AI-enabled investment advice: Will users buy it?

Abstract

This paper develops an attitude-perception-intention (API) model of AI acceptance to explain individuals' behavioral intention to accept AI-based recommendations as a function of attitude toward AI, trust and perceived accuracy with risk-level as a moderator. The API model was empirically validated through a between-participants experiment (N = 368) using a simulated AI-enabled investment recommendation system. One experimental condition depicted low-risk investment recommendation involving blue-chip stocks while the other depicted high-risk investment recommendation involving penny stocks. Attitude toward AI predicted behavioral intention to accept AI-based recommendations, trust in AI, and perceived accuracy of AI. Furthermore, risk level emerged as a significant moderator. When risk was low, a favourable attitude toward AI seemed sufficient to promote algorithmic reliance. However, when risk was high, a favourable attitude toward AI was a necessary but no longer sufficient condition for AI acceptance. The API model contributes to the human-AI interaction literature by not only shedding light on the underlying psychological mechanism of how users buy into AI-enabled advice but also adding to the scholarly understanding of AI recommendation systems in tasks that call for intuition in high involvement services such as finance where human counsel is usually preferred to machine-generated advice.

Keywords: AI-based recommendation, Decision Sciences, Investment decision, Technology adoption, Trust.

1. Introduction

The diffusion of artificial intelligence (AI) technologies into our daily lives has picked up considerable momentum in recent years (Gursoy et al., 2019). The global AI market size, which was valued at US$27.23 billion in 2019, is expected to reach a staggering US$267 billion by 2027 (Fortune Business Insights, 2020). From self-driving cars to voice-activated home assistance devices, AI has effectively taken over routine tasks that were previously done by humans (Bickmore, 2018; Chong et al., 2022; Liu & Tao, 2022; Sloane & Silva, 2020).

To ease decision-making, AI solutions are now available not only for low-stake activities such as personalized shopping (Ashoori & Weisz, 2019) and news recommendation

(Diakopoulos & Koliska, 2017) but also for situations when choices are highly consequential as in cancer screening (Jha & Topol, 2016) and prison sentencing (Ashoori & Weisz, 2019). Yet, public opinion on the general outlook of AI remains divided. Some envision a rose-tinted future while others see a calamitous apocalypse (Markoff, 2016; Tegmark, 2017; Wu et al., 2020). Evidence that people buy into machine-generated advice has been mixed (Bigman & Gray, 2018; Dietvorst et al., 2015; Wickramasinghe et al., 2020). This paper is therefore motivated by the limited understanding of the conditions under which user acceptance of AI can be influenced.

Even as research on human-AI interaction continues to gain traction, two gaps could be identified. First, the underlying psychological mechanism of how users decide to accept AI-enabled advice is not yet well understood. In tandem with the launch of new AI recommendation systems, there have been calls for research to better explain humans' algorithmic reliance (Kleinberg et al., 2018; Logg, 2017). Second, the literature is silent on the way the level of risk alters the behavioral intention to accept AI-enabled advice (Bao et al., 2022). Any decision entails some degree of risk, especially if it has to be made in high involvement contexts such as healthcare and finance where human counsel is usually preferred to machine-generated advice (Longoni et al., 2019; Zhang et al., 2021). Hence, the question of how AI uptake can be promoted in such high involvement services remains open.

To address the first research gap, this paper builds on the literature on user behavior toward technology. From early works (e.g., Ajzen, 1985; Ajzen & Fishben, 1980; Venkatesh et al., 2003) to contemporary studies (e.g., Dwivedi et al., 2019), attitude has been shown consistently to predict behavioral intention to engage with technological innovations. Attitude toward AI is thus expected to relate positively to the acceptance of AI-based recommendations. With this as the starting point, this paper further argues that attitude could also be positively associated with trust (Cheng et al., 2019; Chong et al., 2022; Ho et al.,

2017) and perceived accuracy (Jacobsen et al., 2020; Schaffer et al., 2015), especially when AI is intended to make estimates and forecasts. Trust and perceived accuracy are important to be studied given the growing concern of how much black-box AI algorithms promote the core values of credence, fairness and usefulness (Araujo et al., 2020; Liang et al., 2021; Ochmann et al., 2021). In this paper, trust refers to users' willingness to depend on AI for decision-making based on gut-feeling (Ferrario et al., 2019; Komiak & Benbasat, 2006) while perceived accuracy is the perception of the extent to which an AI-generated advice reflects the ideal recommendation free of human biases and errors (Smith & Mentzer, 2010).

Additionally, to address the second research gap, this paper considers the role of risk associated with financial investment. In particular, stock market investment was used as the context of investigation because there is currently keen research and practical interests with applying AI in capital markets (Ho et al., 2017; Sun, 2020). Moreover, the volatility of the stock market lends itself readily to the study of risk, which involves unforeseen contingencies (Ho et al., 2017; Pavlou & Fygenson, 2006; Schwert, 1989). Depending on the level of risk, the readiness to buy into AI's advice could change. However, the literature remains largely silent on how risk level interacts with attitude, trust and perceived accuracy in shaping users' inclination toward AI.

For these reasons, the objective of this paper is to develop and empirically validate a conceptual model that explains the behavioral intention to accept AI-based recommendations as a function of attitude toward AI, trust, perceived accuracy and risk level. The proposed model is tested through a between-participants experiment using a simulated AI-enabled investment recommendation system. A total of 368 participants were randomly and evenly assigned to one of two experimental conditions, one depicting low-risk investment recommendation while the other depicting high-risk investment recommendation.

The paper is significant for both theory and practice. While prior research suggests attitude to be a strong predictor of behavioral intention (Gool et al., 2015; Pember et al., 2018; Sanakulov & Karjaluoto, 2015; Sanne & Wiese, 2018), this paper takes the relationship as the point of departure and unpacks it to offer deeper insights. Specifically, it proposes an attitude-perception-intention (API) model of AI acceptance with the level of risk expected to play a moderating role. Perception is conceptualized as trust in AI and perceived accuracy of AI. In so doing, the paper contributes to the growing body of literature on human-AI interaction. On the practical front, the findings shed light on the conditions in which AI acceptance could be enhanced. This can be useful for policy-makers and practitioners who design interventions to promote society’s behavioral intention to rely on AI. In turn, it can pave the way for the successful commercialization of new AI systems in high consumer involvement industries such as healthcare and finance.

The remainder of the paper proceeds as follows. Section 2 is dedicated to literature review and hypotheses development. Section 3 describes the research design and explains how data were collected and analyzed. Section 4 and Section 5 present the results and the discussion respectively. Section 6 concludes with theoretical and practical implications of the paper, as well as acknowledges the limitations and offers possible research directions.

