Examining Trust and Willingness to Accept AI Recommendation Systems

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ABSTRACT
This paper proposes and tests a conceptual model that identifies the antecedents of trust in AI, which could in turn lead to users' willingness to accept AI recommendation systems. An online survey was conducted in the context of stock market investment. Responses came from 313 participants with prior investment experiences. Data were analyzed using partial least squares structural equation modeling. Results indicate that attitude towards AI and perceived AI accuracy were positively related to users' trust in AI. Users' AI anxiety was negatively related to trust in AI. Furthermore, users' trust in AI was positively related to their willingness to accept AI recommendation systems. The paper extends previous works by explicating the role of users' trust in AI and suggests that the uptake of AI systems can be promoted by fostering favorable attitudes, greater perceived AI accuracy, and lowering AI anxiety.

KEYWORDS
Artificial Intelligence; AI Recommendation Systems; Human-AI Interaction; Technology Adoption; Trust.

INTRODUCTION
Technological breakthroughs have now created enormous opportunities to delegate everyday decision-making to AI recommendation systems. In the realm of FinTech, algorithm-informed stock market investment recommendations with little to no human oversight have now become common (Park et al., 2016). Nonetheless, advice generated by AI is not always readily accepted (Schmitt, 2020; Shin et al., 2021; Dietvorst et al., 2015). At the heart of this reluctance is the issue of trust, which refers to the degree to which AI could be relied upon to make decisions (Merritt et al., 2013; Yu & Li, 2022).

The antecedents of trust in AI are currently not well understood. Research on users' willingness to accept AI recommendation systems is also limited. Previous works often focused on algorithmic or technical performances (Cheng et al., 2010; Tong et al., 2020), ignoring end-users' perspectives. Therefore, this paper proposes and tests a conceptual model (as shown in Figure 1) that identifies the antecedents of trust in AI, which could in turn lead to users' willingness to accept AI recommendations systems.

Informed by the Theory of Planned Behavior and the Technology Readiness Index, and set in the context of stock market investment, this paper is significant both theoretically and in practice. On the theoretical front, it extends previous works by explicating the role of users' trust in AI systems. It also offers insights for companies to promote their AI-driven technologies.

CONCEPTUAL DEVELOPMENT OF THE RESEARCH MODEL
There are at least three factors, namely, attitude towards AI, perceived AI accuracy, and AI anxiety that could predict users' trust in AI. Attitude towards AI is defined as the degree to which a user makes a favorable or unfavorable evaluation of AI-driven technologies (Belanche et al., 2019). Following the theory of planned behavior (Ajzen, 1991), previous works indicate attitude to be a significant predictor of users' behavioral intention to engage with a target behavior (Belanche et al., 2019). For example, attitude towards AI showed positive associations in various contexts such as financial robo-advisors (Belanche et al., 2019), and medical recommendations (Soellner & Koenigstorfer, 2021). In this vein, a favorable attitude towards AI could attain a high receptivity, and create a level of trust in AI. Therefore, this paper hypothesizes the attitude-trust relationship as follows:

H1: Attitude towards AI is positively related to users' trust in AI.
Perceived AI accuracy represents users' perception of the correctness of AI recommendations (He et al., 2019; Shin, 2020). Users are generally unaware of algorithms and their corresponding underlying mechanisms, which are used to make the recommendations. Instead, users are more interested in the accuracy of a given recommendation. A higher level of perceived accuracy of recommendation systems can lead to positive evaluations of the systems. Previous works also acknowledge that a key challenge associated with the trust building mechanism relates to the accuracy of AI systems in the context of human-AI interaction (Lockey et al., 2021). Therefore, the following hypothesis is posited:

Mid-Year Conference of the Association for Information Science & Technology | April 11-13, 2023, Virtual Event.

H2: Perceived AI accuracy is positively related to users' trust in AI.

