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Abstract

Artificial intelligence (AI) has shown increasing potential in assisting users with decision-making. However, the impact of AI decision speed on users' adoption intention has received limited attention compared to the focus on decision quality. Building on cue utilization theory, this study investigates the influence of AI decision speed on users' intention to adopt AI. Three experiments were conducted, revealing that users exhibit a higher intention to adopt AI when AI's decision speed is higher and historical decision quality is better. Furthermore, the perceived intelligence and perceived risk in decision-making act as mediating variables in these effects. Importantly, the study finds that historical decision quality moderates the relationship between AI decision speed and user adoption, weakening the impact in conditions of high quality. These findings contribute to the understanding of AI adoption and offer practical implications for AI service providers and developers.

Keywords: AI decision speed, Historical decision quality, Perceived intelligence, Perceived decision risk, User adoption

Introduction

Artificial Intelligence (AI) technology is becoming an important engine driving economic growth in many countries. On the consumer side, AI has been widely applied in various products and services (Berente et al., 2021), assisting users in making efficient decisions. For example, shopping chatbot helps users screen and select desired products (Gnewuch et al., 2022), and financial assistants assist bank employees in efficiently processing loan applications (Ge et al., 2021). AI's performance in many decision-making areas has reached or even exceeded that of human experts (Esteva et al., 2017; Krakowski et al., 2022).

However, unlike the rapid development of AI decision-making capabilities, the application and adoption of AI is still progressing slowly. Although AI's decision-making effectiveness has shown tremendous potential, in many situations, users have not shown sufficient interest in using AI-assisted decision-making (Solberg et al., 2022; Wang et al., 2021). For example, Dietvorst et al. (2015) found that users exhibit algorithm aversion when making human-machine assisted decisions; Highhouse (2008) found that people prefer to make decisions themselves rather than relying on AI algorithmic predictions; and Longoni et al. (2019) found that people prefer human service providers over AI. How to promote more users to adopt AI-assisted decision-making advices has become an important issue of concern for relevant scholars and service providers.

Previous research on AI adoption and advice taking behaviors have mainly focused on the intelligence level of AI algorithms, namely decision quality. They found that predictive accuracy is an important factor for users to adopt and accept AI (Castelo et al., 2019; Wu et al., 2020). However, IS research indicate that besides the core indicators of decision quality and effectiveness, external attributes and characteristics of the system may also affect people's perception and, thus, their decision and choice to adopt technology (Cenfetelli, 2004). As one of the external manifestations of algorithmic decision efficiency, decision speed is the most obvious system characteristic during AI task processing. The decision speed required for AI to handle different tasks varies, and decision speed may further affect user experience (Gnewuch et al., 2022). For example, a survey by Acquia, a digital experience and digital strategy consulting firm in the United States, found that about 45% of users find chatbots "annoying," mainly because chatbots respond too slowly.

Existing research on decision speed mainly focuses on the impact of AI decision speed in intelligent customer service scenarios. They found that delayed replies from intelligent customer service can enhance users' perception of personalized AI, enhance their sense of social presence, and promote usage intention (Holtgraves and Han, 2007; Gnewuch et al., 2022). However, this conclusion may not directly apply to AI-assisted decision-making scenarios. This is because, in intelligent customer service scenarios, AI intelligent customer service mainly simulates human replies to create continuous interaction, and in this process, if AI can approach the level of human customer service as much as possible, it can bring users a better interactive experience (Gnewuch et al., 2022; Schanke et al., 2021). However, decision support scenarios focus more on decision effectiveness, and related decisions often involve potential risk factors, such as privacy and health risks in AI-assisted medical diagnosis, financial risks in investment, and fairness and ethical risks in judicial judgments. In such scenarios, users are more likely to consider the cost and benefits of decisions, and delayed replies with low speed may increase users' decision risks and costs (Efendić et al., 2020), which may have a negative impact on user adoption (Efendić et al., 2020; Gnewuch et al., 2022; Schanke et al., 2021). Therefore, it is necessary to explore the effect of AI decision speed on users in AI-assisted decision-making scenarios. To this end, this study proposes and attempts to address the following research questions: *1) Does AI decision speed and historical decision quality affect users' AI adoption in AI-assisted decision-making? 2) If so, what are the potential mechanisms?*