2. Literature Review and Hypotheses Development

2.1. Related Works

Users’ behavioral responses to AI broadly lie on the continuum between automation bias and AI aversion (Bigman & Gray, 2018; Chong et al., 2022; Dietvorst et al., 2015; Tomsett et al., 2020; Wickramasinghe et al., 2020). Automation bias occurs when users readily buy into computer recommendations instead of relying on their own judgment. At the other end of the spectrum, AI aversion is exhibited when users reject algorithm-generated advice (Tomsett et al., 2020). Automation bias and AI aversion tendencies could be shaped by a variety of factors including cognitive load (Parasuram & Manzey, 2010), accountability in the decision process (Cummings, 2006), and individuals' level of expertise and training (Manzey et al., 2012).

Research on factors affecting users' behavioral responses to AI can be summarized as those related to system characteristics, user characteristics as well as context characteristics (Rzepka & Berger, 2018). For example, findings suggest that the more transparent the reasoning process of the AI system, the more favorable users will judge its decision quality (Xu et al., 2014), and hence embrace its recommendation. On the other hand, an overly autonomous AI system that displays a high degree of humanness can threaten, and thus repel users (Złotowski et al., 2017). Next, the fit between users' cognitive model and the system presentation also influences acceptance (Shmueli et al. 2016). In the same way, users' demographics such as gender and ethnicity that are congruous to system characteristics such as avatar appearances can lead to positive system perception (Qiu & Benbasat, 2010). On the context of use, automation bias is more likely to occur for functional tasks that call for logic whereas AI aversion is triggered in situations that involve making intuitive and emotional assessments (Gaudiello et al., 2016; Logg, 2017).

System characteristics are not investigated in this paper given that AI systems for investment are typically opaque to protect their commercial advantage and proprietary rights (Rudin et al., 2018). User characteristics such as gender, age and investment self-efficacy (Montford & Goldsmith, 2016) are statistically controlled in testing the hypotheses, which are proposed subsequently for the development of the conceptual model shown in Figure 1. Risk level, a salient characteristic in the context of stock market, is incorporated in the experimental conditions as high-risk and low-risk investments.

2.2. The role of attitude toward AI

Attitude toward any object refers to the mindset of an individual formed by prior knowledge and experience. It turns into a predisposition for how the individual will value the object subsequently (Persson et al., 2021). For the purpose of this paper, attitude toward AI refers to the degree to which one views AI favorably (Lichtenthaler, 2019; Ochmann et al., 2021). In reality, this attitude varies drastically with ebbs and flows of technological breakthroughs (Markoff, 2016; Tegmark, 2017; Wu et al., 2020). While some consider AI to have a positive impact on their everyday lives, others fear that it will result in a loss of their jobs (Bigman & Gray, 2018; Dietvorst et al., 2015; Tegmark, 2017; Wickramasinghe et al., 2020).

Prior works have consistently found attitude to be one of the key predictors of behavioral intention (Pember et al., 2018; Sanakulov & Karjaluoto, 2015; Sanne & Wiese, 2018). This stems from the intrinsic motivation to maintain consistency between attitudes and behaviors (Gool et al., 2015). Hence, attitude toward AI could potentially shape users' inclination to accept the usage of AI in everyday life (Lichtenthaler, 2019; Persson et al., 2021). Those with a favorable attitude toward AI could be more willing to accept AI-based recommendation in the context of stock market investment than those who view AI with disdain. Hence, the following is hypothesized:

H1: Attitude toward AI positively predicts behavioral intention to accept AI-based recommendation.

2.3. The roles of trust and perceived accuracy

For the purpose of this paper, trust refers to users' willingness to depend on AI for decision-making based on gut-feeling (Ferrario et al., 2019; Komiak & Benbasat, 2006), and perceived accuracy is defined as the perception of the extent to which an AI-generated advice reflects the ideal recommendation free of human biases and errors (Smith & Mentzer, 2010). Trust and perceived accuracy are important constructs when it comes to stock market investment. After all, when AI is intended to make predictions, the behavioral intention to accept machine-generated advice could be largely contingent on users' trust in AI (Cheng et al., 2019; Chong et al., 2022; Ho et al., 2017) and perceived accuracy of AI (Jacobsen et al., 2020; Schaffer et al., 2015). The dependence on trust and perceived accuracy could be further heightened due to the opaque nature of typical investment-related AI systems (Araujo et al., 2020; Liang et al., 2021; Rudin et al., 2018).

Given the volatility of the stock market, investors sometimes contend with regret aversion, which refers to the fear of choosing an option that could turn out to be a bad one (Berkelaar et al., 2004; Chang et al., 2008; Noah & Lingga, 2020). This leads either to a preference for inaction (Sautua, 2017) or making the choice more conscientiously to inoculate against self-blame (Reb, 2008). However, there is scant research hitherto on how this dilemma plays out when the burden of decision-making is shifted from the self to technology. Conceivably, when investment decisions are suggested by AI, heightened vigilance in decision-making could cause investors to either maintain the status quo and ignore machine-generated advice, or buy into the recommendations if they consider the technology to be trustworthy and accurate.

Prior research shows that attitude-induced trust promotes behavioral outcomes (Ho et al., 2017; Nguyen et al., 2019). In a similar way, perceived accuracy, which is related positively to attitude, could also motivate behavioral intention (Nourani et al., 2019). Therefore, while a favorable attitude toward AI seems to be positively associated with trust and perceived accuracy, the opposite can be expected with an unfavorable attitude. Moreover, greater levels of trust and accuracy seem likely to result in higher behavioral intention to accept AI-based recommendation and vice-versa (Cheng et al., 2019; Ho et al., 2017; Jacobsen et al., 2020; Schaffer et al., 2015). Thus, the following hypotheses are proposed:

H2: Attitude toward AI positively predicts trust in AI.

H3: Attitude toward AI positively predicts perceived accuracy of AI.

H4: Trust in AI positively predicts behavioral intention to accept AI-based recommendation.

H5: Perceived accuracy of AI positively predicts behavioral intention to accept AI-based recommendation.

2.4. The role of risk level

All investments carry some level of risk. For the purpose of this paper, risk is conceptualized as volatility which refers to how much the price of a stock fluctuates within a short timeframe (Schwert, 1989). Investing in blue-chip stocks which are associated with well-established and financially stable companies is regarded as low risk. Not easily subject to market speculation, the magnitude for their potential upside and downside is muted in the short term. On the other hand, investing in penny stocks is regarded as high risk because of the possible wild gyrations in their stock prices.