AI anxiety refers to users' apprehension when relying on AI to make decisions (Johnson & Verdicchio, 2017; Kang & Kim, 2022). It is closely related to Parasuraman's (2000) concept of Technology Readiness Index (TRI). Even technology optimists apparently experience technology-related anxieties at levels similar to those who are much less enthusiastic about technology to begin with (Parasuraman, 2000). Previous works showed a negative relationship between technology anxiety and technology usage (Kazancoglu & Yarimoglu 2018; Park et al., 2014; Sánchez-Prieto et al., 2016). Emerging AI-driven technologies are often associated with high levels of uncertainty and are likely to create anxiety in the face of human-AI interaction (Seegebarth et al., 2019). Recent works also find that affective feelings such as AI anxiety can affect trust in AI (Gillath et al., 2021). In this vein, this paper proposes the following hypothesis:

H3: AI anxiety is negatively related to users' trust in AI.

Trust plays a significant role in individuals' decision-making, and has been investigated in many different contexts such as information credibility, communications, and marketing (Bart et al., 2005; Lim, 2015). Trust is also viewed as a critical concept in the adoption of new technologies and products. Emerging technologies are often presented with a low level of transparency and greater complexity, requiring users' confidence in the systems (Glikson & Woolley, 2020; Seegebarth et al., 2019). Related to this research, trust in AI could play a significant role in determining users' acceptance of AI systems (Gillath et al., 2021; Merritt 2013; Shin, 2020; Wu & Huang, 2021). The trust building mechanism in human-AI interaction is different from that in interpersonal relations (Bock et al., 2020). Previous works also suggest that building trust is essential for the development of human-AI relationships (Gillath et al., 2021). Hence, the following is hypothesized:

H4: Trust in AI is positively related to users' willingness to accept AI recommendation systems.

Figure 1 depicts the proposed conceptual model.

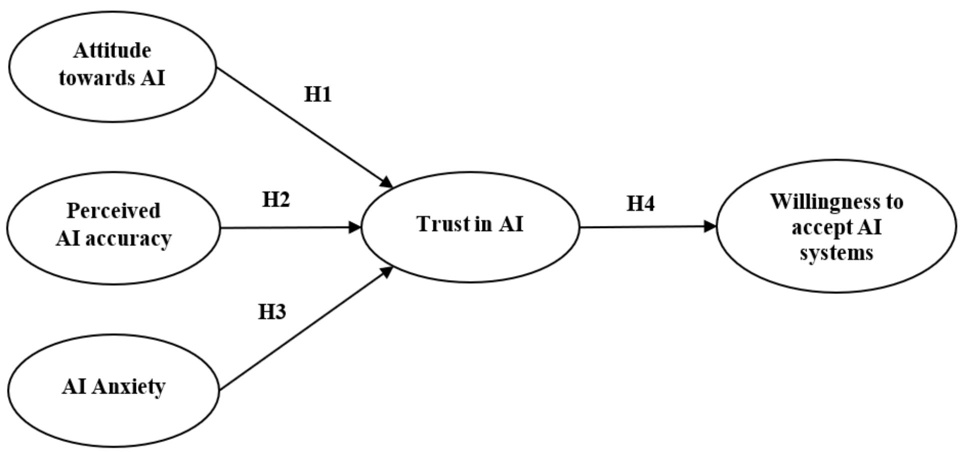

Figure 1. Proposed Conceptual Model

RESEARCH METHODS

Using convenience sampling, 500 participants who must have had some prior experiences in stock market investment were invited for participation in an online survey. Of these, 388 responded and took part in the study. After removing 75 incomplete responses, the remaining 313 were admitted for analysis.

The questionnaire covered five constructs. Guided by previous works (Belanche et al., 2019), attitude towards AI was measured using items such as "Using AI recommendation systems for making investment decisions is a good idea". Perceived AI accuracy was captured using items such as "AI recommendation systems are not affected by human errors" (Gursoy et al., 2019). AI anxiety was measured using items such as "I would feel apprehensive about using AI recommendation systems" (Cobelli et al., 2021). Trust in AI was measured using items such as "I believe AI recommendation systems are reliable" (Jamaludin & Ahmad, 2013). As the final dependent variable, willingness to accept AI recommendation systems was measured using items such as "I am willing to receive information from AI recommendation systems" (Gursoy et al., 2019; Zhang et al., 2020). Responses to these questionnaire items were captured using a seven-point Likert scale. Details about the constructs are available in Table 1. Partial least squares structural equation modeling (PLS-SEM) was used for the purpose of data analysis (Ringle et al., 2005). Path analysis was conducted to test the proposed hypotheses.

