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When algorithms and human experts contradict, whom do users follow?

Abstract:

Drawing on the theory of planned behavior and the risk-taking theory, the objective of this research is to investigate how attitude toward algorithms, attitude toward humans, and willingness to take risks affect user intention to follow in the situation where recommendations from algorithms and human experts contradict. Set in the context of investment decision-making, a 2 (attitude toward algorithms: algorithm aversion vs. algorithm appreciation) x 2 (attitude toward human experts: unfavorable vs. favorable) x 2 (willingness to take risks: low vs. high) quasi-experiment was conducted online (N=804) where contradictory recommendations were presented from algorithms and human sources. Favorable attitudes toward algorithms and human experts promoted the intention to follow algorithm-generated and human-generated recommendations, respectively. A high willingness to take risks increased the intention to follow regardless of the source of the recommendations. Moreover, willingness to take risks moderated the relationship between attitude toward algorithms and the intention to follow the algorithm-generated recommendation as well as that between attitude toward humans and the intention to follow the human-generated recommendation. While the literature has shed light on how individuals evaluate recommendations from algorithms and humans separately, this is one of the earliest efforts to study the situation where algorithms contradict humans.

Keywords: AI recommendation; AI attitude; algorithm-generated recommendation; decision-making; human-algorithm interaction; investment decision.

1. Introduction

1.1. Research background

As an integral part of the digital environment, recommendation systems are increasingly being used to predict users' preferences and support decision-making (Ghasemaghaei, 2020; Hu, 2024; Jin & Zhang, 2025). Trading platforms such as Trade Ideas (https://www.trade-ideas.com) use algorithms to provide investors with buy-or-sell recommendations (Rasmussen, 2024). To improve the quality of recommendations, there are also systems that incorporate expert opinions. Stitch Fix (https://www.stitchfix.com), for example, is an online personal styling service that utilizes a blend of algorithmic and human judgment to offer fashion advice (Logg et al., 2019).

Depending on what is at stake, the preference for either algorithm-generated or human-generated recommendations may change (Chen & Zheng, 2024; Jin & Zhang, 2025; Zhang & Amos, 2024). Algorithm-generated recommendations are data-driven, while human-generated recommendations rely on expert insight. When a decision requires processing large amount of data, such as financial planning, users tend to favor algorithm-generated recommendations (Gunaratne et al., 2018; Logg et al., 2019). However, they are more ready to rely on human-generated recommendations when looking for encouragement, guidance, or emotional support, as in the case of product recommendations (Jin & Zhang, 2025; Wien & Peluso, 2021).

In multi-source recommendation platforms that combine algorithmic and human input, convergence between the two is reassuring. However, when algorithms and humans are at odds, users would be caught in a dilemma as to whose recommendation they should follow (Detjen et al., 2025; Wang et al., 2020). On the scholarly front, the impact of such algorithm-human tension has received limited attention. Hence, the question of how users react to contradictory recommendations from algorithms and human experts remains unaddressed.

Plugging this research gap is important now. After all, the progressive integration of AI into everyday decision-making implies that conflicting recommendations from algorithms and humans are increasingly likely. The current lack of understanding regarding how users reconcile recommendation divergence presents a significant barrier to optimizing user experiences on hybrid AI-human platforms.

In this vein, a major factor at play is users' attitude toward technology. Attitude refers to the extent to which an object is perceived favorably (Ajzen, 1991; Park & Woo, 2022). When users have a favorable attitude toward technology, they are likely to accept and adopt algorithms for decision support. Conversely, users holding an unfavorable attitude would shun any engagement with AI-driven technology. The two ends of the spectrum are known as algorithm appreciation and algorithm aversion. The former reflects an underlying belief that technology is more objective and hence makes better predictions (Logg, 2019), while the latter describes the psychological resistance to technology (Dietvorst et al., 2015). Additionally, users could either hold a favorable or an unfavorable view toward human experts. The extent to which users are willing to bear with the risk of the decision could also tilt the balance (Detjen et al., 2025; Ferri et al., in press). Willingness to take risks is a measure of the degree to which one is inclined to make decisions in pursuit of positive outcomes, despite the possibility of negative impacts (Jasiniak, 2018; Ng & Khor, 2017).

1.2. Research objective and its significance

The objective of this research is to investigate how attitude toward algorithms, attitude toward humans, and willingness to take risks affect user intention to follow in the situation where recommendations from algorithms and human experts contradict. Two influential theories guided the choice of variables: the theory of planned behavior (Ajzen, 1991) and the risk-taking theory (Sitkin & Pablo, 1992). The first theory shows that attitude plays a significant role in predicting users' behavioral intention, while the second accounts for risk perception in decision-making. Therefore, combining the two theories allows for both attitude and risk to be investigated. Set in the context of investment decision-making, data were drawn from 804 participants through a 2 (attitude toward algorithms: algorithm aversion vs. algorithm appreciation) x 2 (attitude toward human experts: unfavorable vs. favorable) x 2 (willingness to take risks: low vs. high) scenario-based online quasi-experiment where contradictory recommendations were presented from algorithms and human sources.

The research is significant for both theory and practice. On the theoretical front, it draws on the theory of planned behavior and the risk-taking theory to study the role of attitudes and willingness to take risks on the intention to follow recommendations. While the literature has shed light on how individuals evaluate recommendations from algorithms and human agents separately (e.g., Dietvorst et al., 2015; Wien & Peluso, 2021; Zhou et al., in press), this research is one of the earliest to study the situation where an algorithm contradicts human counsel. On the practical front, it holds relevance for technology-mediated platforms that concurrently present multiple, potentially conflicting recommendations.

1.3. Article structure

The rest of the article is organized as follows: The next section lays the theoretical background of this research. This is followed by the development of the hypotheses in the third section. The fourth and the fifth sections present the research methods employed and the results, respectively. These results are discussed in the penultimate section of the article. The final section highlights implications of this research for both theory and practice. Limitations and future research directions are also presented.

2. Theoretical Background

Algorithm-generated and human-generated recommendations have distinct characteristics. Algorithm-generated recommendations are derived from large sets of user-data, such as search patterns, purchase histories, browsing behaviors, demographics, and other relevant information (Lim & Kim, 2025). Common techniques used include collaborative filtering methods based on comparisons among peer users, content-based methods that leverage product-related and user-associated data, as well as hybrid methods to identify underlying patterns and relationships (Adomavicius & Tuzhilin 2005; Banker & Khetani, 2019; Marchand & Marx, 2020). In contrast, human-generated recommendations would either come from experts recognized in a field or trusted friends and relatives perceived to be wise (Efendić et al., 2024; Kleinberg et al., 2018).