Literature on risk taking suggests that the intention to perform a behavior depends on level of risk involved (Cullen & Gordon, 2007; Sitkin & Pablo, 1992; Sitkin & Weingart, 1995). Investors' willingness to go for high-risk or low-risk stocks depends on factors such as investment self-efficacy and the perception of the likelihood of loss (Jasiniak, 2018; Montford & Goldsmith, 2016). However, there is a dearth of studies on how individuals decide whether to accept investment recommendations in high-risk and low-risk contexts when advice comes from AI.

To this end, the conservation of resources theory could be brought to bear as it has been widely applied to understand how individuals navigate their way through challenging circumstances (Hobfoll, 1989; 2011). Under stress, the threat of resource loss is viewed more saliently than the hope of resource gain. Hence, the instinct is to invest resources just to protect against resource loss. Applying the theory in the context of investment, this means that the attendant stress of a high-risk situation involving penny stocks may compel individuals to be more vigilant. Even with a favorable attitude toward AI, they would still make a careful assessment of their trust in AI and perceived accuracy of AI before deciding whether to accept the machine-generated advice. In contrast, individuals in a low-risk situation involving blue-chip stocks would be less dictated by loss aversion tendencies. As long as they hold a favorable attitude toward AI, they would be willing to accept the machine-generated advice, regardless of their trust in AI and perceived accuracy of AI.

For these reasons, risk level is expected to play a moderating role among attitude, trust and perceived accuracy in their relationships with intention. In particular, the heightened vigilance triggered under a high-risk investment situation could lead to stronger relations between trust and intention as well as perceived accuracy and intention. This has the inadvertent effect of weakening the relationship between attitude and intention. In other words, the attitude-intention relationship can be expected to be stronger under a low-risk investment situation. Therefore, the following hypotheses are posited:

H6(a): Risk level moderates the relation between attitude toward AI and behavioral intention to accept AI-based recommendation. The relation is stronger in the low-risk situation involving blue-chip stocks.

H6(b): Risk level moderates the relation between trust in AI and behavioral intention to accept AI-based recommendation. The relation is stronger in the high-risk situation involving penny stocks.

H6(c): Risk level moderates the relation between perceived accuracy of AI and behavioral intention to accept AI-based recommendation. The relation is stronger in the high-risk situation involving penny stocks.

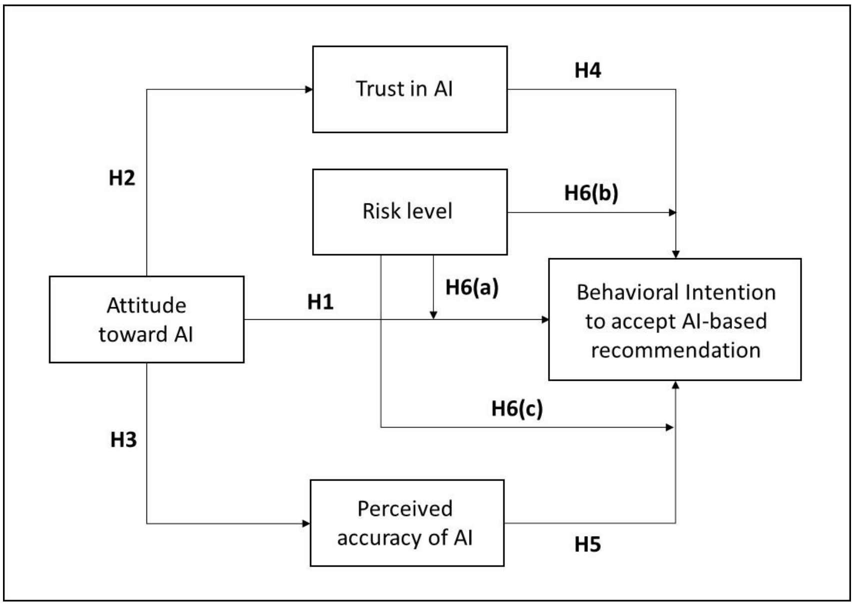

Figure 1. Attitude-perception-intention (API) model of AI acceptance.

3. Methods

3.1. Research Design

A scenario-based between-participants online experiment was conducted to test the hypotheses in the proposed API model of AI acceptance. Two experimental conditions were set up to manipulate the level of risk. One induced low-risk investment with recommendations for blue-chip stocks while the other induced high-risk investment with recommendations for penny stocks.

Prior to the experiment, a pilot study was conducted for the purpose of manipulation check. A total of 10 participants selected using convenience sampling were asked to rate the level of risk associated with the two scenarios (Figure 2 and Figure 3) as either high or low.

There was unanimous agreement that both experimental conditions reflected their intended risk levels.

3.2. Data Collection Procedure

Participants were recruited based on a combination of purposive and snowball sampling. The inclusion criterion was that they must have prior experiences with stock market investment. Data collection proceeded through the following two steps. First, after informed consent was obtained, participants responded to a screening question to confirm they had previously invested in the stock market. They also completed a short questionnaire to provide demographic data and indicate their investment self-efficacy. Thereafter, they were asked to imagine they were investors looking to increase their portfolio and were introduced to SMART-AI-TRADER, a simulated AI system created for this study. Participants were told that it uses a proprietary AI algorithm that learns from stocks' fundamentals, price and volume history to provide unbiased advice to investors. The system has recommended Stock A.

In the second step, participants were randomly and evenly assigned to one of the two experimental conditions using Qualtrics randomizer, with descriptions of either blue-chip or penny stocks provided. This was to ensure they understood the level of risk the stock carried. Participants were then exposed to the AI-based recommendation. Shown in Figure 2, SMART-AI-TRADER has provided a BUY recommendation for a blue-chip stock. Figure 3 shows a BUY recommendation for a penny stock. After that, participants were asked to indicate their intentions to accept AI-based recommendation. Finally, they responded to a set of questionnaire items measuring their trust in AI, perceived accuracy of AI, and attitude toward AI. All items followed a seven-point Likert scale (1=strongly disagree, 7=strongly agree).

Figure 2: Experimental stimulus depicting low-risk investment recommendation.

