-term investing" to clarify the meaning. I also contrasted long-term investing with swing trading, as swing trading's time period is longer than day trading, which makes the experiment design more conservative. In Study 1A, I compared the choice percentages of AI versus human advisors between long-term investing and swing trading (H2). Study 1B tested H2 in a different experiment design. I manipulated both stock market approach and advisor type, and participants responded to a measure of willingness to buy a financial product. Study 2 examined whether the perceived importance of carefulness in stock market approaches mediates the effect observed in Study 1A (H1, H3) and ruled out several alternative accounts such as the level of abstract thinking, uncertainty and advisors' ability. Study 3 attempted to show the mediating effect of carefulness in a different way (H1, H3). It compared the impact of perceived carefulness in determining the preference for advisors between long-term investing and swing trading. Lastly, Study 4 tested whether humans' supervision of AI advisors reduces algorithm aversion in long-term investing (H4).

All studies collected data through Prolific, an online research platform that connects researchers with diverse participants. As our studies were conducted in English, I only accepted participants who reside in the UK, USA and Canada and whose first language is English. To provide participants with the choice to take our survey, I introduced our survey beforehand, explaining that I were interested in consumer decisions about financial products and that it would take about 2–3 min to complete. Aiming to recruit a minimum 50 participants per cell, Studies 1A, 1B and 4 were conducted from May to July 2023, while Studies 2 and 3 were conducted in March 2024 and October 2023, respectively.

5. Study 1
Study 1 aims to test H2 that an AI advisor is less preferred to a human advisor for long-term investing. However, this effect is expected to lessen for swing trading. I conduct two studies with different experimental designs to ensure the robustness of the results. Specifically, Study 1A asks participants to choose between an AI advisor and a human advisor and then

compares the choice patterns between investing and trading. In contrast to Study 1A, Study 1B manipulates both advisor type and stock market approach and assesses participants' willingness to buy a financial product.

5.1 Study 1A

5.1.1 Method. A total of 202 participants (114 females, 88 males; 172 whites, 8 Asians, 8 African American, 14 others; $M_{age} = 40.7$) recruited from Prolific participated in a one-way between-subjects study. Participants were randomly exposed to either a long-term investing scenario ($n = 99$) or a swing trading scenario ($n = 103$).

All participants were presented with the definition of both long-term investing and swing trading as below. Then the participants in the long-term investing (swing trading) condition were told to imagine that they chose a long-term investing approach (swing trading approach) and found two proper financial products after searching. One was managed by AI advisors and the other one was managed by human advisors. Afterward, participants were asked to choose one product that would be better for their approach to the stock market. Lastly, they reported their risk-seeking tendency in finance with one item on a seven-point scale (1 = *I do not take the risk of losing money*, 7 = *I take a risk for high return*). Since risk preference is domain-specific (Weber *et al.*, 2002) and positively related to novelty seeking (Wang *et al.*, 2015) and new technology adoption (Wang and Zhao, 2019), I measured participants' risk-seeking in finance to control for its influence on the choice of advisor. Appendix A presents the stimuli of Study 1A.

> *[Long-term investing]*
>
> Long-term investing in stock markets involves buying stocks with the intention to remain invested in them for a long period. This could generally be five years or more. Long-term investing aims to build wealth over a longer period through portfolio construction.
>
> *[Swing trading]*
>
> Swing trading is a type of trading strategy in which security, such as a stock, is held for a time period that could range from a few days to a few weeks. Swing trading requires an investor to buy and sell shares frequently. Since this is short to medium-term, investors aim to earn higher profits through price fluctuations.

5.1.2 Results. A chi-square test showed that advisor choice was significantly different depending on the stock market approach ($\chi^2(1) = 6.03, p = 0.014$). In the long-term investing condition, the choice of AI advisors was significantly lower than that of human advisors (34.3 vs 65.7%; $\chi^2(1) = 9.71, p = 0.002$). However, in the swing trading condition, the difference diminished, being not significant (51.5 vs 48.5%; $\chi^2(1) = 0.09, p = 0.768$). Figure 2 depicts the result.

A logistic regression on the choice of advisor (0 = human, 1 = AI) with stock market approach as an independent variable (0 = swing, 1 = long-term) and risk-seeking in finance, gender and age as covariates showed a consistent result (Table 1). The participants in the long-term investing condition were less likely to choose AI than those in the swing trading condition ($b = -0.86, p = 0.005$). Risk-seeking in finance was significant ($b = 0.40, p = 0.001$), whereas gender and age were not significant (ps > 0.460). All taken together, these results supported H2.

5.1.3 Discussion. Study 1A provides preliminary evidence supporting that resistance to AI advisors is stronger in investing than in swing trading. Despite these results, one can argue that introducing the two stock market approaches together and presenting both types of advisors in a choice set may create demand artifacts. That is, the experimental design of Study 1A may lead participants to easily infer the researchers' intentions and respond

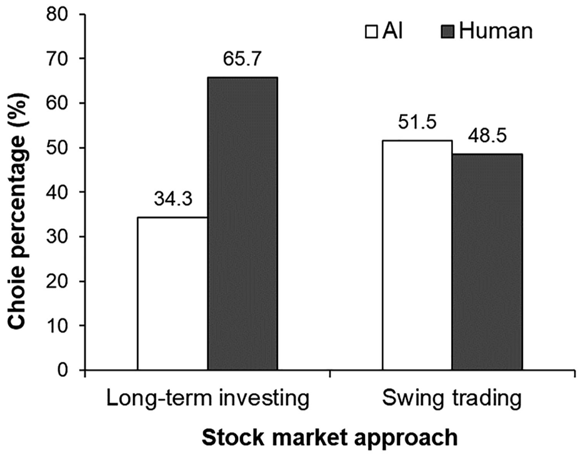

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Figure 2. Advisor choice percentage for each stock market approach in Study 1A

Variables	*B*	SE	*Z*	*p*
Stock market approach	−0.86	0.31	−2.78	0.005
Risk-seeking in finance	0.40	0.12	3.40	0.001
Gender	−0.07	0.16	−0.40	0.689
Age	0.01	0.01	0.74	0.460
Pseudo (Nagelkerke) R^2	0.13			

Note(s): Observed frequency of advisor choice: human = 115, AI = 87
Source(s): Created by author

Table 1. Logistic regression results in Study 1A

accordingly. To remove this possibility, Study 1B adopts a different experimental design to test H2. Also Study 1A revealed that risk-seeking in finance significantly drives the acceptance of AI advisors. Based on this finding, all subsequent studies include risk-seeking in finance as a covariate.