To respond to these questions, we employ the clue utilization theory for further model development and analysis. According to the cue utilization theory, users make decisions based on cues provided by the product, which can be classified into internal and external cues. In this study, it is proposed that the AI decision speed serves as an external cue for users to intuitively evaluate performance, while the historical decision quality of AI decision-making is an internal cue that is related to the task. The external cue of AI decision speed can influence user decision-making, and its impact is also related to the internal cue of AI historical decision quality. Three experiments were conducted to test the proposed hypotheses. The study contributes to the understanding of underlying mechanism of AI decision speed to users' adoption intention, and can provide specific guidance for companies on how to design and present AI system features to encourage user advice taking.

Literature Review

AI Adoption

AI is a machine that mimics human cognitive thinking through computers and algorithms, possessing capabilities such as perception, reasoning, autonomous learning, and problem-solving (Rai et al., 2019).

Currently, AI demonstrates promising prospects in business scenarios such as e-commerce (Longoni and Cian, 2022), financial investment (Ge et al., 2021), medical diagnosis (Jussupow et al., 2021), corporate recruitment (van den Broek et al., 2021), and employee training (Luo et al., 2021). However, extensive research has found that individuals commonly exhibit algorithm aversion, whereby people tend to favor human decisions over algorithmic decisions, even if intelligent algorithms outperform human decision-making in predicting performance. For example, despite the performance of AI algorithms in medical diagnosis tasks exceeding or even surpassing human expert intuition or experience (Longoni et al., 2019; Esteva et al., 2017), users' acceptance of AI algorithm decisions is significantly lower than their high-performance indicators (Castelo et al., 2019; Dietvorst et al., 2015; Dietvorst et al., 2018). Additionally, many studies have pointed out that AI adoption can be influenced by various factors such as design features, task environment factors, and user characteristics.

Regarding design features, some literature mainly discusses from a perspective of anthropomorphism. For example, the use of human or mechanized avatar images (Wang et al., 2021), communication style (Roy and Naidoo, 2021), and social identity roles (helpers or substitutes, etc.) (Wirtz et al., 2018) and other anthropomorphic elements can affect users' social presence, psychological distance, and other perceptions, which in turn affect their willingness to adopt AI's advices.

For task environment factors, existing studies found that users are more willing to accept AI for objective and low-creativity recommendation tasks, and more averse to AI performing subjective or high-creativity tasks (Castelo et al., 2019; Wu et al., 2020). For example, in the healthcare field, compared to human services, users perceive AI as incapable of fully considering their unique personal needs, resulting in lower adoption willingness (Granulo et al., 2021; Longoni et al., 2019). Given the objectivity of AI algorithms in task processing, differential pricing generated by AI customer service is more readily accepted by users than that generated by human customer service (Yalcin et al., 2022; Song and He, 2020).

As for user characteristics, gender and age have a direct impact on AI adoption (Ezer et al., 2009); implicit personality (Wang et al., 2021) and extraversion (Dietvorst and Bharti, 2020) and other personality traits, as well as the level of experience and knowledge in decision-making tasks (Logg et al., 2019) and privacy concerns (Vimalkumar et al., 2021) can also affect users' AI adoption intention.

In summary, existing research has mostly focused on internal features of AI algorithm design and situational factors such as decision tasks and user traits, and lacks sufficient understanding of the external feature of AI decision speed. The following section will review the relevant literature on AI decision speed and further identify the gaps in existing research.