Algorithm-generated and human-generated recommendations have unique advantages and disadvantages (Jin & Zhang, 2025; Zhang & Amos, 2024). Computer algorithms are capable of processing vast amounts of data and providing recommendations at scale (Marchand & Marx, 2020; van Capelleveen et al., 2021). They follow pre-defined rules and data-driven patterns without being influenced by emotions or biases even though skewed algorithmic outputs can occasionally arise due to the partiality of feature selection and weight assignments (Silva & Kenney, 2019).

Human experts, on the other hand, can handle nuances and subjective factors and can better appreciate users' specific requirements or unique situations (Jin & Zhang, 2025; Longoni et al., 2019; Xu et al., 2020). With specialized knowledge based on their deep understanding of the subject matter, they could even surpass the capabilities of algorithms in niche areas (Hudecek et al., 2024; Im & Lee, 2023). Cognition aside, experts can empathize with users, lay out options that cater to users' risk profiles, and provide an emotionally resonant experience. On the downside, recommendations from experts are susceptible to human biases and errors (Efendić et al., 2024; Kleinberg et al., 2018).

The literature has demonstrated the efficacy of both algorithm-generated and human-generated recommendations, albeit with varying degrees of effectiveness across different contexts. For example, the intention to follow algorithm-generated recommendations is typically greater for tasks of low complexity, while human-generated recommendations are favored for tasks of high complexity (Xu et al., 2020). While algorithm-generated recommendations are preferred when purchasing material products, human-generated recommendations are more likely to be followed when purchasing experiential products (Jin & Zhang, 2025; Wien & Peluso, 2021). Engineers' willingness to follow algorithm-generated recommendations has been suggested to decline over time as they observe the technology making errors (Chacon et al., 2025). When seeking health information concerning others, individuals are open to algorithm-generated recommendations. However, as patients, they place higher confidence in medical advice from human physicians (Hudecek et al., 2024).

As machines run purely on cold logic while humans can draw on intuition, algorithm-generated recommendations and expert advice could sometimes contradict. However, the literature has yet to shed light on how users reconcile such contradictions. User responses to the algorithm-human tension can be explained by three salient factors drawn from the theory of planned behavior (Ajzen, 1991) and the risk-taking theory (Sitkin & Pablo, 1992). These include attitude toward algorithms, attitude toward human experts, and the willingness to take risks. The theory of planned behavior shows the link between attitude and behavioral intention. It informed the inclusion of attitude toward algorithms and attitude toward human experts in this research. The risk-taking theory highlights the role of risk perception in decision-making. Users' willingness to take risks was thus taken into account.

3. Hypothesis Development

3.1. Role of attitude

The role of attitude in decision-making can be explained by the theory of planned behavior (Ajzen, 1991). In fact, behavioral intention is closely affected by attitude (Babiker et al., in press; Gan & Wang, 2017). For example, users with a positive attitude toward algorithms have been shown to be willing to embrace algorithm-generated recommendations when making financial (Belanche et al., 2019) and medical decisions (Soellner & Koenigstorfer, 2021). By extending previous works that focus on the effect of attitude on behavioral intention, this research examines how users' attitudes toward algorithms and human experts drive their intentions to follow algorithm-generated and human-generated recommendations when the two are at odds.

Some users find algorithm-generated recommendations to be dubious in applications such as stock prices, student performance, and healthcare (Dietvorst et al., 2015; Longoni et al., 2019; Önkal et al., 2009). Even after information about the algorithm's superior performance has been presented, doubts remain (Castelo et al., 2019). This unfavorable attitude toward algorithms is known as algorithm aversion where users prefer experts to machines (Dietvorst et al., 2015). Causes of algorithm aversion include the assumption that algorithms cannot learn effectively, fail to incorporate qualitative insight, and are dehumanizing (Mahmud et al., 2022). Furthermore, there is a greater sense of comfort in depending on human judgment rather than machines, especially in tasks that appear subjective or emotion-oriented (Castelo et al., 2019; Chen & Zheng, 2024; Zhang & Amos, 2024). Previous works in the contexts of financial management (Önkal et al., 2009) and hedonic product purchases (Longoni & Cian, 2022) also found human counsel to be more influential than algorithmic advice.

On the other hand, there are some users who readily accept algorithm-generated recommendations. The belief that technology is objective and hence makes more accurate predictions than humans do is known as algorithm appreciation (Logg et al., 2019). For example, in the context of online saving systems (Gunaratne et al., 2018) and public health (Araujo et al., 2020), users readily embraced algorithmic inputs. Given that algorithm aversion and algorithm appreciation can lead to different behaviors (Berger et al., 2021; Joris et al., 2021), the following hypothesis is proposed:

H1: Attitude toward algorithms (algorithm aversion vs. algorithm appreciation) affects the intention to follow the algorithm-generated recommendation.

Meanwhile, there are differing attitudes toward human experts. Some believe humans are less suited than machines for tasks that require extensive data processing (Akhtar et al., 2022). After all, human judgement could be impaired by biases, heuristics, and fatigue (Efendić et al., 2024; Kleinberg et al., 2018). Those who previously took the advice of an expert and suffered negative consequences may also lose their confidence in human expertise.

In contrast, some individuals value human insights (Wien & Peluso, 2021). They believe human experts possess specialized skills and can grasp the complexities and nuances of an issue (Oberst et al., 2021). Additionally, users often look for emotional support and reassurance in decision-making. While technology can augment the process, the human touch is indispensable. Thus, users who appreciate human connection often prefer the recommendations from human experts (Chalmers & Reuter, 2020). Therefore, where recommendations from algorithms and human experts contradict, the following hypothesis is proposed:

H2: Attitude toward human experts (favorable vs. unfavorable) affects the intention to follow the human-generated recommendation.

Moreover, under such a condition, the intention to follow human-generated recommendation is expected to be strong when one's attitude toward human experts is favorable while that toward algorithms is unfavorable. This is guided by the theory of planned behavior (Ajzen, 1991). Users tend to take the advice from those they perceive to be authoritative. This inclination is based on factors such as perceived expertise, experience, and credibility (Detjen et al., 2025; Hudecek et al., 2024). On the other hand, people may have a less favorable attitude toward algorithms due to reasons including concerns about accountability, transparency, and a lack of understanding of how algorithms work (Shin, 2020).

Conversely, the intention to follow human-generated recommendation would be weak when one's attitude toward human experts is unfavorable but that toward algorithms is favorable. Such users could have suffered negative consequences by taking human advice previously, whereas algorithm-generated recommendations can be viewed as data-driven and free from human biases (Efendić et al., 2024; Kleinberg et al., 2018).