5.2 Study 1B

Study 1B aims to test the robustness of the effect observed in Study 1A. Different from Study 1A, Study 1B manipulated both stock market approach and advisor type as between-subject factors to minimize the possibility that participants guessed the intention of researchers.

5.2.1 Method. A total of 202 participants (120 females, 82 males; 177 whites, 6 Asians, 10 African American, 9 others; $M_{\text{age}} = 42.4$) recruited from Prolific participated in a 2 (stock market approach: long-term investing vs swing trading) × 2 (advisor type: AI vs human) between-subjects study (See Table 2). Participants were presented with a stock

	AI advisor	Human advisor
Long-term investing	50	50
Swing trading	51	51

Source(s): Created by author

Table 2. Number of participants in each condition of Study 1B

market approach and its advisor, after which they indicated their willingness to buy the financial product.

All participants were told to imagine that they were searching for financial products and came across one. They were then presented with a description of the product. In the long-term investing condition, the description said that the financial product belongs to long-term investing and AI (a fund manager) is managing the product in the AI (human) condition. Then the same definition of long-term investing as Study 1A was presented. In the swing trading condition, the description said that the financial product belongs to swing trading and AI (a fund manager) manages the product in the AI (human) condition. This was followed by the swing trading's definition used in Study 1A. After reading the description, participants indicated their willingness to buy the product with one item on a seven-point scale (1 = *not at all*, 7 = *very much*) and risk-seeking in finance as Study 1A. Appendix B presents the stimuli of Study 1B.

5.2.2 Results. A two-way ANCOVA was run on the willingness to buy the financial product with risk-seeking in finance, gender and age as covariates. The main effects of stock market approach and advisor type were significant, indicating that the long-term investing product (M = 3.86) was more preferred to the swing trading product (M = 3.22, $F(1, 195) = 10.28$, $p = 0.002$) and AI (M = 3.27) was less preferred to human (M = 3.81, $F(1, 195) = 7.15$, $p = 0.008$). Risk-seeking in finance was significant ($F(1, 195) = 32.67$, $p < 0.001$), whereas gender and age were not significant (ps > 0.506). More importantly, the interaction of stock market approach and advisor type was significant ($F(1, 195) = 7.45$, $p = 0.007$). The cell mean contrasts showed that AI was less preferred to humans in the long-term investing condition ($M_{AI} = 3.32$ vs $M_{human} = 4.40$, $F(1, 195) = 14.46$, $p < 0.001$) whereas the preference between AI and humans was not significantly different ($M_{AI} = 3.22$ vs $M_{human} = 3.21$, $F(1, 195) = 0.001$, $p = 0.972$) in the swing trading condition. Figure 3 depicts the interaction.

5.2.3 Discussion. Study 1B yielded consistent results supporting H2 despite the changes in the experiment design. Study 1A employed a joint evaluation mode where participants compare and evaluate both AI and human advisors against each other, whereas Study 1B utilized a separate evaluation mode where participants assess one of the advisors individually without direct comparisons to the other. Previous research has documented

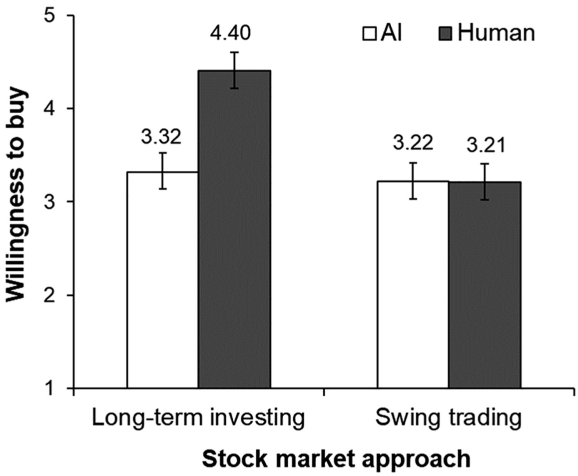

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Figure 3.
Willingness to buy as a function of stock market approach and advisor type in Study 1B

that these two evaluation modes can lead to contrasting effects on information processing and consumer preferences (e.g. Kogut and Ritov, 2005). Nonetheless, I found consistent results in Studies 1A and 1B, ensuring the robustness of the hypothesized effect. As the next step, Study 2 tests the psychological mechanism underlying the effect. I contend that people perceive that, compared to swing trading, long-term investing places a greater weight on carefulness, which results in the avoidance of AI advisors.

6. Study 2

The purpose of Study 2 is twofold. First, I investigate the mechanism underlying the results in Study 1. Specifically, people may perceive that making careful decisions is more important for long-term investing compared to swing trading (H1), which consequently lowers the preference for AI advisors compared to human advisors (H3). Second, I aim to eliminate alternative accounts. First, Kim and Duhachek (2020) showed that AI is perceived as low-construal agents lacking high-construal abilities. Thus, when persuasion messages given by AI are described in high-construal terms, the messages are perceived as less appropriate. Given that long-term investing needs to look at a more distant future than swing trading, participants may recognize that using high-level construals, in other words, abstract thinking, is necessary for long-term investing, which renders AI advisors inappropriate and results in algorithm avoidance. Second, people use algorithms less in domains with high uncertainty (Dietvorst and Bharti, 2020). Due to long-term investing's extended time horizon, participants may perceive greater uncertainty, leading to avoidance of AI advisors in the long-term investing condition. Third, people may understand that investors are required to have more expertise and knowledge than traders as long-term investing involves in-depth research and analyses of companies' fundamentals, valuation and industry trends. AI advisors, however, are perceived as having low expertise (Zhang *et al.*, 2021) and knowledge (Luo *et al.*, 2019). This perceived lack of AI's capability can lower the preference for algorithm advisors in the long-term investing condition.