AI Decision Speed

AI decision speed refers to the output speed of AI algorithms for computing results (Holtgraves and Han, 2007). Existing research uses terms such as response latency, communication delay, and response time to characterize the decision speed of AI, most of which are examined from the perspective of users' perception of AI decision speed in terms of the time they wait for AI to process tasks. Regarding how the speed of artificial intelligence decision-making affects user cognition and behavior, current academic research provides explanations from two perspectives.

The first perspective is the anthropomorphic perspective, which is rooted in the "human-like" attributes of artificial intelligence that simulate or replace human interaction. In the context of intelligent customer service, feedback delay serves as a social clue for human-to-human language communication, and an appropriate delay may enhance users' perception of the "human-like" qualities of chatbots (Schanke et al., 2021). For example, adding delay to intelligent customer replies can enhance the perception of personalized AI (Holtgraves and Han, 2007), enhance users' social presence, and promote their willingness to use AI (Gnewuch et al., 2022).

The second perspective is the algorithmic performance perspective. This perspective considers AI as an algorithmic program that does not possess life, and the services provided by AI rely on the processing of existing data by pre-set algorithms. Decision speed is a direct manifestation of its predictive performance (Efendić et al., 2020). Therefore, delays may also be interpreted by users as not working as expected, and their occurrence may be seen as a hindrance to service delivery and interruption of customers' completion of self-service, resulting in lower service evaluations by users (Taylor, 1994). The main research findings from these two perspectives are shown in Table 1.

Source	Contexts	Independent Variables	Dependent Variables	Main Findings
Gnewuch, et al. (2022)	Chatbot	Response time (Instant vs. Delayed)	Intention to Use	Delayed response time positively influences novice users' social presence perceptions and chatbot usage intentions, the effect is negative for experienced users
Lew, et al. (2018)	Online chat	Chronemic response latency (fast vs. slow)	Satisfaction with a chat episode	Slow latency can promote users' higher trust and satisfaction
Cheng, et al. (2022)	Chatbots	Communication Delay	Trust in chatbots	Communication delay negatively affects consumers' perceived trust
Schanke, et al. (2021)	Chatbots	Communication Delay	Transaction	Anthropomorphism of communication delay is beneficial for transaction outcomes.
Efendic, et al. (2017)	Algorithm assistant	Response time (fast vs. slow)	Prediction accuracy	The response time affects the individual's perception of the algorithm's effort, which leads to the perception of the prediction accuracy
Park, et al. (2019)	Algorithm assistant task	Decision speed (fast vs. slow)	Accuracy evaluation	The slow decision speed gives users time to compare and identify the performance of algorithms, then they can more fully evaluate and adopt algorithm decisions.

Table 1 Summary of Relevant Research in AI Speed

Based on the existing literature, we formulate three knowledge gaps as following. Firstly, existing research has focused on intelligent customer service scenarios that emphasize the anthropomorphized feature of AI decision-making speed. However, there is a lack of attention to the characteristics of algorithm performance that AI decision-making speed may reflect. Moreover, whether from the perspective of anthropomorphism or algorithm performance, the explanation of the impact of AI decision-making speed on user behavior is based on users' perceived intelligence, ignoring the possibility that AI decision-making speed may also arouse users' perception of decision-making risks, ultimately affecting user adoption (Featherman and Pavlou, 2003). In the current decision-making practices widely applied in the field of financial investment, medical health diagnosis, and autonomous driving, decision tasks themselves carry certain risks (Hengstler et al., 2016). As decision-making speed may affect users' perception of decision-making risks by reflecting algorithm performance, it is necessary to consider the impact of decision-making speed on user adoption behavior by changing their perception of decision-making risks.

Secondly, existing research has only focused on the impact of AI decision-making speed on users independently, ignoring the interaction of AI's historical decision quality that may occur. Discussing efficiency and effectiveness are classic topics in algorithm task implementation, as well as important considerations for users in the shopping decision-making process (Babin et al., 1994). When users do not obtain sufficient system information, inaccurate understanding of the system may occur. As AI's historical decision quality is an important indicator widely used to reflect AI algorithm effectiveness in practice (You et al., 2022), it is urgent to explore the boundary mechanism of how AI decision-making speed affects user adoption willingness when decision-makers obtain relevant information about historical decision quality.