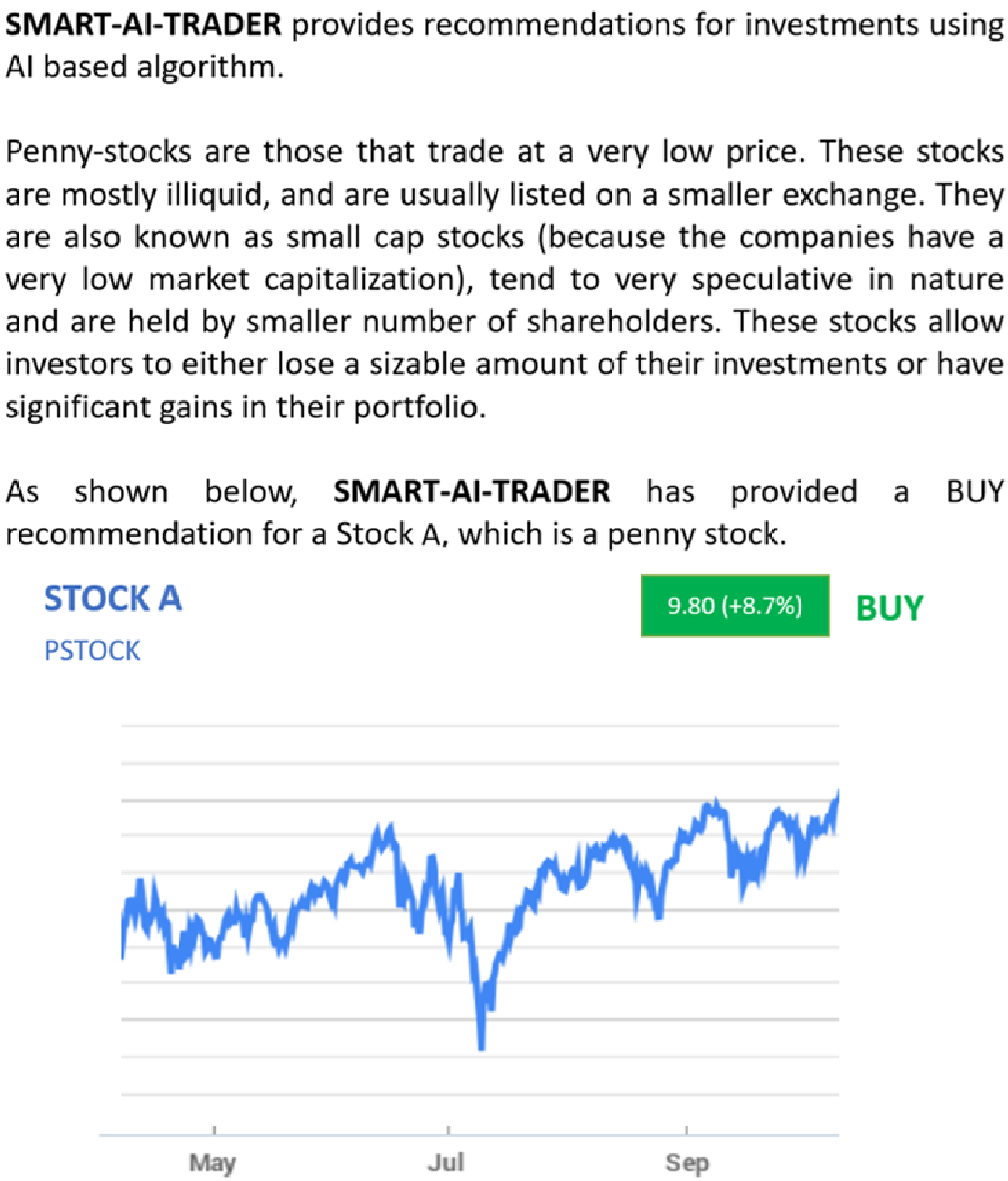

Figure 3: Experimental stimulus depicting high-risk investment recommendation.

3.3. Measures

Participants' gender, age, and investment self-efficacy were used as control variables in all analyses. Gender was captured as either male or female. Age was captured in years. Investment self-efficacy was measured using items adapted from Montford and Goldsmith

(2016). The final dependent variable in the API model shown in Figure 1 is behavioral intention to accept AI-based recommendation. This was measured using items adapted from Gursoy et al. (2019). Attitude toward AI is the independent variable in the conceptual model. It was measured using items adapted from Belanche et al. (2019). The other two variables in the model include trust in AI and perceived accuracy of AI. These were measured using items adapted from Jamaludin and Ahmad (2013) and Gursoy et al. (2019) respectively. The questionnaire items for each of the constructs are listed in Table 1.

Table 1: Questionnaire items for the constructs.

Constructs	**Questionnaire Items**
Investment self-efficacy (Montford & Goldsmith, 2016)	**Item 1:** I believe I have the required skills and knowledge in making stock investment decisions. **Item 2:** I rely on my previous experiences in making stock investment decisions for my next investment. **Item 3:** I am able to analyze stock prices reasonably well based on my own knowledge, skills and abilities.
Behavioral intention to accept AI-based recommendation (Gursoy et al. 2019)	**Item 1:** I would like to follow the call based on AI recommendation. **Item 2:** I intend to accept the call based on AI recommendation. **Item 3:** I would prefer to follow the call based on AI recommendation.
Attitude toward AI (Belanche et al., 2019)	**Item 1:** Using AI-based recommendation systems for making investment decisions is a good idea. **Item 2:** Using AI-based recommendation systems for making investment decisions is a wise idea. **Item 3:** I am open to use AI-based recommendation systems for making investment decisions.
Trust in AI (Jamaludin & Ahmad, 2013)	**Item 1:** I believe AI-based recommendation systems are trustworthy. **Item 2:** I believe AI-based recommendation systems are reliable. **Item 3:** AI-based recommendation systems cannot be trusted, there are too many uncertainties. (R)
Perceived accuracy of AI (Gursoy et al. 2019)	**Item 1:** AI-based recommendation systems are more accurate than human beings. **Item 2:** AI-based recommendation systems are not affected by human errors. **Item 3:** AI-based recommendation systems are more consistent than human beings.

3.4. Data Analyses

Data were analyzed using partial least squares structural equation modeling (PLS-SEM). To ensure reliability of the measures, Cronbach's alpha and composite reliability were used. Validity was checked in terms of convergent validity and discriminant validity. Common method bias was tested using Harman's one-factor test. It included all items in a principal component factor analysis (Podsakoff & Organ, 1986; Shiau & Luo, 2012). More than one factor emerged, indicating that common method bias was not a problem. The assessment of the structural model included the coefficient of determination (R^2), and the cross-validated redundancy measure (Q^2).