Study 2 measures the importance of carefulness and abstract thinking, the degree of uncertainty and the required capability of advisors for each stock market approach. Then I examine the mediating effect of the importance of carefulness (H1, H3) and test whether the three alternative accounts can be ruled out. In addition, I measure and control participants' subjective knowledge and self-assessed experiences in the financial market as covariates. Subjective knowledge refers to the extent to which an individual believes that they are knowledgeable about a certain domain, and it is a valuable predictor for acceptance of new technologies (Staab and Liebherr, 2024). Similarly, self-assessed financial experience affects the willingness to use a robo-advisor (Hohenberger *et al.*, 2019). Thus, participants with high subjective knowledge or experience in the financial market can be more receptive to AI financial advisors.

6.1 Method

A total of 196 participants (113 females, 83 males; 164 whites, 12 Asians, 9 African Americans, 11 others; $M_{\text{age}} = 40.4$) recruited from Prolific Academic participated in a one-way between-subjects study manipulating stock market approach ($n = 97$ for long-term investing, $n = 99$ for swing trading). Study 2 was the same as Study 1A, except that I measured the variables that presumably mediate the effect of stock market approach on preference for AI advisors and participants' financial literacy using subjective knowledge and self-assessed experience.

As Study 1A, after being presented with the definitions of both long-term investing and swing trading, the participants in the long-term investing (swing trading) condition were told that they had selected the long-term investing approach (swing trading approach) and found two products: One managed by AI advisors and the other one managed by human advisors. Participants made a choice between two as in Study 1A. Then I collected data about mediators. The seven pairs of factors considered important for investing or trading were listed on a semantic differential scale ranging from 1 to 7. The participants in the long-term investing (swing trading) condition were asked to decide which element in each pair is more essential for long-term investing (swing trading). Three of these pairs measured the importance of abstract thinking (1 = *data-driven thought* vs 7 = *insight or intuition*, 1 = *concrete thinking* vs 7 = *abstract thinking*, 1 = *analytical perspective* vs 7 = *holistic perspective*; $\alpha = 0.69$), with higher scores indicating that abstract thinking was deemed more important than concrete thinking. The four remaining pairs measured the importance of careful decision-making compared to fast decision-making (1 = *fast decision* vs 7 = *careful decision,* 1 = *quick assessment* vs 7 = *cautious assessment,* 1 = *speedy judgment* vs 7 = *prudent judgment,* 1 = *rapid decision* vs 7 = *circumspect decision*; $\alpha = 0.96$).

I also measured the perceived uncertainty of stock market approach using three items. After being presented with the definitions of uncertainty, ambiguity and complexity, the participants in the long-term investing (swing trading) condition indicated the level of each factor's association with long-term investing (swing trading) on a seven-point scale (1 = *very low*, 7 = *very high*; $\alpha = 0.73$). Uncertainty was defined as "uncertainty stems from a lack of information, consequently making predictions of future events difficult," ambiguity as "ambiguity is a situation in which something has more than one possible meaning and may therefore cause confusion," and complexity as "complexity is the state of having many parts and being difficult to understand or find an answer." In addition, I measured the required capability of advisors with three items. The participants in the long-term investing (swing trading) condition indicated how much expertise, knowledge, and experience the advisors of long-term investing (swing trading) are required to have on a seven-point scale (1 = *not at all*, 7 = *very much*; $\alpha = 0.93$). Lastly, risk-seeking in finance, subjective knowledge ("*How would you access your overall knowledge about investment?*" 1 = *very low*, 7 = *very high*), and experience in the financial market ("*Do you have experience of investing money in financial products (e.g., shares, bonds, etc.)?*" 1 = *never*, 7 = *a lot)* were measured on a seven-point scale.

6.2 Results

6.2.1 Choice of advisor. Consistent with the previous studies, advisor choice (Figure 4) was significantly different depending on the stock market approach ($\chi^2(1) = 10.39, p = 0.001$). The choice of AI advisors was significantly lower than that of human advisors (22.7 vs 77.3%, $\chi^2(1) = 28.96, p < 0.001$) in the long-term investing condition whereas the choices of AI and human advisors were not significantly different in the swing trading condition (44.4 vs 55.6%, $\chi^2(1) = 1.22, p = 0.269$). A logistic regression on the choice of advisor (0 = human, 1 = AI) with the stock market approach as an independent variable (0 = swing, 1 = long-term) and risk-seeking in finance, subjective knowledge, self-assessed experience, gender and age as covariates showed coherent results (Table 3). The participants in the long-term investing condition were less likely to choose AI ($b = -1.12, p = 0.001$). Risk-seeking in finance was significant ($b = 0.25, p = 0.047$) while none of the other covariates was significant (ps > 0.232).