Constructs	M ± SD	Cronbach's α	Composite Reliability	Average Variance Extracted
Attitude towards AI	4.20 ± 1.39	0.93	0.95	0.87
Perceived AI accuracy	3.85 ± 1.53	0.89	0.93	0.83
AI anxiety	4.21 ± 1.18	0.81	0.88	0.64
Trust in AI	4.01 ± 1.27	0.78	0.87	0.69
Willingness to accept AI systems	4.03 ± 1.51	0.93	0.95	0.78

Table 1. Descriptive statistics, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted

RESULTS

Of 313 participants, 188 (60.1%) were male and 125 (39.9%) were female. Table 2 reports the demographics of the sample.

Characteristics	Categories	N
Gender	Male	188 (60.1%)
	Female	125 (39.9%)
Age		Avg. = 31.50 years (Min = 21 years, Max = 58 years)
Education level	Diploma Level	13 (4.2%)
	Bachelor level	158 (50.5%)
	Master level	130 (41.5%)
	Doctoral level	12 (3.8%)
Stock market investment experience	< 1 year	85 (27.2%)
	1 year to < 3 years	88 (28.1%)
	3 years to < 6 years	102 (32.6%)
	>= 6 years	38 (12.1%)

Table 2. Demographics of the Sample (N = 313)

As shown in Figure 2, attitude towards AI was positively related to participants' trust in AI ($\beta = 0.34$, $t = 2.72$, $p < 0.01$), supporting H1. Next, perceived AI accuracy was positively related to participant' trust in AI ($\beta = 0.45$, $t = 3.89$, $p < 0.001$), supporting H2. Participants' AI anxiety was negatively related to trust in AI ($\beta = -0.19$, $t = 2.38$, $p < 0.05$), therefore, supporting H3. Finally, participants' trust in AI was positively related to their willingness to accept AI recommendation systems ($\beta = 0.54$, $t = 6.30$, $p < 0.001$). Thus, H4 was supported.

DISCUSSION & CONCLUSION

Four key findings can be gleaned from the results. First, users' attitude towards AI was positively related to their trust in AI. Based on the theory planned behavior, the concept of attitude is often recognized as a significant predictor of performing a target behavior in different contexts, including new technology adoption (Cobelli et al., 2021). This paper is thus consistent with previous works which found that attitude towards AI has a positive influence on users' likelihood to use technology-driven services in the context of AI and FinTech (Belanche et al., 2019; Rahman et al., 2021).

Second, perceived AI accuracy was positively related to users' trust in AI. Algorithms are developed to produce accurate predictions. However, the underlying mechanism in terms of the breadth, depth and scope of the analysis involved in algorithmic recommendations remain a black-box to end-users, and therefore, presents a growing concern in terms users' acceptance. Instead of being opaque, this paper shows AI recommendation systems that are transparent and can convince users about their accuracy are likely to promote trust.