To examine the moderating effect of risk level, a multi-group analysis was conducted to compare data from the two experimental conditions of low-risk and high-risk investment recommendations. Measurement invariance was tested. As reported in Appendix A, the loadings between the latent variables and their indicators were similar for both the groups, allowing for a meaningful cross-group analysis. Thereafter, the group comparison method was applied to identify if the standardized path coefficients for the two groups of participants differed significantly (Keil et al., 2000). The roles of gender, age and investment self-efficacy were controlled in all the PLS-SEM analyses. In particular, the three control variables were added by connecting them to the main endogenous variable (users' intention to accept AI-based recommendation).

4. Results

4.1. Sample, Measurement Evaluation and Descriptive Statistics

An initial pool of 416 participants were invited to this study. Of these, 16 participants did not respond to the invitation, 19 did not pass the screening check as they had never invested in the stock market, and 13 dropped midway. Complete responses from 368 (416 -

16 - 19 - 13) participants were thus admitted for analysis. Such a sample size is comparable with recent studies (Shin, 2020; Williams, 2021).

Specifically, 191 participants were assigned to the low-risk investment condition while 190 were assigned to the high-risk investment condition. Eight from the first condition and five from the second dropped midway. The final tallies were 183 participants in the low-risk investment condition and 185 in the high-risk investment condition.

In terms of demographics, 213 (57.9%) were male and 155 (42.1%) were female. The average age was 31.77 years (Min = 21, Max = 63, SD = 10.80). In terms of educational qualification, 164 (44.6%) participants had a bachelor's degree, 144 (39.1%) had a master's degree, 23 (6.3%) had 'O' or 'A' level qualifications, 21 (5.7%) were at diploma/advanced diploma level, and the other 16 (4.3%) participants had a doctoral degree. In terms of participants' experience in the stock market investment, 97 (26.4%) had less than one-year experience, 126 (34.2%) had one year to less than three years of experience, 97 (26.4%) had three years to less than six years of experience, and 48 (13%) had greater than six years of experience. Table 2 presents the descriptive statistics of the sample.

Table 2: Descriptive statistics of the sample.

Constructs	**Full Dataset (N = 368)**	**Low-Risk Level (n = 183)**	**High-Risk Level (n = 185)**
Gender (frequency)			
Male	213 (57.9%)	107 (58.5%)	106 (57.3%)
Female	155 (42.1%)	76 (41.5%)	79 (42.7%)
Age (M ± SD)	31.77 ± 10.80	34.33 ± 11.68	29.24 ± 9.19
Education (frequency)			
'O' or 'A' Levels	23 (6.3%)	0 (0%)	23 (12.4%)
Diploma/Advanced Diploma	21 (5.7%)	5 (2.7%)	16 (8.6%)
Bachelor	164 (44.6%)	82 (44.8%)	82 (44.3%)
Master	144 (39.1%)	88 (48.1%)	56 (30.3%)
Doctoral	16 (4.3%)	8 (4.4%)	8 (4.3%)
Investment experience (frequency)			
< 1 year	97 (26.4%)	50 (27.3%)	47 (25.4%)
1 year to less than 3 years	126 (34.2%)	78 (42.6%)	48 (25.9%)

3 years to less than 6 years	97 (26.4%)	26 (14.2%)	71 (38.4%)
>= 6 years	48 (13%)	29 (15.8%)	19 (10.3%)
Investment self-efficacy (M ± SD)	3.89 ± 1.41	4.08 ± 1.42	3.70 ± 1.38
Behavioral intention to accept AI-based recommendation (M ± SD)	4.34 ± 1.65	4.85 ± 1.47	3.84 ± 1.66
Attitude toward AI (M ± SD)	4.20 ± 1.46	4.42 ± 1.33	3.98 ± 1.56
Trust in AI (M ± SD)	4.03 ± 1.32	4.10 ± 1.29	3.95 ± 1.34
Perceived accuracy of AI (M ± SD)	3.85 ± 1.54	3.84 ± 1.64	3.86 ± 1.44

Cronbach's Alpha (α), composite reliability (CR), and average variance extracted (AVE) for all the constructs are reported in Table 3. The Cronbach's α values exceeded the threshold of 0.7, confirming internal consistency of the measures (Nunnally, 1978). All CR and AVE values exceeded 0.7 and 0.5 respectively, indicating acceptable convergent validity (Fornell & Larcker, 1981). Moreover, all items loaded on their respective constructs as shown in Table 4. Thus, discriminant validity was confirmed.

Table 3: Internal consistency reliability and convergent validity.

Constructs	**Cronbach's α**	**CR**	**AVE**
Investment self-efficacy	0.86	0.91	0.78
Behavioral intention to accept AI-based recommendation	0.89	0.93	0.82
Attitude toward AI	0.94	0.96	0.90
Trust in AI	0.79	0.87	0.70
Perceived accuracy of AI	0.87	0.92	0.79

Table 4: Item loadings and cross loadings.

Constructs	**Items**	**(1) Investment self-efficacy**	**(2) Behavioral intention to accept AI-based recommendation**	**(3) Attitude toward AI**	**(4) Trust in AI**	**(5) Perceived accuracy of AI**
(1)	**Item 1**	**0.89**	0.31	0.44	0.30	0.30
	Item 2	**0.85**	0.32	0.51	0.32	0.31
	Item 3	**0.88**	0.28	0.38	0.20	0.26

(2)	**Item 1**	0.32	**0.94**	0.53	0.37	0.33
	Item 2	0.33	**0.96**	0.55	0.40	0.35
	Item 3	0.35	**0.95**	0.54	0.39	0.34
(3)	**Item 1**	0.47	0.54	**0.94**	0.63	0.65
	Item 2	0.50	0.52	**0.94**	0.68	0.65
	Item 3	0.45	0.54	**0.93**	0.67	0.61
(4)	**Item 1**	0.39	0.41	0.71	**0.89**	0.72
	Item 2	0.30	0.36	0.61	**0.90**	0.61
	Item 3	0.01	0.23	0.47	**0.72**	0.47
(5)	**Item 1**	0.31	0.37	0.63	0.70	**0.92**
	Item 2	0.22	0.27	0.53	0.59	**0.87**
	Item 3	0.35	0.33	0.67	0.69	**0.93**

Note. The bolded values indicate the loading of each item to a construct in the respective columns. The other values indicate the cross loadings.