6.2.2 Mediation of the importance of carefulness. I examined the relationship between stock market approach and the importance of carefulness. As expected, carefulness was perceived as more essential in the long-term investing condition than the swing trading condition ($M_{\text{long-term}} = 5.60$ vs $M_{\text{swing}} = 3.03, F(1, 194) = 150.82, p < 0.001$). Then I conducted

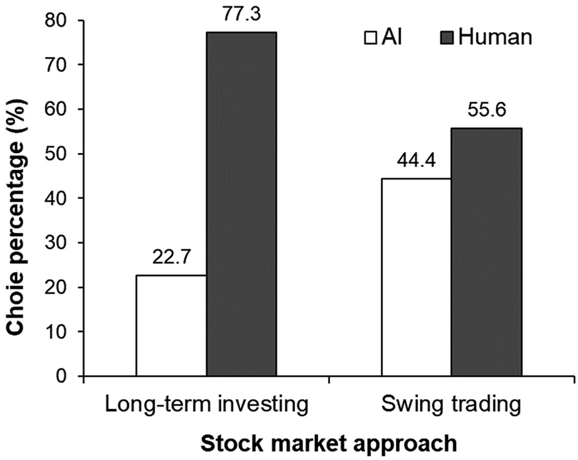

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Figure 4. Advisor choice percentage for each stock market approach in Study 2

Variables	b	SE	Z	p
Stock market approach	−1.12	0.34	−3.34	0.001
Risk-seeking in finance	0.25	0.12	1.99	0.047
Subjective knowledge	−0.13	0.17	−0.80	0.424
Self-assessed experience	0.13	0.13	0.99	0.322
Gender	−0.42	0.35	−1.20	0.232
Age	0.001	0.01	0.06	0.948
Pseudo (Nagelkerke) R^2	0.14			

Note(s): Observed frequency of advisor choice: human = 130, AI = 66
Source(s): Created by author

Table 3. Logistic regression results in Study 2

the mediation analysis using PROCESS, Model 4 (5,000 bootstrap samples and a 95% confidence interval) with risk-seeking in finance, subjective knowledge, self-assessed experience, gender and age as covariates. The results showed that the importance of carefulness mediated the effect of stock market approach on the advisor choice ($b = -0.68$, SE = 0.33, CI = [−1.45, −0.13]). These results confirmed H1 and H3.

To rule out alternative accounts, I examined whether abstract thinking, perceived uncertainty and advisors' capability differ by the stock market approach. Abstract thinking ($M_{\text{long-term}} = 2.97$ vs $M_{\text{swing}} = 3.11$) and advisors' capability ($M_{\text{long-term}} = 5.99$ vs $M_{\text{swing}} = 5.78$) were not significantly different ($F(1, 194) < 1.34$, ps > 0.249), thus I ruled out these two constructs as alternative accounts. Perceived uncertainty was, contrary to our expectation, higher in the swing trading condition ($M = 4.96$) than in the long-term investing condition ($M = 4.20$, $F(1, 194) = 22.23$, $p < 0.001$), and its mediating effect was not significant ($b = -0.10$, SE = 0.13, CI = [−0.39, 0.12]). Based on the result, perceived uncertainty was also eliminated as an alternative mechanism.

Further, I reexamined the mediating effect of the importance of carefulness, including abstract thinking, perceived uncertainty, advisors' capability, risk-seeking in finance, subjective knowledge, self-assessed experience, gender and age as covariates. Even after controlling all the variables, the mediation of the importance of carefulness remained ($b = -0.64$, SE = 0.34, CI = [−1.44, −0.08]). This result corroborated H3.

6.3 Discussion

As expected, a preconception exists that long-term investing necessitates more careful thinking and decisions, which increases AI avoidance for long-term investing compared to swing trading. Furthermore, I eliminated the alternative accounts based on abstract thinking, perceived uncertainty and advisors' capability. In the case of covariates, subjective knowledge and self-assessed experience did not have a significant impact on the choice of a financial advisor. All these findings lend support to our contention that the greater emphasis on careful decisions in long-term investing discourages consumers from choosing AI advisors.

Despite these findings, two things haven't been tested yet. The first is whether, compared to humans, AI is perceived as incapable of making careful decisions. The second is whether the perceived lack of AI's carefulness has a differential impact between investing and trading. In the next study, I address these two questions.

7. Study 3

Study 3 has two purposes. First, I explicitly show that AI is perceived as less capable of making careful decisions than human advisors, both for investing and trading. Second, I investigate whether the extent to which perceived carefulness affects preferences for advisors varies by the stock market approach. I expect that, for investing, perceived carefulness is a major factor in determining the preference for an advisor. However, for trading, I expect that other factors, beyond perceived carefulness, also come into play and affect the preference for an advisor.

7.1 Method

A total of 281 participants (182 females, 99 males; 239 whites, 14 Asians, 9 African American, 19 others; $M_{\text{age}} = 40.6$) recruited from Prolific Academic participated in a 2 (stock market approach: long-term investing vs swing trading) × 2 (advisor type: AI vs human) between-subjects study (Table 4). Study 3 was the same as Study 1B except that I measured the perceived carefulness of advisors.

As in Study 1B, the participants were presented with a product description of either long-term investing or swing trading and an advisor, either AI or human. After reading the description, participants indicated their willingness to buy the product as in Study 1B. Then, to measure the perceived carefulness of the advisor, I asked participants to what extent the advisor can make "careful decisions," "cautious assessment," "prudent judgment," and "circumspect decisions" on a seven-point scale (1 = *not at all*, 7 = *very much*; $\alpha = 0.93$), followed by a measure of risk-seeking in finance.

7.2 Results

7.2.1 Perceived carefulness of advisor and willingness to buy. A two-way ANOVA on the perceived carefulness of advisors showed that only the main effects of stock market approach and advisor type were significant. The advisor was perceived as making less careful

Table 4. Number of participants in each condition of Study 3

	AI advisor	Human advisor
Long-term investing	69	71
Swing trading	71	70

Source(s): Created by author

decisions in the swing trading condition than in the long-term investing condition ($M_{\text{long-term}} = 4.40$ vs $M_{\text{swing}} = 3.97$, $F(1, 277) = 7.32$, $p = 0.007$). Also, AI advisors were perceived as less capable of making careful decisions than human advisors ($M_{AI} = 3.83$ vs $M_{human} = 4.54$, $F(1, 277) = 19.76$, $p < 0.001$). However, as expected, the interaction was not significant ($F(1, 277) = 0.431$, $p = 0.512$). These findings indicate that the perceived lack of AI's carefulness manifests in both long-term investing and swing trading conditions. Figure 5a depicts the results.