Thirdly, existing research mainly uses the objective waiting time that users face when making decisions on AI as a measure of decision-making speed (Gnewuch et al., 2022; Schanke et al., 2021). However, waiting time is a subjective concept for users (Baker and Cameron, 1996). In the human-machine collaborative decision-making scenario, users are more likely to compare AI decision-making features with human decision-making situations (Dietvorst et al., 2015; Longoni et al., 2019). Therefore, when there is a deviation in decision-making speed between artificial intelligence and human experts, it is still not sufficiently explored whether users' adoption preference for AI also exists with algorithm aversion or appreciation effects.

In summary, decision-making speed and historical decision quality, as two types of clues in decision-making, are likely to jointly affect users' AI adoption decisions. Based on this, this study will use the clue utilization theory to construct a research model that examines how AI decision-making speed influences user decision-making behavior.

Theoretical Background and Hypotheses Development

Cue Utilization Theory (CUT)

The cue utilization theory is one of the classic theories that explains user behavior and is widely used to explain user product evaluation and adoption of emerging technologies (Eroglu et al., 2001; Parboteeah et al., 2009; Wells et al., 2011). A cue refers to a signal released by an encoder (merchant) and received by a decoder (user) that is used as a standard for evaluating product quality (Cox, 1967; Olson & Jacoby, 1972). According to the cue utilization theory, a product is composed of a series of signals that can be used by users to evaluate product quality. Depending on the type, these signals can be divided into internal cues and external cues (Olson & Jacoby, 1972; Richardson et al., 1994). Internal cues are rooted in the physical properties of the product itself, such as the raw materials, size, shape, or color of the product. External cues are not related to the physical properties of the product and usually include factors such as price, brand, and after-sales service (Richardson et al., 1994).

The importance of cues in user judgment (also known as diagnosticity) is determined by the predictive value and confidence value of the cues. The predictive value refers to the degree to which users associate a specific cue with product quality, representing the reliability of the cue and the likelihood of successfully using the cue to evaluate product quality (Dick et al., 1990). Confidence value is the degree of confidence that users have in their ability to use and judge cues accurately (Cox, 1967; Olson & Jacoby, 1972). This theory suggests that internal cues usually have higher predictive value and are directly related to product quality (such as CPU model for computer products and raw materials for food products). However, when it is difficult for ordinary users to perceive and utilize internal cues, they tend to rely more on external cues (such as price) to make decisions.

The Impact of Decision Speed on AI Adoption Intentions

We propose that AI decision speed and historical decision quality belong to external and internal clues, respectively. AI decision speed is a system feature clue that users can directly observe and understand, which, although not leading to the final decision quality, can reflect the decision performance of the AI algorithm to some extent as an efficiency representation of the decision and is more easily manipulated by algorithm developers. Thus, it conforms to the external clue feature. In contrast, AI's historical decision quality is a direct reflection of the accuracy of AI predictions, highly related to the decision quality of AI and has a high predictive value. Thus, it conforms to the internal clue feature. Based on the above assumptions, this article deduces that AI decision speed and historical decision quality will affect users' decision adoption.

According to the clue utilization theory, when there is limited decision information or internal clues are missing, users will actively search for and rely on external clues to make decisions. As one of the external clues that reflect the efficiency of AI algorithms, decision speed is likely to be used by users to judge whether to adopt AI. When the AI decision speed is high, users may perceive that the AI is embedded with intelligent algorithms sufficient to handle tasks, leading them to perceive higher intelligence in AI. They believe that AI can autonomously operate towards decision goals, adapt to user task requirements, and provide effective output quickly. On the other hand, decision speed may also affect users' perception of AI decision risk. Perceived AI decision risk refers to users' estimation of the possibility of prediction errors by AI, which may result in unexpected performance and individual losses.