4.2. Inferential Statistics

As described in Section 3.4, each of the hypotheses was tested using PLS-SEM. The statistical significance of the path coefficients was assessed. The control variables (gender, age, and investment self-efficacy) were consistently non-significant (gender: $\beta = -0.03$, $t = 0.34$, $p > 0.05$; age: $\beta = -0.004$, $t = 0.05$, $p > 0.05$; self-efficacy: $\beta = 0.08$, $t = 0.77$, $p > 0.05$).

After accounting for the control variables, the following hypothesized relationships were found to be significant: Attitude toward AI was positively associated with behavioral intention to accept AI-based recommendation ($\beta = 0.54$, $t = 3.62$, $p < 0.001$). This lends support to H1. Next, attitude toward AI was positively associated with trust in AI ($\beta = 0.71$, $t = 10.42$, $p < 0.001$) and perceived accuracy of AI ($\beta = 0.68$, $t = 10.13$, $p < 0.001$), which lend support to H2 and H3 respectively.

However, the relationships of trust and perceived accuracy with behavioral intention to accept AI-based recommendation were not significant. Therefore, H4 and H5 are not supported. Table 5 summarizes the results of testing the hypotheses H1-H5 using PLS-SEM.

Table 5: Hypotheses testing results for H1-H5.

	Full dataset (N=368)

	β	Std. Error	t-stat
H1: Attitude toward AI → Behavioral intention to accept AI-based recommendation	0.54	0.15	3.62***
H2: Attitude toward AI → Trust in AI	0.71	0.07	10.42***
H3: Attitude toward AI → Perceived accuracy of AI	0.68	0.07	10.13***
H4: Trust in AI → Behavioral intention to accept AI-based recommendation	0.06	0.14	0.40
H5: Perceived accuracy of AI → Behavioral intention to accept AI-based recommendation	-0.08	0.15	0.53
R^2 Value			
Trust in AI		50.4%	
Perceived accuracy of AI		46.2%	
Behavioral intention to accept AI-based recommendation		33.5%	

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Control variables: Gender, Age, Investment self-efficacy.

The R^2 values for the endogenous constructs including trust in AI, perceived accuracy of AI, and behavioral intention to accept AI-based recommendation were 50.4%, 46.2% and 33.5% respectively. The cross-validated redundancy measure (Q^2) was also examined. With an omission distance of seven, the positive Q^2 ($Q^2 > 0$) values for the endogenous constructs ensured that the model fit well with the data (Hair et al., 2019).

To test the moderating effect of risk level, a multi-group PLS analysis was conducted. Statistical tests were performed to check the homogeneity of the two groups in terms of the control variables of gender, age, and investment self-efficacy. With respect to gender, Chi-square results indicated no significant difference ($\chi 2(1, N = 368) = 0.05$, Cramer's $V = 0.01$, $p > 0.05$). With respect to age, there was a significant difference between the two groups; $t(345.03) = 4.65$, $p < 0.01$. Participants' age in the low-risk condition (34.33 ± 11.68) was significantly higher than that in the high-risk condition (29.24 ± 9.19). With respect to investment self-efficacy, there was a statistically significant difference between the two groups; $t(366) = 2.66$, $p < 0.01$. Participants' investment self-efficacy in the low-risk condition (4.08 ± 1.42) was significantly higher than that in the high-risk condition (3.70 ± 1.38). That said, the control variables remained consistently non-significant in the high-risk condition (gender: β = 0.03, t = 0.44, p > 0.05; age: β = 0.02, t = 0.4, p > 0.05; self-efficacy: β = 0.11, t = 1.2, p > 0.05) as well as the low-risk condition (gender: β = -0.1, t = 1.04, p > 0.05; age: β = -0.03, t = 0.3, p > 0.05; self-efficacy: β = 0.01, t = 0.1, p > 0.05). The results of the API model for the low-risk and the high-risk conditions are depicted in Figure 4 and Figure 5 respectively.

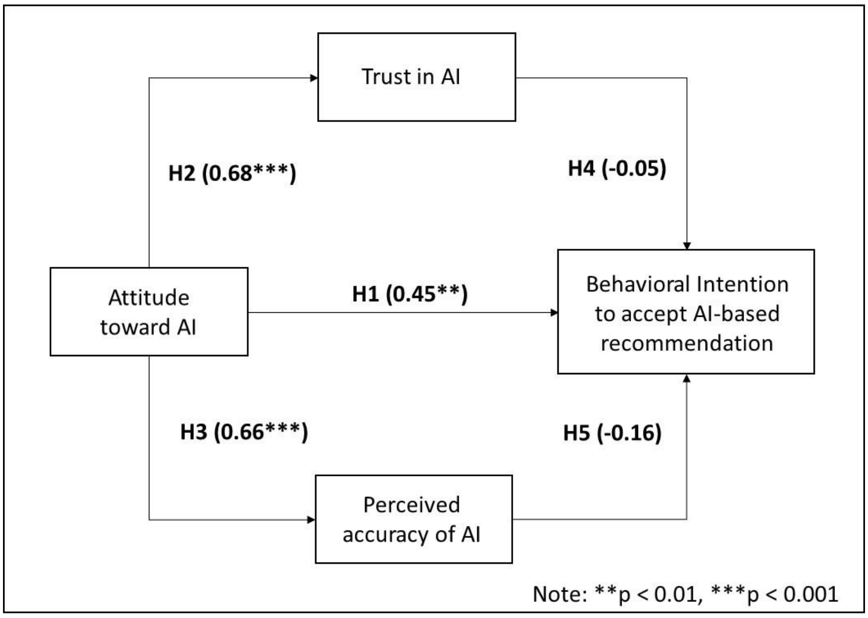

Figure 4. Path coefficients for the low-risk condition.

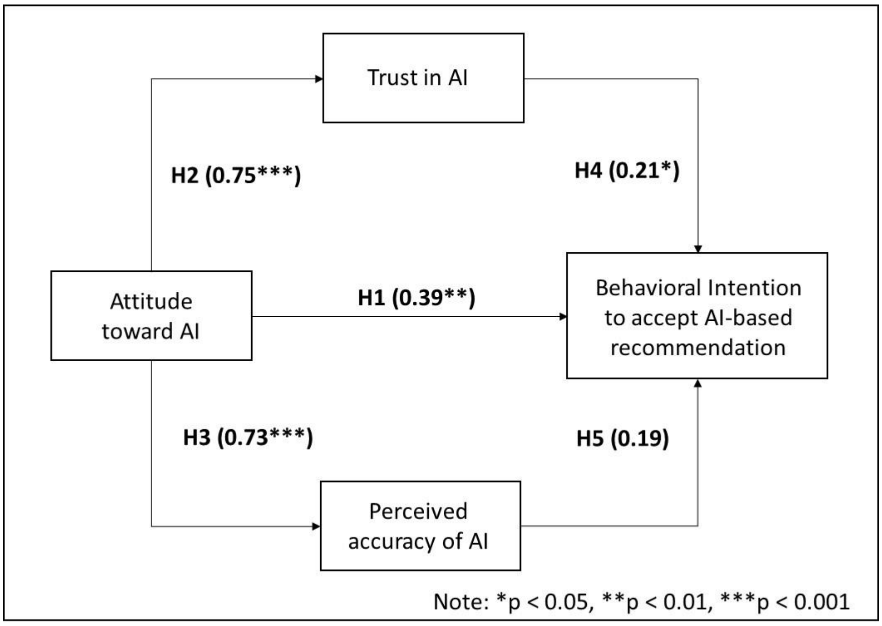

Figure 5. Path coefficients for the high-risk condition.