Furthermore, the intention to follow human-generated recommendation is expected to be moderate when one's attitudes toward algorithms and human experts are both favorable or both unfavorable (Fietta et al., 2021). Put differently, the relationship between individuals' attitude toward human experts and their intention to follow the human-generated recommendation seems to be dependent on their attitude toward algorithms. Therefore, the third hypothesis is posited as follows:

H3: Attitude toward algorithms (algorithm aversion vs. algorithm appreciation) moderates the relationship between attitude toward human experts (favorable vs. unfavorable) and the intention to follow the human-generated recommendation.

Likewise, based on the theory of planned behavior (Ajzen, 1991), intention to follow algorithm-generated recommendation should be strong when one's attitude toward algorithms is favorable but that toward human experts is unfavorable. Conversely, intention to follow algorithm-generated recommendation should be weak when one's attitude toward algorithms is unfavorable but that toward human experts is favorable. Furthermore, intention to follow algorithm-generated recommendation could be moderate when one's attitude toward algorithms and human are both favorable or both unfavorable (Fietta et al., 2021). Stated otherwise, the relationship between individuals' attitude toward algorithms and their intention to follow the algorithm-generated recommendation could be reliant on their attitude toward humans. Therefore, the fourth hypothesis is posited as follows:

H4: Attitude toward human experts (favorable vs. unfavorable) moderates the relationship between attitude toward algorithms (algorithm aversion vs. algorithm appreciation) and the intention to follow the algorithm-generated recommendation.

3.2. Role of willingness to take risks

When investigating the acceptance of investment recommendations, the risk-taking theory is appropriate. After all, the decision to follow such recommendations is an inherently risk-taking behavior (Sitkin & Pablo, 1992). Users may be uncertain about the reliability of algorithmic recommendations, especially if they do not fully understand how the algorithms work and what consequences they must bear. As such, the risk-taking theory explains how users make decisions by weighing between potential gains and losses in the context of their investment decision-making (Sitkin & Pablo, 1992; Xu et al., 2010).

In particular, attracted by the upside, users with a higher willingness to take risks are more predisposed to embrace novelty (Kim et al., 2021). In the context of investment, they might view the use of algorithms as opportunities to explore innovative solutions, potentially exploiting the rapidly evolving stock market before human traders could react. The sense of thrill derived could also satisfy their risk appetite.

In contrast, concerned with the downside possibilities, users with a lower willingness to take risks would rather accept a lower but an assured return than to face the prospect of either gaining or losing a greater amount. To cope with uncertainty, they tend to take a more conservative approach. They might prefer a personal touch tailored toward their risk appetite. This could be manifested in the form of seeking recommendations from human experts. Given the role of risk-taking, the following hypothesis is posited:

H5: Willingness to take risks affects (a) the intention to follow the algorithm-generated recommendation, and (b) the intention to follow the human-generated recommendation.

Furthermore, users' willingness to take risks could moderate the attitude-intention relationship. Based on the risk-taking theory (Sitkin & Pablo, 1992), investment decisions involve risk. A high willingness to take risks could increase the likelihood of following algorithm-generated recommendations for those who view algorithms favorably (Ferri et al., in press; Poon & Tung, 2023). In contrast, users with a low risk tolerance may be skeptical about following such recommendations even if they hold a positive attitude toward algorithms. A negative attitude toward algorithms can further exacerbate this aversion, leading to a reduced reliance on algorithm-generated recommendations (Dietvorst et al., 2015), as explained by the theory of planned behavior (Ajzen, 1991).

In a similar vein, users' risk tolerance can moderate the relationship between their attitude toward experts and their willingness to heed human advice (Aren & Hamamci, 2020; Larkin et al., 2022). A high willingness to take risks can enhance the likelihood of following human-generated recommendations, especially for those who heavily depend on investment experts (Larkin et al., 2022). On the contrary, risk-averse users who hold a favorable attitude toward human experts may prefer human interaction because they could ask questions, seek clarification, and engage in a meaningful dialogue (Detjen et al., 2025; Hudecek et al., 2024). Furthermore, risk-averse users with an unfavorable attitude toward human advice could be less inclined to follow human-generated recommendations as they have reservations about what experts have to offer (Lee, 2018). Hence, the final two hypotheses are posited:

H6: Willingness to take risks moderates the relationship between attitude toward algorithms (algorithm aversion vs. algorithm appreciation) and the intention to follow the algorithm-generated recommendation.

H7: Willingness to take risks moderates the relationship between attitude toward human experts (favorable vs. unfavorable) and the intention to follow the human-generated recommendation.

Fig. 1 shows the conceptual model depicting all the hypothesized relationships.

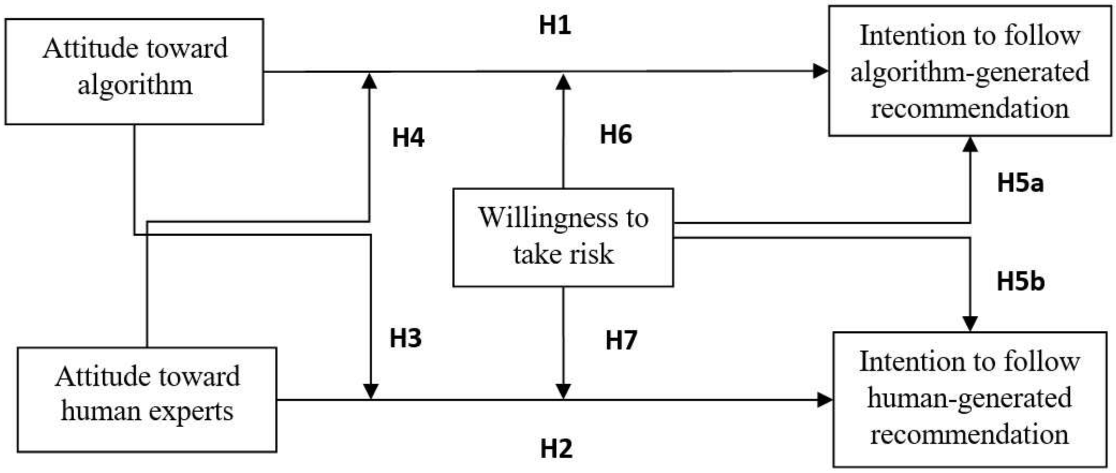

Fig. 1. Conceptual model.