I ran a two-way ANCOVA on the willingness to buy the financial product with risk-seeking in finance, gender and age as covariates. The main effect of stock market approach is significant, revealing that the long-term investing product was preferred to the swing trading product ($M_{\text{long-term}} = 3.87$ vs $M_{\text{swing}} = 3.21$, $F(1, 274) = 16.07$, $p < 0.001$), but the advisor type was not significant ($F(1, 274) = 1.71$, $p = 0.192$). Risk-seeking in finance ($F(1, 274) = 47.85$, $p < 0.001$) and gender ($F(1, 274) = 5.62$, $p = 0.018$) appeared significant whereas age was not significant ($p = 0.892$). More importantly, the interaction of stock market approach and advisor type was significant ($F(1, 274) = 5.38$, $p = 0.021$). As expected, AI was less preferred to humans in the long-term investing condition ($M_{AI} = 3.57$ vs $M_{human} = 4.17$, $F(1, 274) = 6.59$, $p = 0.011$), but the difference in preference between AI and human advisors was not significant ($M_{AI} = 3.29$ vs $M_{human} = 3.12$, $F(1, 274) = 0.505$, $p = 0.478$) in the swing trading condition (Figure 5b). These replicated the results of Study 1B.

In sum, for long-term investing, perceived carefulness and willingness to buy are consistent in the pattern, that is, when the advisor was perceived as less careful, the willingness to buy the product decreased. In contrast, for swing trading, despite a significant difference in perceived carefulness between the advisors, the willingness to buy did not change significantly. I investigate why this variance by the stock market approach occurs in the following.

7.2.2 Determinants of willingness to buy. I tested the moderated mediation model using PROCESS, Model 15 (5,000 bootstrap samples and a 95% CI). I set advisor type (-1 = human, 1 = AI) as the IV, perceived carefulness as a mediator, willingness to buy as the DV and risk-seeking in finance, gender and age as covariates. Importantly, stock market approach (-1 = swing, 1 = long-term) was set as a moderator of two pathways: one between perceived

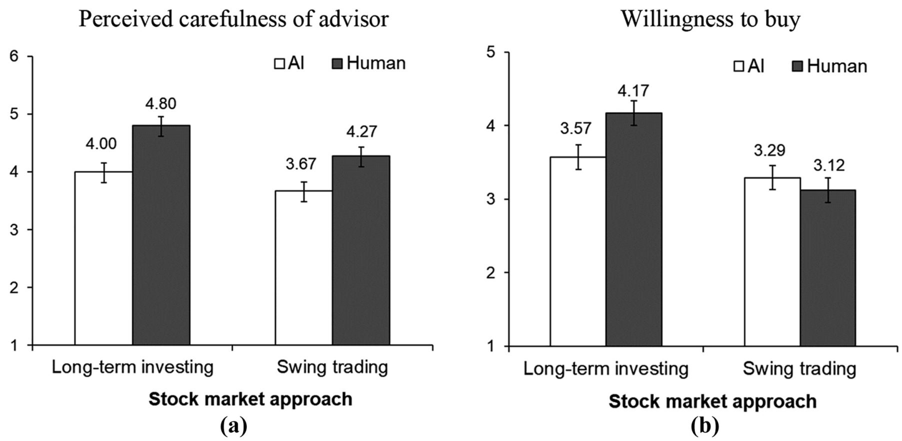

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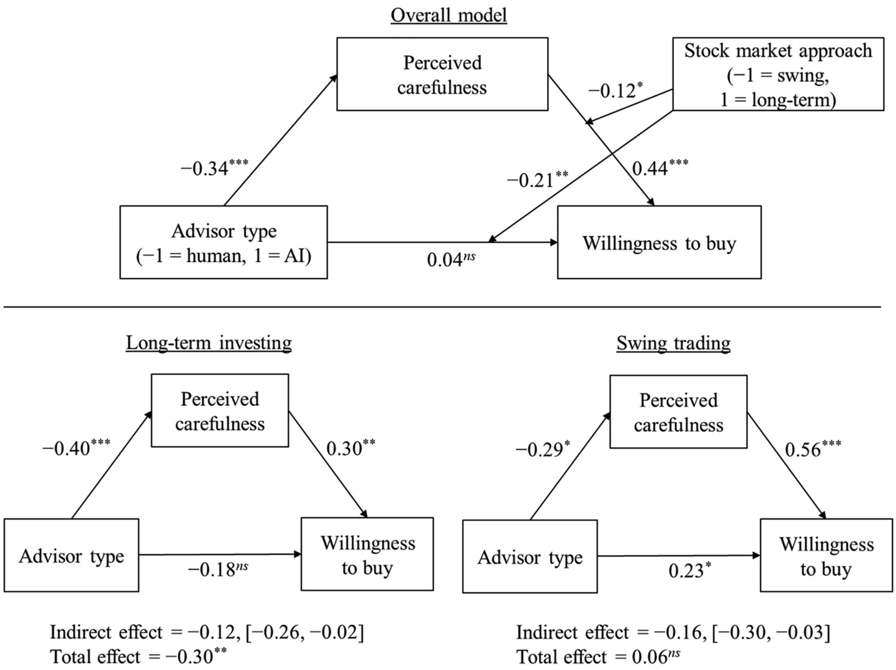
Figure 5. Perceived carefulness and willingness to buy as a function of stock market approach and advisor type in Study 3

carefulness and willingness to buy and the other one between advisor type and willingness to buy. The analysis of the overall model (see the upper section of Figure 6) revealed that the moderated mediation was not significant (b = 0.08, SE = 0.04, CI = [−0.01, 0.17]) and the interaction of advisor type and stock market approach remained significant (b = −0.21, SE = 0.08, p = 0.008).