As shown in Table 6, the group comparison method showed a significant difference between the two groups for the relationship between attitude toward AI and behavioral intention to accept AI-based recommendation. Compared with the participants in the high-risk situation, those in the low-risk situation showed a stronger relation ($t = 4.08$, $p < 0.001$). This lends support to H6(a).

Furthermore, there was a significant difference between the two groups for the relationship between trust in AI and behavioral intention to accept AI-based recommendation. Compared with the participants in the low-risk situation, those in the high-risk situation showed a stronger relation ($t = -20.54$, $p < 0.001$). Hence, H6(b) is supported.

Finally, there was also a significant difference between the two groups for the relationship between perceived accuracy of AI and behavioral intention to accept AI-based recommendation. Compared with the participants in the low-risk situation, those in the high-risk situation showed a stronger relation (t = -24.79, p < 0.001). This lends support to H6(c).

Table 6: PLS multi-group results for H6.

	Low-risk (blue-chip: n=183)		**High-risk (penny: n=185)**		**t-stat**
	β	**Std. Error**	**β**	**Std. Error**	
H6(a): Attitude toward AI → Behavioral intention to accept AI-based recommendation	0.45**	0.14	0.39**	0.12	4.08***
H6(b): Trust in AI → Behavioral intention to accept AI-based recommendation	-0.05	0.16	0.21*	0.10	-20.54***
H6(c): Perceived accuracy of AI → Behavioral intention to accept AI-based recommendation	-0.16	0.16	0.19	0.12	-24.79***
R^2 Value					
Trust in AI	46%		56.3%		
Perceived accuracy of AI	43.3%		53.7%		
Behavioral intention to accept AI-based recommendation	12.2%		62%		

Note. * p < 0.05, ** p < 0.01, *** p < 0.001.
Control variables: Gender, Age, Investment self-efficacy.

5. Discussion

Four major findings could be gleaned from this research. First, based on the results corresponding to H1, attitude toward AI was positively associated with behavioral intention to accept AI-based recommendations (β = 0.54, p < 0.001). Although recent evidence suggests that the attitude toward AI could be less favorable for black-box vis-à-vis transparent systems (Ochmann et al., 2021), this paper reveals that users' attitude still plays a crucial role in the case of opaque AI systems. As long as they hold a favorable attitude toward AI systems, users seem to accept their inability to understand the underlying computational complexities.

Second, from the results corresponding to H2 and H3, attitude toward AI was positively associated with trust in AI ($\beta = 0.71$, $p < 0.001$) and perceived accuracy of AI ($\beta = 0.68$, $p < 0.001$). This is generally consistent with long-standing research findings (e.g., Dwivedi et al. 2019; Venkatesh et al., 2003) that attitude is not only a key predictor of embracing technology but also shapes trust and perceived accuracy of what technology can offer. This persistent importance of attitude has implications for research in human-AI interaction. Going forward, as AI becomes more pervasive, it is important for public debate surrounding AI to avoid veering toward either exaggerated optimism or helpless pessimism. Neither automation bias nor AI aversion is helpful to society (Bigman & Gray, 2018; Chong et al., 2022; Dietvorst et al., 2015; Tomsett et al., 2020; Wickramasinghe et al., 2020). Instead, it would be wise to focus realistically on what AI can do, appreciate its potential, and acknowledge its limits.

Third, the results corresponding to H4 and H5 show that neither trust in AI nor perceived accuracy of AI was significantly associated with behavioral intention to accept AI-based recommendations in the full sample. This is at odds with prior research (Ho et al., 2017; Liu & Tao, 2022; Schaffer et al., 2015) and could be attributed to the unique context of investigation of investment recommendation involving blue-chip and penny stocks, which has not been explored hitherto. Thus, the paper not only expands the contextual scope of the human-AI interaction literature but also enriches it with a counter-intuitive finding that warrants further inquiry. Future research is needed to shed light on how perception-related constructs such as trust in AI and perceived accuracy of AI hold different connotations in different contexts.

Fourth, from the results corresponding to H6, risk level moderated how attitude, trust and perceived accuracy varied with behavioral intention to accept AI-based recommendations. In particular, trust ($t = -20.54$, $p < 0.001$) and perceived accuracy ($t = -$

24.79, $p < 0.001$) were found to better explain AI acceptance intention in high risk rather than low risk situations. It is evident that the forces affecting users' decision to embrace AI are contextually dependent on the level of risk (Rzepka & Berger, 2018).

Prior research suggests that users tend to rely on automation for tasks that call for logic (Gaudiello et al., 2016; Logg, 2017). Extending the literature, this paper shows that even for a task such as investment decision-making that may also involve intuition, users could be open to AI-based recommendations. However, the underlying psychological mechanism of accepting machine-generated advice depends on the level of risk. When risk is low, a favourable attitude toward AI seems sufficient to promote machine reliance. However, when risk is high, a favourable attitude toward AI is a necessary but no longer sufficient condition for AI acceptance. Instead, to cope with the risk, users carefully deliberate on their trust and perceived accuracy of AI before deciding whether to accept machine-generated advice. In other words, compared with the low-risk condition involving blue-chip stocks, the high-risk condition involving penny stocks compelled the participants to be more vigilant in their decision-making.

6. Conclusion

This paper seeks to explain the behavioral intention to accept AI-based recommendations as a function of attitude toward AI, trust, perceived accuracy and risk level. A conceptual model was proposed and tested through a between-participants experiment using a simulated AI-enabled investment recommendation system. The results reveal that attitude toward AI is positively associated with behavioral intention to accept AI-based recommendations, trust in AI and perceived accuracy of AI. Additionally, risk level moderates how attitude, trust and perceived accuracy vary with behavioral intention to accept AI-based recommendations.