4. Research Methods

4.1. Research design

The research design involved a 2 (attitude toward algorithms: algorithm aversion vs. algorithm appreciation) x 2 (attitude toward human experts: unfavorable vs. favorable) x 2 (willingness to take risks: low vs. high) scenario-based, between-participants, online experiment. In particular, it was a factorial quasi-experiment because all the three factors are naturally occurring individual differences. Participants were categorized in terms of their attitude toward algorithms, attitude toward human experts, and willingness to take risks using median splits of their responses (Ghasemaghaei, 2020; Veneziani et al., 2024; Williams et al., 2024; Youn, & Jin, 2021). The main advantage of using a scenario-based experiment, rather than a field experiment, was the ability to effectively control potential confounding factors (Hudecek et al., 2024; Zhou et al., in press). Conducting the experiment online facilitated convenient data collection from a large sample.

After receiving the Institutional Review Board approval, the advertisement to participate in the study was disseminated through a combination of online (e.g., social media) and offline (e.g., notice board of a large public university) channels. The sampling was purposive with two eligibility criteria: First, participants' must be between 21 and 60 years old. This was necessary to exclude vulnerable groups. Second, participants must be interested in investing in the stock market or have some prior related experience. Only those who expressed a willingness to take part in the study based on the eligibility criteria were permitted to proceed.

4.2. Data collection procedure

A total of 876 participants started the study but 72 dropped midway. Complete responses from the remaining 804 participants were analyzed. The sample included 472 (58.7%) males and 332 (41.3%) females. It comprised 408 (50.7%) individuals with undergraduate degrees as their highest qualification, 354 (44%) with postgraduate degrees, and 42 (5.2%) with doctorates. The average age was 32.1 years (Min = 21, Max = 60, SD = 10.863).

The study participation involved two steps. In the first step, participants were asked to imagine they were about to make a critical investment decision based on a recommendation portal that displays recommendations from two distinct sources: algorithms and human experts. Then, they were exposed to the stimulus where contradictory recommendations were presented. In half of the cases, the stimulus involved a "BUY" recommendation from the algorithm, but a "SELL" recommendation from the human experts for a stock. Conversely, in the other half, the algorithm offered a "SELL" recommendation, while the human experts offered a "BUY" recommendation. The perceived contradictory nature of these recommendations was confirmed through a pre-test that involved 10 participants.

To provide some background to the algorithm-generated recommendation, the following text was displayed, "*Invest-AI uses a proprietary AI algorithm that learns from the stock's price and volume history, as well as the stock's fundamentals to provide this recommendation for the investor.*" Conversely, the basis of the human-generated recommendation was explained with the following text, "*This recommendation has been prepared by a group of analysts from Trading Invest Research, which covers analyses of each stock based on the stock's latest financial statements and its historical price and volume records.*" A fictitious email address was provided to contact *Trading Invest Research*. The 10 pre-test participants confirmed that a recommendation from Invest-AI would be perceived as algorithm-generated, whereas one from Trading Invest Research would be deemed as human-generated. To facilitate immediate comparison, both the recommendations were displayed side-by-side in the main experiment.

In the second step, participants completed the questionnaire, which comprised three parts. The first part contained items to capture participants' intention to follow the algorithm-generated recommendation and the human-generated recommendation, as shown in the stimulus. The second part of the questionnaire included items to measure attitude toward algorithms, attitude toward human experts, and willingness to take risks. Investment-related self-efficacy was also captured for inclusion in the analyses as a control variable. Each of these items was presented using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). The final part of the questionnaire sought demographic details including age and gender.

4.3. Measures

Intention to follow the algorithm-generated recommendation was measured using three items, such as "*I would like to follow the call based on algorithmic recommendation*"

(Gursoy et al., 2019). Responses to these items were averaged to create a composite index with higher scores indicating greater intention to follow the algorithm (M = 3.98, SD = 1.58, Cronbach's α = 0.95, CR = 0.97, AVE = 0.90).

Similarly, intention to follow the human-generated recommendation was measured using three items, such as "*I would like to follow the call provided by the group of analysts*" (Gursoy et al., 2019). Responses to these items were averaged to create a composite index with higher scores indicating greater intention to follow the human experts (M = 3.73, SD = 1.61, Cronbach's α = 0.95, CR = 0.97, AVE = 0.91).

Attitude toward algorithms was measured using three items, such as "*Using algorithm-based recommendation systems for making investment decisions is a good idea*" (Belanche et al., 2019). Responses to these items were averaged to create a composite index with higher scores indicating greater algorithm appreciation (M = 4.03, SD = 1.59, Cronbach's α = 0.95, CR = 0.97, AVE = 0.90). Based on median split (Chua et al., 2021; Ghasemaghaei, 2020; Veneziani et al., 2024; Williams et al., 2024; Youn, & Jin, 2021), the algorithm aversion group comprised 338 participants (42%, M = 2.45, SD = 0.85), while the algorithm appreciation group comprised 466 participants (58%, M = 5.18, SD = 0.83).

Attitude toward human experts was measured using two items, such as "*Relying on recommendations from human experts for making investment decisions is a good idea*" (Belanche et al., 2019). Responses to these items were averaged to create a composite index with higher scores indicating a more favorable attitude toward humans (M = 3.82, SD = 1.44, r = 0.53, CR = 0.87, AVE = 0.76). Based on median split (Chua et al., 2021; Ghasemaghaei, 2020; Veneziani et al., 2024; Williams et al., 2024; Youn & Jin, 2021), there were 414 participants with a favorable attitude (51.5%, M = 4.89, SD = 0.96) and 390 participants with an unfavorable attitude (48.5%, M = 2.68, SD = 0.89) toward human experts.

Willingness to take risks was measured using two items, including the reverse-coded statement, "*When investing money, the word safety is more important for me than the word return*" (Ahmad et al., 2020). Responses to these items were averaged to create a composite index with higher scores indicating a greater willingness to take risks (M = 4.39, SD = 1.71, r = 0.87, CR = 0.97, AVE = 0.93). Based on median split (Chua et al., 2021; Ghasemaghaei, 2020; Veneziani et al., 2024; Williams et al., 2024; Youn & Jin, 2021), the sample included 406 high risk-takers (50.5%, M = 5.86, SD = 0.71) and 398 low risk-takers (49.5%, M = 2.89, SD = 0.97).

Investment-related self-efficacy was measured using three items, such as "*I believe I have the required skills and knowledge in making stock investment decisions*" (Montford & Goldsmith, 2016). Responses to these items were averaged to create a composite index with higher scores indicating greater investment-related self-efficacy (M = 3.84, SD = 1.46, Cronbach's α = 0.86, CR = 0.92, AVE = 0.78). Correlations among the constructs are reported in Table 1.