The perception of AI intelligence and the perception of AI decision risks can both further influence user adoption of AI. The perception of intelligence reflects to some extent the evaluation of AI technology quality and functional service quality by users (Moussawi et al., 2021). Research has found that the perception of intelligence can increase users' perception of usefulness and trust in using intelligent products, thereby promoting their adoption of AI technology, particularly during the initial interaction process between users and AI products. When users search for any available information to help them make trust inferences, a high perception of intelligence can facilitate their trust in AI products and ultimately enhance their willingness to adopt AI decisions (Moussawi et al., 2021). With regard to the perception of AI decision risks, research indicates that an important motivator of user adoption behavior is the evaluation of the benefits and risks associated with the technology (Featherman and Pavlou, 2003). When users perceive higher risks, they will have a higher sense of suspicion and technological anxiety about decisions (Im et al., 2008), and the technological anxiety caused by high risk will further inhibit their use of new technology (Kummer et al., 2017).

H1: Users have a higher intention to adopt AI with high (low) decision speed.

H1a: Perceived AI intelligence mediates the impact of decision speed on users' AI adoption intention.

H1b: Perceived AI decision risk mediates the impact of decision speed on users' AI adoption intention.

AI historical decision quality is widely regarded as an important indicator for evaluating the effectiveness of AI algorithms in practical settings. As a cue, AI historical decision quality is used by users to assess and judge the credibility and effectiveness of AI recommendations. When the historical decision quality is higher, users form a positive impression of the intelligence level of AI. Compared to humans, individuals are more likely to adopt decision from intelligent algorithms when presented with performance indicators such as prediction accuracy, thus reducing cognitive costs.

According to cue utilization theory, individuals consider past experiences and performances to evaluate the predictive value of future decisions in the decision-making process. If individuals perceive that AI systems have performed well in past decisions, i.e., high historical decision quality, they may attribute greater predictive value to the system and believe it will achieve favorable outcomes in future decisions. Additionally, individual decision adoption behavior is influenced by perceived predictive value. If individuals perceive that AI systems have higher predictive value, indicating favorable future decision outcomes, they are more likely to adopt the AI recommendations. At the same time, historical decision quality impacts perceived intelligence. If AI systems have demonstrated high historical decision quality, individuals are more likely to perceive the system as highly intelligent. Furthermore, perceived intelligence influences individual decision adoption behavior. If individuals perceive that AI systems possess a high level of intelligence, they believe the system's decisions are accurate and reliable, thereby increasing their willingness to adopt its recommendations. If individuals perceive that AI systems entail decision risks, they will decrease their confidence and trust in the system, thereby reducing their intention to adopt its recommendations. Additionally, historical decision quality affects the perception of decision risks. If AI systems have demonstrated good performance in past decisions, individuals are more likely to perceive lower decision risks associated with the system.

H2: Users have a higher intention to adopt AI with high (low) historical decision quality.

H2a: Perceived AI intelligence mediates the impact of historical decision quality on users' AI adoption intention.

H2b: Perceived AI decision risk mediates the impact of historical decision quality on users' AI adoption intention.

The Interaction Effect of AI Decision Speed and Historical Decision Quality

This study posits that the decision-making process and outcomes of users may change when historical decision quality information is present. According to the clue utilization theory, when internal clues are scarce, users mainly rely on external clues for decision-making judgments. However, when internal clues are abundant and easily accessible to users, the impact of external clues on their product evaluation will weaken or even disappear (Miyazaki et al., 2005). When individuals face multiple clues, they tend to use the more diagnostic (predictive) ones as the basis for evaluation (Purohit and Srivastava, 2001). Based on the assumption above, decision speed is an external clue in the user's decision-making process, while historical decision quality is an internal clue. Compared to decision speed, historical decision quality has higher predictive value. Therefore, when both decision speed and historical decision quality information are present, users are likely to use both in making their decisions.