To delve into the results of the overall model, I conducted the simple mediation model using PROCESS, Model 4 (5,000 bootstrap samples and a 95% CI) for long-term investing and swing trading separately. For long-term investing (Figure 6, lower left side), the indirect effect of perceived carefulness was significant (b = −0.12, SE = 0.06, CI = [−0.26, −0.02]) but the direct effect of advisor type was not significant (b = −0.18, SE = 0.11, p = 0.105). This indicates that the effect of advisor type was fully mediated by perceived carefulness, suggesting that perceived carefulness of advisors takes the dominant role in shaping preference for advisors. In contrast, for swing trading (Figure 6, lower right side), both the indirect effect of perceived carefulness (b = −0.16, SE = 0.07, CI = [−0.30, −0.03]) and the direct effect of advisor type (b = 0.23, SE = 0.11, p = 0.042) were significant. Furthermore, the indirect effect and the direct effect had an opposite direction, with the negative indirect effect being canceled out by the positive direct effect. Consequently, the total effect of advisor type was not significant (b = 0.06, SE = 0.13, p = 0.622). This implies that factors other than perceived carefulness also influence the preference for swing trading advisors, thereby supporting our contention that, in contrast to long-term investing, perceived carefulness loses its dominant importance for swing trading.



Note(s): ns p > 0.05, *p < 0.05, **p < 0.01, ***p < 0.001

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Figure 6.
Determinants of willingness to buy in Study 3

7.3 Discussion

Consistent with our theory, the results of Study 3 indicate that an AI advisor is perceived as lacking in carefulness compared to a human advisor and that this perception remains consistent across both stock market approaches. More importantly, the mediation analyses reveal that perceived carefulness plays a pivotal role in determining purchase intention for long-term investing, while other factors are involved in shaping purchase intention for swing trading. This result suggests that consumers weigh perceived carefulness more heavily in investing than in trading, in support of H1.

8. Study 4

The purpose of Study 4 is to investigate how to improve the perception of AI. I suggest that complementing AI with humans' oversight can increase the perceived carefulness of AI because humans' support signals that effort has been made. As a result, consumers would have a higher willingness to buy a long-term investing product managed by AI when humans' intervention is highlighted (H4). Note that Study 4 only used a long-term investing scenario because the previous studies showed no significant difference between AI and humans for swing trading.

8.1 Method

A total of 210 participants (132 females, 78 males; 180 whites, 13 Asians, 7 African American, 10 others; $M_{\text{age}} = 39.1$) recruited from Prolific Academic participated in a one-way between-subjects study. All participants were given a scenario of buying a long-term investing product, but the advisor was randomly presented as one of three types: AI ($n = 71$), human ($n = 69$), and AI supervised by human ($n = 70$). Participants answered their willingness to buy the product and other measures.

The stimuli of AI and human conditions were identical to those used in the long-term investing conditions in Study 1B. The stimuli of AI supervised by human condition were the same as that of AI condition but included the description of human's oversight of AI. Specifically, the description said "There is one particular thing about the AI advisor. Before deploying AI in the real world as long-term investing managers, human supervision and intervention stepped into the AI's training process. Specifically, this involved human reviewers, subject matter experts, or human-in-the-loop setups, where the human judgment was incorporated to validate or override AI decisions when necessary." After reading the stimuli, participants indicated the willingness to buy the product as Study 1B. Then, I measured the perceived carefulness of the advisor ($\alpha = 0.92$) and risk-seeking in finance as in Study 3. Appendix C presents the stimuli of AI supervised by human condition of Study 4.

8.2 Results

8.2.1 Perceived carefulness of advisor and willingness to buy. An ANOVA showed that the advisor type affected perceived carefulness ($M_{AI} = 3.61$ vs $M_{human} = 4.86$ vs $M_{AIbyHuman} = 4.20$, $F(2, 207) = 18.18$, $p < 0.001$; Figure 7a). As expected, AI was perceived as less careful than human ($F(1, 207) = 36.33$, $p < 0.001$) and AI supervised by human ($F(1, 207) = 8.39$, $p = 0.004$). AI supervised by human was perceived as less careful than a human advisor ($F(1, 207) = 9.80$, $p = 0.002$).

I also compared participants' willingness to buy using an ANCOVA with risk-seeking in finance, gender and age as covariates. An omnibus test showed a marginally significant effect of the advisor type ($M_{AI} = 3.44$ vs $M_{human} = 3.97$ vs $M_{AIbyHuman} = 3.87$, $F(2, 204) = 2.71$, $p = 0.069$; Figure 7b). Risk-seeking in finance was a significant covariate ($F(1, 204) = 31.56$, $p < 0.001$), but gender and age were not (ps > 0.209). A series of cell-mean contrasts confirmed our expectations. The willingness to buy in the AI condition was significantly lower than the human condition

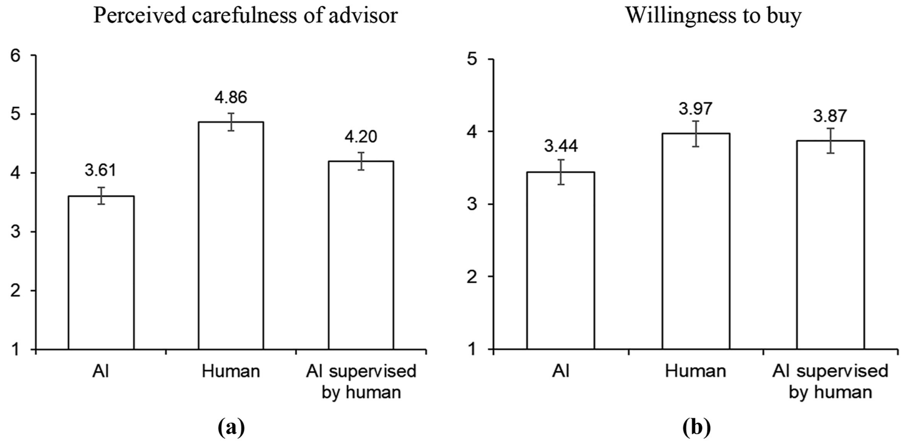

Figure 7. Perceived carefulness and willingness to buy by advisor type in Study 4