Table 1. Correlations among the study constructs.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
(1) Intention to follow algo recommendation					
(2) Intention to follow human recommendation	0.37				
(3) Attitude toward algorithms	0.69	0.46			
(4) Attitude toward human experts	0.14	0.51	0.17		
(5) Willingness to take risks	0.23	0.26	0.31	0.24	
(6) Investment-related self-efficacy	0.35	0.40	0.50	0.34	0.22

5. Results

This research employed a 2 (attitude toward algorithms: algorithm aversion vs. algorithm appreciation) x 2 (attitude toward human experts: unfavorable vs. favorable) x 2 (willingness to take risks: low vs. high) three-way analysis of covariance (ANCOVA) for each of the two dependent variables: intention to follow algorithm-generated recommendation and intention to follow human-generated recommendation. Participants' age, gender, highest educational qualification, and self-efficacy in investment decision-making were added as covariates.

There was a significant main effect of attitude toward algorithms on intention to follow the algorithm-generated recommendation [$F(1,792) = 209.94$, $\eta^2 = 0.21$, $p < 0.001$], supporting H1. Specifically, participants' intention to follow the algorithm-generated recommendation was higher for those who exhibited algorithm appreciation ($M_{\textbf{Follow algo}} = 4.71$, $SD_{\textbf{Follow algo}} = 1.27$) compared with those who exhibited algorithm aversion ($M_{\textbf{Follow algo}} = 2.98$, $SD_{\textbf{Follow algo}} = 1.41$).

Likewise, there was a significant main effect of attitude toward human experts on intention to follow the human-generated recommendation [$F(1,792) = 100.11$, $\eta^2 = 0.11$, $p < 0.001$], supporting H2. Specifically, participants' intention to follow the human-generated recommendation was higher for those who had a favorable attitude toward human experts ($M_{\textbf{Follow human}} = 4.42$, $SD_{\textbf{Follow human}} = 1.49$) than those who had an unfavorable attitude ($M_{\textbf{Follow human}} = 2.99$, $SD_{\textbf{Follow human}} = 1.40$).

The two-way interaction between attitude toward algorithms and attitude toward human experts on intention to follow the human-generated recommendation was non-significant [$F(1,792) = 0.76$, $\eta^2 = 0.00$, $p > 0.1$]. In other words, attitude toward algorithms did not moderate the relationship between attitude toward human experts and the intention to follow the human-generated recommendation. Therefore, H3 was not supported.

However, the two-way interaction between attitude toward algorithms and attitude toward human experts on intention to follow the algorithm-generated recommendation was significant [$F(1,792) = 4.13$, $\eta^2 = 0.01$, $p < 0.05$]. Attitude toward human experts moderated the relationship between attitude toward algorithms and the intention to follow the algorithm-generated recommendation, lending support to H4. As shown in Fig. 2, the intention to follow the algorithm-generated recommendation was the highest ($M_{\text{Follow algo}} = 4.80$, $SD_{\text{Follow algo}} = 1.22$) when participants had not only algorithm appreciation but also a favorable attitude toward humans. In contrast, it was the lowest ($M_{\text{Follow algo}} = 2.88$, $SD_{\text{Follow algo}} = 1.37$) when they had algorithm aversion and a favorable attitude toward humans. Thus, when algorithms and experts contradict, individuals' intention to follow algorithm-generated recommendations depends not only on their attitude toward algorithms but also that toward humans.

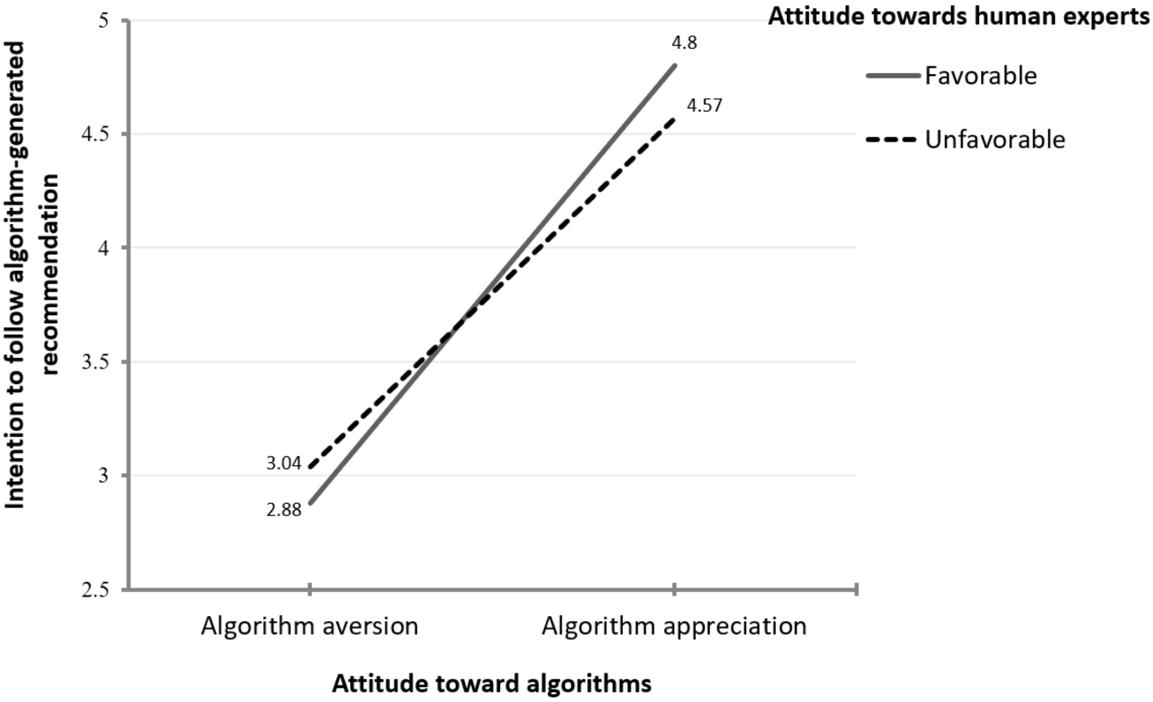

Fig. 2. The moderating effect of attitude toward human experts on the relationship between attitude toward algorithms and the intention to follow the algorithm-generated recommendation (H4).