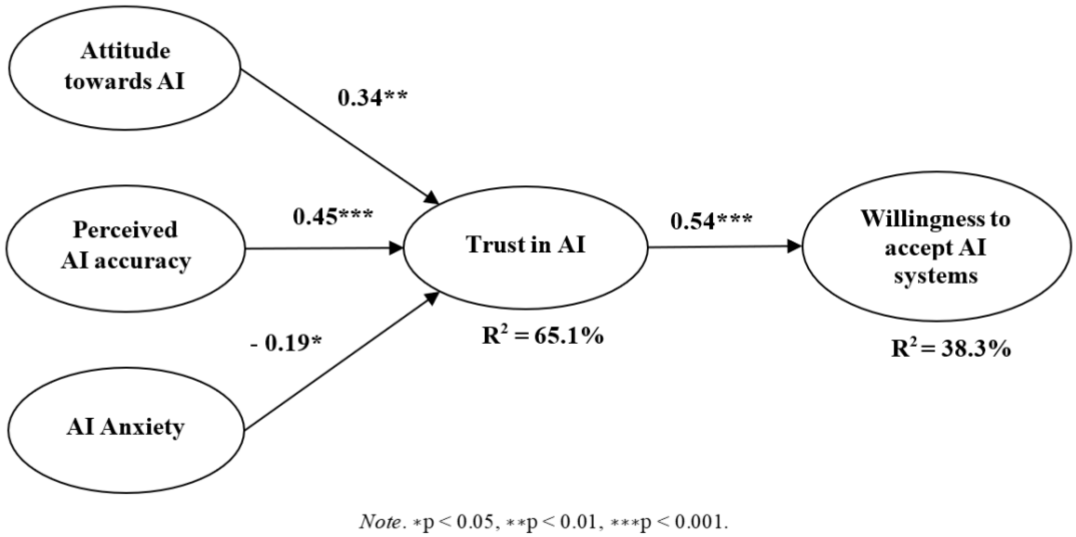

Figure 2. Path Coefficients of the Conceptual Model

Third, this paper establishes a relationship between AI anxiety and users' trust in AI. The significant though negative influence of anxiety on trust indicates that individual's apprehensions about using AI systems would create distrust in AI. Furthermore, AI anxiety can be understood as a type of deterrent emotions that occur when individuals feel they have limited to no control over the outcome from the AI systems (Omrani et al., 2022). The significant influence of anxiety suggests that individuals utilize their affective perception along with cognition when deciding whether to trust in AI.

Fourth, while trust is a construct commonly associated with human relationships, it can also be developed with non-human agents such as AI advisors (Wu & Huang, 2021). In the context of human-AI interaction, trust in AI is a function of three factors, namely, attitude towards AI, perceived AI accuracy, and AI anxiety. The first two factors were positively associated with trust while the third was negatively related.

This paper offers three theoretical contributions. First, drawing on the theory of planned behavior (Ajzen, 1991), it finds that attitude towards AI has a significant role in building trust in AI, and a favorable attitude contributes towards enhancing trust, which in turn, increase willingness to accept AI systems. By extending previous works that dominantly focuses on the attitude-intention relationship (Cobelli et al., 2021), this paper establishes the attitude-trust-intention relationship in the context of human-AI interaction.

Second, augmenting the concept of technology readiness (Flavián et al., 2021; Parasuraman, 2000), this paper suggests that negative emotion engendered by AI anxiety leads to a decreased trust in AI. Emerging AI technologies are often associated with high levels of uncertainty, and are likely to create anxiety (Seegebarth et al., 2019). As such, technology readiness is a crucial factor, and the lack of readiness could exhibit an extra overhead when interacting with AI-technologies.

Third, previous works suggest that trust is a key factor in users' acceptance of technologies (Bart et al., 2005; Lim, 2015). Trust is therefore clearly a critical element for understanding users' behavior towards AI (Merritt et al., 2013; Yu & Li, 2022). This paper adds to previous works by showing that trust is an essential factor in consumer evaluations of AI-driven technologies. To enhance AI acceptance, this paper recommends exploring ways of driving favorable attitude, enhancing perceived accuracy, and reducing AI anxiety to foster trust in AI. Compared to interpersonal relationships, it emphasizes new means of creating trust to non-human agents in the face of human-AI interaction (Gillath et al., 2021).

The paper also has practical significance. Companies are increasingly investing and leveraging AI technologies to provide services to consumers who may be skeptical (Lu et al., 2019). This paper suggests that uptake of AI recommendation systems can be promoted by fostering favorable attitudes, greater perceived accuracy, and lowering AI anxiety. Highlighting performance metrics such as accuracy and reliability in promotional materials may contribute to building humans' trust in AI. When AI recommendation systems are introduced in domains such as investment and healthcare, marketing efforts should actively be trained on alleviating users' concerns.

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