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(M_{AI} = 3.44 vs M_{human} = 3.97, F(1, 204) = 6.50, p = 0.012) and the AI supervised by human condition ($M_{AIbyHuman}$ = 3.87, F(1, 204) = 4.28, p = 0.040). In contrast, the willingness to buy in the human condition was not significantly different from that in the AI supervised by human condition (F(1, 204) = 0.22, p = 0.643). These results support H4.

8.2.2 Mediation of perceived carefulness. I conducted a mediation analysis using PROCESS, Model 4 (5,000 bootstrap samples and a 95% CI), with the advisor type as a multicategorical predictor. I set the AI condition as the reference group and included risk-seeking in finance, gender and age as covariates. For the AI and the human conditions, perceived carefulness mediated the effect of advisor type on the willingness to buy (b = 0.94, SE = 0.16, CI = [0.62, 1.26]). Similarly, for the AI and the AI supervised by human conditions, the results revealed the significant indirect effect of perceived carefulness (b = 0.42, SE = 0.16, CI = [0.11, 0.75]). Further, after combining the human and the AI supervised by human conditions, I conducted the same mediation analysis for the combined condition and the AI condition. The result showed that the mediating effect of perceived carefulness was consistently significant (b = 0.64, SE = 0.14, CI = [0.38, 0.92]).

8.3 Discussion

Study 4 replicated the findings of Study 3, confirming that participants perceive AI as deficient in carefulness. This leads to the conclusion that AI is not a proper source of recommendations for tasks that place importance on caution and prudence (i.e., long-term investing). Study 4 also showed how to alleviate the biased perception. When the message emphasizes humans' involvement in AI's training and development, the perceived carefulness of AI rebounds, increasing purchase intention. These findings are consistent with our contention that algorithms are perceived as less capable of making careful decisions than humans, and they suggest that human-AI collaboration can contribute to consumer acceptance of AI, especially in domains where caution and prudence are valued traits.

9. General discussion

The current research examined the relationship between an approach to the stock market and the avoidance of AI financial advisors. The five empirical studies consistently supported that people are more reluctant to rely on algorithm advisors for investing than trading. In Study 1A where participants made a choice between AI and human advisors, the likelihood of choosing AI was lower than that of choosing a human for investing whereas the difference in likelihood was not statistically significant for trading. In Study 1B, which adopted a separate evaluation mode, I also found that the purchase intention in the investing condition was lower when the recommendation came from an algorithm than a human. In contrast, participants in the trading condition were indifferent to the advisor's type. Study 2 not only found evidence that the greater importance of careful decisions in investing prevented participants from choosing algorithm advisors, but also ruled out alternative accounts that the observed effect may arise from the difference in abstract thinking, uncertainty and the advisor's capability. Study 3 explicitly showed that AI advisors are perceived as inadequate at making careful decisions. This perception, in turn, intensifies algorithm aversion for investing, whereas, for trading, other advisor-related factors mitigate the effect of perceived carefulness on algorithm aversion. Lastly, Study 4 demonstrated that the unfavorable response to AI for investing is attenuated by humans' supervision of algorithms.

9.1 Theoretical contributions

The current research makes three main contributions. First, our findings extend the literature on algorithm advisors in the financial industry. Previous research has attempted to identify the antecedents of the usage intention of AI advisors, specifically consumer-related variables such as consumers' technology acceptance, sociodemographic variables and service experiences (Hentzen *et al.*, 2022). Adding to this literature, I tested a novel hypothesis that preference for AI advisors depends on whether the approach to the stock market is investing or trading. Since research examining firm-related variables as antecedents comprises a small portion of the literature (Hentzen *et al.*, 2022), our work represents a significant contribution to the scope of the existing research.

Second, I identify carefulness as a psychological mechanism explaining consumers' reluctance to use algorithm advisors in finance, especially investing. Prior research has documented trust (Zhang *et al.*, 2021), emotion (Riedel *et al.*, 2022), AI's problem-solving ability (Northey *et al.*, 2022) and interpersonal emotion regulation goal attainment (Henkel *et al.*, 2020) as mediators. The current research contributes new findings to the literature on AI in finance by shedding light on the role of AI's perceived capability to deliberate carefully. This finding is also in line with prior research showing that uniqueness neglect (Longoni *et al.*, 2019), lack of a human mind (Bigman and Gray, 2018) and perceived reductionism (Newman *et al.*, 2020) cause negative responses to algorithms because these factors might be related with a lack in careful deliberation.

Third, our work proposes that the effort heuristic can be effective in the financial domain. Consumers frequently use employee or manufacturer effort as a cue for quality judgments, and this association is evident from physical products (Söderlund *et al.*, 2017) to intangible services (Garcia-Rada *et al.*, 2022). The current research suggests that financial customers are subject to the effort heuristics without exception. Furthermore, it also implies that simply manipulating the advisor type as either an algorithm or a human can activate the effort heuristics, even in the financial market where the return rate is the one and only concern.

9.2 Practical implications

Management of financial institutions actively promotes the integration of algorithms and robots into their operations. This technology smoothly fulfills diverse roles in the finance domain, including risk management, fraud detection, personalized financial service and regulatory compliance, while significantly increasing cost savings and efficiency gains. However, a potential barrier slowing down the rapid adoption exists, which is consumers' algorithm aversion. The current research suggests how to overcome the psychological hurdle.