Furthermore, willingness to take risks affected the intention to follow the algorithm-generated recommendation [$F(1,792) = 6.17$, $\eta^2 = 0.01$, $p < 0.05$], and the intention to follow the human-generated recommendation [$F(1,792) = 3.94$, $\eta^2 = 0.01$, $p < 0.05$]. Thus, H5(a) and H5(b) were both supported. Specifically, participants' intention to follow the algorithm-generated recommendation was higher for those who exhibited high willingness to take risks ($M_{\textbf{Follow algo}}$ = 4.39, $SD_{\textbf{Follow algo}}$ = 1.63) than those who exhibited low willingness to take risks ($M_{\textbf{Follow algo}}$ = 3.57, $SD_{\textbf{Follow algo}}$ = 1.43). Likewise, the intention to follow the human-generated recommendation was higher for those with high risk tolerance ($M_{\textbf{Follow human}}$ = 4.17, $SD_{\textbf{Follow human}}$ = 1.66) than those with low risk tolerance ($M_{\textbf{Follow human}}$ = 3.28, $SD_{\textbf{Follow human}}$ = 1.43). Regardless of the recommendation source, willingness to take risks promoted intention to follow.

The two-way interaction between willingness to take risks and attitude toward algorithms on intention to follow the algorithm-generated recommendation was significant [$F(1,792) = 20.26$, $\eta^2 = 0.03$, $p < 0.001$], supporting H6. As shown in Fig. 3, among participants with algorithm aversion, intention to follow the algorithm-generated recommendation was higher for those who had low willingness to take risks ($M_{\textbf{Follow algo}}$ = 3.09, $SD_{\textbf{Follow algo}}$ = 1.30) vis-à-vis those who had high willingness to take risks ($M_{\textbf{Follow algo}}$ = 2.74, $SD_{\textbf{Follow algo}}$ = 1.60). To the algorithm-averse individuals with low risk tolerance, following the algorithm's suggestion might have been seen as a way to minimize potential negative outcomes. They might have perceived the algorithm as a safety net, a way to avoid the anxiety of making a high-risk decision on their own. However, among those with algorithm appreciation, intention to follow was higher for those who had high willingness to take risks ($M_{\textbf{Follow algo}}$ = 4.98, $SD_{\textbf{Follow algo}}$ = 1.17) vis-à-vis those who had low willingness to take risks ($M_{\textbf{Follow algo}}$ = 4.24, $SD_{\textbf{Follow algo}}$ = 1.32). High-risk takers with algorithm appreciation were more open to relying on the algorithm's ability to exploit high-potential opportunities.

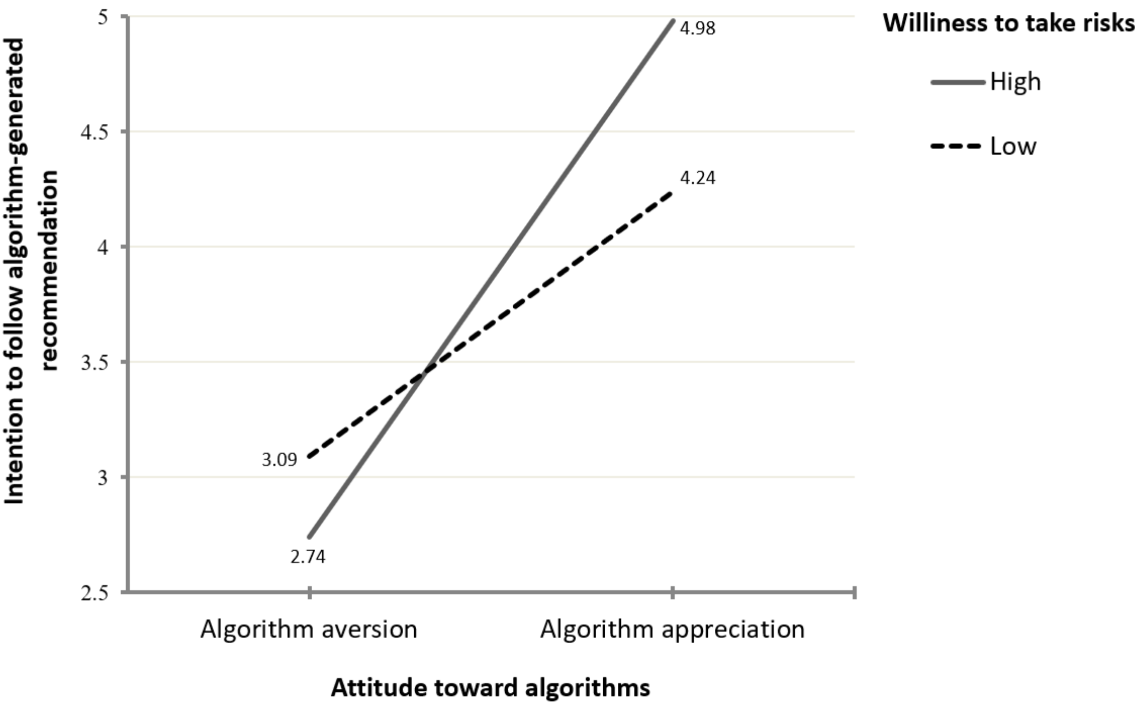

Fig. 3. The moderating effect of willingness to take risks on the relationship between attitude toward algorithms and the intention to follow the algorithm-generated recommendation (H6).

The two-way interaction between willingness to take risks and attitude toward human experts on intention to follow the human-generated recommendation was also significant [$F(1,792) = 9.61$, $\eta^2 = 0.01$, $p < 0.01$]. Therefore, H7 was supported. As shown in Fig. 4, among participants with an unfavorable attitude toward human experts, intention to follow the human-generated recommendation was largely comparable between those who had high willingness to take risks ($M_{\textbf{Follow human}} = 3.11$, $SD_{\textbf{Follow human}} = 1.57$) and those who had low willingness to take risks ($M_{\textbf{Follow human}} = 2.94$, $SD_{\textbf{Follow human}} = 1.30$). However, among participants with a favorable attitude toward human experts, intention to follow was higher for those who had high willingness to take risks ($M_{\textbf{Follow human}} = 4.71$, $SD_{\textbf{Follow human}} = 1.43$) vis-à-vis those who had low willingness to take risks ($M_{\textbf{Follow human}} = 3.88$, $SD_{\textbf{Follow human}} = 1.46$). Thus, when algorithms and experts contradict, individuals' unfavorable attitude toward human experts is sufficient to limit their intention to follow human-generated recommendations, regardless of their willingness to take risks.