6.1. Theoretical Contributions

On the theoretical front, the paper contributes to the human-AI interaction literature in three ways. First, it proposes an attitude-perception-intention (API) model that sheds light on the underlying psychological mechanism of how users decide to accept AI-enabled advice. The model enhances current understanding of the relation between attitude toward AI and behavioral intention to accept AI-based recommendation (Ho et al., 2017; Liu & Tao, 2022; Schaffer et al., 2015) by taking into account trust, perceived accuracy and risk level. It shows users' decision to embrace AI is contextually-dependent (Rzepka & Berger, 2018), and specifically, on the level of risk. When risk is low, a favourable attitude toward AI is enough. However, when risk is high, a favourable attitude alone is no longer sufficient for AI acceptance. In a state of heightened alert, users become more careful in assessing their trust in AI and their perceived accuracy of AI before deciding to accept AI-based recommendations. Put differently, the API model not only deepens the understanding of the attitude-intention relation in the AI landscape but also adds risk-level as a boundary condition.

Two, the paper adds to the scholarly understanding of AI recommendation systems in tasks that call for intuition in finance—an example of a high involvement service—where human counsel is usually preferred to machine-generated advice (Longoni et al., 2019; Zhang et al., 2021). Prior research suggests that users readily accept AI especially when dealing with rule-based and routine work (Gaudiello et al., 2016; Logg, 2017). Extending the literature, this paper argues that users are also amenable to AI-based recommendations for tasks such as making investment decisions that demand intuitive judgements. Depending on attitude, trust, perceived accuracy and risk level, there could be a case for AI acceptance.

Three, this paper represents one of the earliest attempts to apply the conservation of resources theory in the context of stock market investment. It validates the argument that the threat of resource loss is viewed saliently in challenging circumstances involving penny stocks (Hobfoll, 1989; 2011). On the other hand, when investing in blue-chip stocks where the threat of resource loss is perceived to be minimal, users tend to let their guard down in making decisions. Additionally, this paper adds to the literature on risk (Bao et al., 2022) by showing how the level of risk plays a moderating role in AI acceptance. Specifically, in a high-risk situation, high trust and perceived accuracy are needed for users to buy into AI-based recommendations.

6.2. Practical Implications

On the practical front, the paper offers insights into how the uptake of AI recommendation systems can be promoted in high involvement industries such as healthcare and finance where machine-generated advice has received much resistance (Longoni et al., 2019; Zhang et al., 2021). As new AI recommendation systems proliferate, it is important for policymakers to ensure that the public develops a realistic attitude toward AI.

Furthermore, marketing communication for AI recommendation systems should be tailored according to the decision-making context. For example, in situations where there is high risk, successful performance of the systems in the past could be recounted to inspire user confidence. AI systems offering recommendations under high risk should be designed in ways so as to enhance perceptions of trust and accuracy.

6.3. Limitations and Future Research Directions

Two limitations in this paper need to be acknowleged. One, as with all quantitative studies, it was not possible to gain richer insights into how the participants made decisions whether to accept AI-enabled advice. Future research could build on the proposed API model by using interviews or focus groups to identify other constructs that further explain the relationship between attitude toward AI and behavioral intention to accept AI.

Another limitation is the methodological parsimony of the experimental setup. No amount of investable assets was specified in the experiment. Neither were participants presented with scenarios where an investment portfolio could comprise both high-risk and low-risk stocks in different proportions. Hence, future research could consider refining the experiment to reflect a more realistic context under which investment decisions are made. Hopefully, this will deepen our understanding of how users decide whether to embrace AI.

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Appendix A

Table A1: Item loadings and cross loadings for high-risk condition.

Constructs	Items	(1) Investment self-efficacy	(2) Behavioral intention to accept AI-based recommendation	(3) Attitude toward AI	(4) Trust in AI	(5) Perceived accuracy of AI
(1)	Item 1	**0.88**	0.46	0.48	0.36	0.39
	Item 2	**0.82**	0.48	0.57	0.40	0.41
	Item 3	**0.88**	0.51	0.45	0.27	0.35
(2)	Item 1	0.44	**0.94**	0.70	0.63	0.65
	Item 2	0.46	**0.97**	0.72	0.68	0.65
	Item 3	0.38	**0.97**	0.73	0.64	0.63
(3)	Item 1	0.54	0.71	**0.94**	0.69	0.72
	Item 2	0.59	0.72	**0.95**	0.71	0.70
	Item 3	0.51	0.70	**0.94**	0.72	0.67
(4)	Item 1	0.49	0.67	0.77	**0.84**	0.72
	Item 2	0.30	0.54	0.59	**0.88**	0.51
	Item 3	0.17	0.49	0.50	**0.82**	0.50
(5)	Item 1	0.42	0.66	0.68	0.67	**0.91**
	Item 2	0.32	0.50	0.53	0.53	**0.83**
	Item 3	0.44	0.61	0.72	0.64	**0.92**

Note. The bolded values indicate the loading of each item to a construct in the respective columns. The other values indicate the cross loadings.

Table A2: Item loadings and cross loadings for low-risk condition.

Constructs	Items	(1) Investment self-efficacy	(2) Behavioral intention to accept AI-based recommendation	(3) Attitude toward AI	(4) Trust in AI	(5) Perceived accuracy of AI
(1)	Item 1	**0.89**	0.12	0.37	0.26	0.23
	Item 2	**0.87**	0.12	0.43	0.25	0.21
	Item 3	**0.89**	0.12	0.29	0.15	0.18
(2)	Item 1	0.12	**0.93**	0.27	0.08	0.06
	Item 2	0.13	**0.96**	0.31	0.12	0.10
	Item 3	0.13	**0.93**	0.27	0.14	0.11
(3)	Item 1	0.38	0.31	**0.93**	0.59	0.61
	Item 2	0.39	0.26	**0.93**	0.66	0.62
	Item 3	0.37	0.28	**0.92**	0.64	0.60
(4)	Item 1	0.30	0.16	0.67	**0.89**	0.73
	Item 2	0.28	0.11	0.65	**0.90**	0.72
	Item 3	0.17	0.06	0.26	**0.72**	0.47
(5)	Item 1	0.23	0.14	0.62	0.75	**0.94**
	Item 2	0.14	0.06	0.55	0.66	**0.93**
	Item 3	0.27	0.05	0.65	0.74	**0.87**

Note. The bolded values indicate the loading of each item to a construct in the respective columns. The other values indicate the cross loadings.