First, reluctance to use AI advisors differs by the approach to the stock market. Therefore, management needs to allocate resources to persuade consumers more in the field of investing than in trading. Second, our research yielded insight into the key reason for algorithm aversion: perceived carefulness. When designing marketing programs to make AI advisors more appealing, marketers should aim to increase the perceived carefulness of algorithms. For example, Litterscheidt and Streich (2020) showed that AI advisors are more favored by providing financial education to potential investors. Marketers in finance need to incorporate content emphasizing the meticulous procedures that AI undertakes into consumer education programs. Third, the results of Study 4 indicate that augmenting AI advisors with humans' intervention increases the perceived carefulness of AI advisors. This suggests that providing in-depth explanations of how human labor is involved in algorithmic operations can make AI advisors more acceptable.

9.3 Limitations and future research

While the current research makes clear contributions to theory and practice in algorithms and finance, there are some limitations that offer opportunities for future research. First, I attempted to manipulate the time frame (long vs short) by comparing investing and trading, but this comparison may have confounding factors. For example, investing typically buys shares and mutual funds, whereas trading only considers shares. Additionally, investing generally profits from the rising price of the assets purchased, whereas trading profits from both rising (i.e., long side) and falling (i.e., short side) prices. These differences in product composition and profit-generating pattern may affect the dependent variables, potentially compromising internal validity. Future research can address this issue by employing a more refined research design to control for potential confounding factors. Second, as all participants in our studies were randomly assigned to either the investing or trading condition, the current research could not reflect their natural preference for investing or trading. Thus, I propose that future research allows participants to choose between investing or trading and then reveals the type of financial advisor (AI or human), followed by a question asking whether they change their choice of stock market approach. This attempt could provide insight into consumers' implicit expectations regarding the type of financial advisor and their acceptance or rejection of the particular advisor. Third, I have focused on comparing long-term investing and swing trading. This comparison was intended to achieve a more conservative experimental design, yet it would be worth to also compare long-term investing with day trading. Given that the time period of day trading is shorter than that of swing trading, which consequently favors fast decision-making, I expect algorithm appreciation to appear in day trading, in contrast to investing. Fourth, past research has provided abundant evidence supporting the association between carefulness and exerting effort, but I did not explicitly test the relationship. Future work would explore the relationship and its contribution to improving the acceptance of AI advisors. Also, future research should examine the determinants of the perceived effort of AI advisors. For human work, taking a longer time is positively correlated with the perception of greater effort and consequently a higher perceived quality of the outcome (Kruger *et al.*, 2004). However, this relationship can be reversed for algorithmic works (Efendić *et al.*, 2020). Given that people have different expectations regarding the capabilities of humans and computers, this question presents valuable and timely chances to understand how to improve reliance on AI. Lastly, financial knowledge and experience have been reported as important antecedents of consumer behaviors in the financial market. For example, Zhao and Zhang (2021) reported that both financial literacy and investment experience positively influence cryptocurrency, with investment experience having a greater impact. However, the current research did not pay enough attention to these factors. Although Study 2 showed that subjective knowledge and self-assessed experience in financial products were not significant covariates, more extensive measurements need to be employed to investigate the role of an individual's financial literacy. For example, Piehlmaier (2022) assessed overconfidence in one's financial knowledge by measuring both subjective knowledge and knowledge accuracy. Future research can examine the effect of overconfidence on the interaction between stock market approach and advisor type.

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Appendix A

Study 1A: Stimuli

*Long-term investing (*swing trading*) condition*

There are two types of approaches to the stock market: Long-term investing and swing trading.

(1) Long-term investing Long-term investing in stock markets involves buying stocks with the intention to remain invested in them for a long period. This could generally be five years or more. Long-term investing aims to build wealth over a longer period through portfolio construction.

(2) Swing trading Swing trading is a type of trading strategy in which security, such as a stock, is held for a time period that could range from a few days to a few weeks. Swing trading requires an investor to buy and sell shares frequently. Since this is short to medium-term, investors aim to earn higher profits through price fluctuations.

Suppose that you choose long-term investing (swing trading) and search for proper financial products. The search shows two products, X and Y: Product X is managed by artificial intelligence agents, and Product Y by human agents.

Appendix B

Study 1B: Stimuli

Long-term investing condition: AI (human) condition

Suppose that you are searching for financial products for long-term investing. After searching, you found the following products.

> This financial product belongs to long-term investing and artificial intelligence (a fund manager) manages the product. Long-term investing in stock markets involves buying stocks with the intention to remain invested in them for a long period. This could generally be five years or more. Long-term investing aims to build wealth over a longer period through portfolio construction.

Swing trading condition: AI (human) condition

Suppose that you are searching for financial products for swing trading. After searching, you found the following products.

> This financial product belongs to swing trading and artificial intelligence (a fund manager) manages the product. Swing trading is a type of trading strategy in which security, such as a stock, is held for a time period that could range from a few days to a few weeks. Swing trading requires buying and selling shares frequently. Since this is short to medium-term, we aim to earn higher profits through price fluctuations.

Appendix C

Study 4: AI supervised by human condition stimuli

Suppose that you are searching for financial products for long-term investing. After searching, you found the following products.

This financial product belongs to long-term investing and artificial intelligence manages the product. Long-term investing in stock markets involves buying stocks with the intention to remain invested in them for a long period. This could generally be five years or more. Long-term investing aims to build wealth over a longer period through portfolio construction.

There is one particular thing about the AI trader. Before deploying AI in the real world as long-term investing managers, human supervision and intervention stepped into the AI's training process. Specifically, this involved human reviewers, subject matter experts or human-in-the-loop setups, where the human judgment was incorporated to validate or override AI decisions when necessary.

Corresponding author
Jieun Koo can be contacted at: jieunkoo@pknu.ac.kr