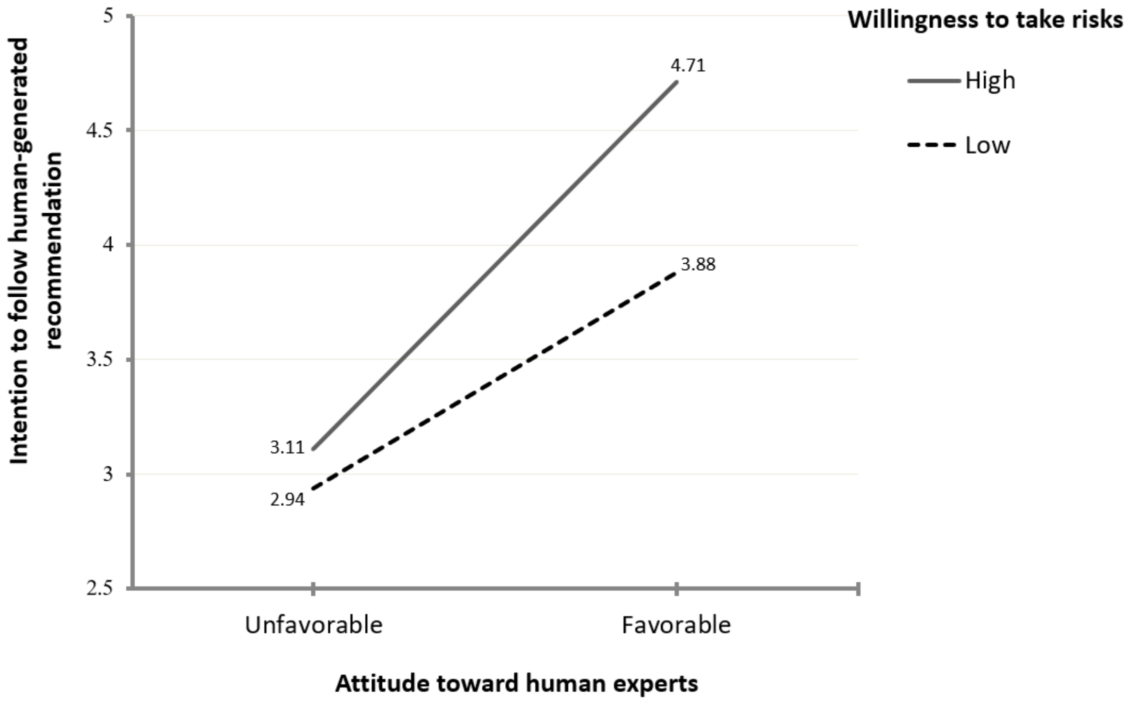

Fig. 4. The moderating effect of willingness to take risks on the relationship between attitude toward human experts and the intention to follow the human-generated recommendation (H7).

To assess the robustness and sensitivity of these results, the analyses were repeated with varying covariate combinations: (a) age and investment self-efficacy, (b) gender and investment self-efficacy, (c) highest educational qualification and investment self-efficacy, and (d) investment self-efficacy alone. The results remained largely consistent, as shown in Table 2. The hypotheses test results are summarized in Table 3.

Table 2. Robustness test results.

Hypotheses	Different covariate combinations in the ANCOVA analyses			
	Age, Self-efficacy	**Gender, Self-efficacy**	**Education, Self-efficacy**	**Self-efficacy**
H1	F = 212.49, $p < 0.001$	F = 211.03, $p < 0.001$	F = 208.35, $p < 0.001$	F = 210.91, $p < 0.001$
H2	F = 100.36, $p < 0.001$	F = 100.81, $p < 0.001$	F = 99.92, $p < 0.001$	F = 100.48, $p < 0.001$
H3	F = 0.766, $p > 0.1$	F = 0.724, $p > 0.1$	F = 0.777, $p > 0.1$	F = 0.750, $p > 0.1$
H4	F = 4.63, $p < 0.05$	F = 3.81, $p = 0.05$	F = 3.56 $p = 0.06$	F = 3.91, $p < 0.05$
H5a, H5b	(a) F = 5.10, $p < 0.05$ (b) F = 3.90, $p < 0.05$	(a) F = 4.55, $p < 0.05$ (b) F = 4.12, $p < 0.05$	(a) F = 4.84, $p < 0.05$ (b) F = 3.69, $p = 0.06$	(a) F = 4.024, $p < 0.05$ (b) F = 3.87, $p = 0.05$
H6	F = 22.98, $p < 0.001$	F = 23.05, $p < 0.001$	F = 20.27, $p < 0.001$	F = 23.21, $p < 0.001$
H7	F = 9.405, $p < 0.01$	F = 9.72, $p < 0.01$	F = 9.57, $p < 0.01$	F = 9.563, $p < 0.01$

Table 3. Summary of hypotheses testing results.

Hypotheses	Results
H1: Attitude toward algorithms (algorithm aversion vs. algorithm appreciation) affects the intention to follow the algorithm-generated recommendation.	Supported
H2: Attitude toward human experts (favorable vs. unfavorable) affects the intention to follow the human-generated recommendation.	Supported
H3: Attitude toward algorithms (algorithm aversion vs. algorithm appreciation) moderates the relationship between attitude toward human experts (favorable vs. unfavorable) and the intention to follow the human-generated recommendation.	Rejected
H4: Attitude toward human experts (favorable vs. unfavorable) moderates the relationship between attitude toward algorithms (algorithm aversion vs. algorithm appreciation) and the intention to follow the algorithm-generated recommendation.	Supported
H5: Willingness to take risks affects (a) the intention to follow the algorithm-generated recommendation, and (b) the intention to follow the human-generated recommendation.	(a) Supported (b) Supported
H6: Willingness to take risks moderates the relationship between attitude toward algorithms (algorithm aversion vs. algorithm appreciation) and the intention to follow the algorithm-generated recommendation.	Supported
H7: Willingness to take risks moderates the relationship between attitude toward human experts (favorable vs. unfavorable) and the intention to follow the human-generated recommendation.	Supported

6. Discussion

6.1. Key findings

This research yields three key findings. First, the results of H1 and H2 show that favorable attitudes toward algorithms and human experts promoted intention to follow algorithm-generated and human-generated recommendations, respectively. Previous works, grounded in the theory of planned behavior, have consistently demonstrated that a favorable attitude toward an object drives behavioral intention related to the object (Ajzen, 1991; Belanche et al., 2019; Gan & Wang, 2017). However, this research considers the context where users evaluate algorithm-generated versus human generated recommendations concurrently. Extending prior research, it finds that even when the two recommendation sources are at odds, the relationship between attitude and behavioral intention toward each source remained robust.

Further extending the attitude-intention literature (Babiker et al., in press; Belanche et al., 2019; Gan & Wang, 2017), this research reveals how attitudes toward two co-existing, contradictory objects interact. As revealed from the results of H3, attitudes toward algorithm and human experts did not interact to affect intention to follow the human-generated recommendation. A favorable attitude toward human experts was a sufficient condition to drive intention to follow the human-generated recommendation regardless of the sentiment toward algorithm.

However, a favorable attitude toward algorithms was, on its own, insufficient to drive intention to follow the algorithm-generated recommendation. The results of H4 detected a significant interaction. As expected, intention to follow the algorithm-generated recommendation was the lowest among participants who had not only algorithm aversion but also a favorable attitude toward humans (see Fig. 2). Counter-intuitively however, intention to follow the algorithm-generated recommendation did not turn out to be the highest among those with algorithm appreciation coupled with an unfavorable attitude toward human experts. Instead, it was the highest among individuals with algorithm appreciation and a favorable attitude toward human experts. This suggests that a favorable attitude toward human experts does not necessarily sway individuals away from algorithm-generated recommendations. In other words, it is plausible for people to embrace technology while holding a favorable view of human expertise. Given the favorable attitude toward both algorithms and humans, these individuals were probably not perturbed by the contradictory recommendations and hence were willing to rely on algorithms.

The second finding, which stems from the results of H5, is that willingness to take risks influenced intention to follow both algorithm-generated and human-generated recommendations. Specifically, users with a high-risk appetite were inclined to follow investment recommendations whole-heartedly regardless of the source of the advice. In contrast, those who had a low willingness to take risks appeared circumspect. Their middling scores on both intentions to follow algorithms and human experts could be vestige of the inherent dilemma in the study situation. Nonetheless, the finding that risk intolerance hinders investment-related behavioral intentions is consistent with the wider risk-taking literature (Kim et al., 2021; Sitkin & Pablo, 1992; Xu et al., 2010).

The third finding has to do with the moderating effect of willingness to take risks. Arising from the results of H6, willingness to take risks moderated the relationship between attitude toward algorithms and intention to follow the algorithm-generated recommendation. Prior research suggests that algorithm appreciation might contribute to a strong intention to follow algorithm-generated recommendations, particularly for users with a high willingness to take risks (Ferri et al., in press; Poon & Tung, 2023). Consistent with the literature, intention to follow the algorithm-generated recommendation was the highest among those with algorithm appreciation and a high willingness to take risks (see Fig. 3).

A similar pattern emerged when it comes to the moderating effect of willingness to take risks on the relationship between attitude toward human experts and intention to follow the human-generated recommendation. As revealed from the results of H7, the intention was at its peak among users possessing both a favorable attitude toward human experts and a high willingness to take risks (see Fig. 4). Intention to follow the human-generated recommendation was, however, largely comparable among users with an unfavorable attitude toward human experts regardless of their willingness to take risks.

6.2. Limitations and future research directions

The findings of this research need to be viewed considering three limitations, which create new avenues for further research. First, it was not possible to determine how much attention participants paid to the contradictory recommendations. It would be interesting to carry out eye-tracking studies to better ascertain how visual attention, measured in terms of variables such as fixation duration and fixation frequency, to the two recommendations affect subsequent decision-making.

Second, the outcome measured was cross-sectional intention to follow. While intention is a known predictor of behavior, future research should carry out field experiments to study how contradictory recommendations from technology and humans translate into actual actions. Longitudinal studies could also be conducted to better elucidate the temporal evolution of user responses to the algorithm-human tension in recommendations.

Finally, investment decision-making was chosen as the context of investigation. The use of a self-selected sample of individuals limits the generalizability of the findings to the broader investor population. Future studies should prioritize recruiting more representative samples. Interested scholars are also encouraged to study other decision-making contexts, such as hiring and medical diagnoses, to assess the generalizability of the current findings.

7. Conclusion

This research has investigated how attitude toward algorithms, attitude toward humans, and willingness to take risks affect user intention to follow in the situation where recommendations from algorithms and human experts contradict. Set in the context of investment decision-making, a scenario-based online quasi-experiment was conducted where contradictory recommendations were presented from algorithms and human sources. Results indicated that favorable attitudes toward algorithms and human experts promoted intention to follow algorithm-generated and human-generated recommendations, respectively. A high willingness to take risks enhanced intention to follow investment recommendations regardless of the source of the advice. Moreover, willingness to take risks moderated the relationship between attitude toward algorithms and intention to follow the algorithm-generated recommendation as well as that between attitude toward human experts and intention to follow the human-generated recommendation.

7.1. Theoretical contributions

This research contributes to the literature in three ways. First, while previous works have investigated individuals' perceptions and evaluations of recommendations from algorithms and human agents separately (Dietvorst et al., 2015; Logg, 2019; Wien & Peluso, 2021), few have considered the situation where an algorithm contradicts human counsel. By exploring such an under-investigated context involving algorithm-human tension, this research advances the literature on the evaluation of recommendation systems (Chen & Zheng, 2024; Detjen et al., 2025; Ghasemaghaei, 2020; Hu, 2024).

Second, this research advances the scholarly understanding of algorithm appreciation and algorithm aversion (Jin & Zhang, 2025; Logg, 2019; Wien & Peluso, 2021) by showing that a favorable attitude toward algorithms alone is not guaranteed to maximize individuals' intention to follow algorithm-generated recommendations. The intention to follow algorithm-generated recommendations emerged as being the highest among those with algorithm appreciation and a favorable attitude toward human experts. In contrast, however, a favorable attitude toward human experts was sufficient to drive intention to follow human-generated recommendations regardless of the sentiment toward algorithms. This is a novel finding that warrants further exploration.

Third, this research extends the application of the theory of planned behavior. The potential of the theory to explain the role of users' attitude toward technology in shaping their technology-related behavioral intentions has already been discussed (e.g., Babiker et al., in press; Park & Woo, 2022). Adding to the literature, this research shows that even when two co-existing objects are at odds, the relationship between attitude and behavioral intention toward each object remains robust.

7.2. Practical implications

On the practical front, this research suggests that technology platforms which present contradictory recommendations from different sources run the risk of being alienated by users with low risk tolerance. Being overly cautious, these users may be confused or even frustrated when faced with clashing opinions. One suggestion is to provide details of the logic, enhancing the transparency and explainability of the process through which each recommendation has been derived. Distinct visual cues and icons could be utilized to enable users quickly identify the recommendation sources. Another option is to present the recommendations along a quantified percentage of confidence. This would not only facilitate decision-making for those with low risk-appetite but will also likely be appreciated by risk-takers. To empower users even further, platforms could allow users to customize the balance between algorithm-generated and human-generated recommendations based on their individual attitudes and risk profiles.

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