When historical decision quality is low, users perceive lower intelligence in AI usage (Kim et al., 2021; You et al., 2022). In this case, if AI decision speed is also low, it will further reduce the perception of AI intelligence and increase decision risk perception. Therefore, using AI for decision assistance cannot effectively help users with their decision-making, leading to a lower willingness to use AI for decision assistance. However, if the AI decision speed is high, it can increase the perception of AI intelligence and reduce the perception of decision risk, thereby helping to mitigate the negative impact of AI and provide new effective information for the user's decision-making, making users more likely to use AI for decision assistance. That is to say, when historical decision quality is low, users are more willing to adopt AI when the decision speed is high, compared to when the decision speed is low.

When historical decision quality is high, users perceive higher intelligence in AI usage (You et al., 2022). In this case, if AI decision speed is low, it will reduce the perception of AI intelligence and increase the perception of decision risk. However, since historical decision quality information has already provided good predictive value and is more diagnostic than decision speed information (Lew and Walther, 2022), users may still be willing to use AI for decision assistance. If AI decision speed is high, the perception of AI intelligence increases and the perception of decision risk decreases, making users willing to use AI for decision assistance. Therefore, when historical decision quality is high, users generally prefer to use AI for decision assistance, and the influence of decision speed information on their willingness to adopt AI may be relatively small. Based on this, the following hypothesis is proposed:

H3: When historical decision quality is high (vs. low), the impact of decision speed on users' intention to adopt AI advice is weakened.

Study 1

Study 1 aims to firstly examine the influence of artificial intelligence (AI) decision speed on user adoption intention (H1) and verify the mediating effect of perceived AI intelligence and perceived AI decision risk on the aforementioned mechanisms of influence (H1a and H1b).

Procedures and Measures

The experiment used a between-subject design based on decision speed (high vs. low). 80 participants (43 males and 37 females) from an online survey platform (Credamo) were recruited for the study, with an average age of 31 years.

The experiment employed an AI investment advisor from a financial app as the experimental materials. The AI investment advisor is a new product and service in the financial investment field. After the experiment began, participants were randomly assigned to one of two experimental groups (high or low decision speed). They were instructed to imagine themselves using a financial management mobile app to conduct investment business. After entering personal financial information, risk preferences, and investment needs, the app could provide professional investment advice for free through an investment advisor. The app offered two choices: human advisor and AI advisor. The human advisor was composed of a team of experienced and capable managers, and waiting for a human advisor's investment advice took 60 seconds. The AI investment advisor, based on deep learning algorithms, could analyze market investment data and personal data and provide financial recommendation reports. AI decision speed was manipulated by adjusting the waiting time for obtaining AI advisor investment advice. According to the estimated time of several AI products in practice, the high-speed group was set to wait 5 seconds, and the low-speed group was set to wait 120 seconds. Afterwards, participants completed a questionnaire on their adoption willingness and perception, as well as demographic information such as gender and age. The experiment then ended.

All variables in the experiment were adapted from mature scales. The users' AI adoption Intention was measured using three 7-point Likert scales, which were adapted from Komiak and Benbasat (2006). The items were "I am more willing to use intelligent advisors than human advisors to help me make investment decisions", "I am more willing to let intelligent advisors assist me in evaluating which funds to purchase compared to human advisors", and "I am more willing to accept investment portfolio recommendations from intelligent advisors compared to human advisors" ($\alpha = 0.943$). The perceived AI intelligence was measured using four Likert scales, adapted from Moussawi et al. (2022). The items included: "Compared to human advisors, intelligent advisors are able to complete tasks more quickly", "Intelligent advisors are better at understanding my needs compared to human advisors", "Intelligent advisors are better at identifying and processing investment information compared to human advisors", and "Intelligent advisors can provide me with more useful advice than human advisors" ($\alpha = 0.876$). The perceived AI risk of decision-making was measured using three Likert scales adapted from Featherman and Pavlou (2003). The items were "Overall, I feel that using intelligent investment advisors involves a lot of risk", "Compared to human advisors, using intelligent advisors will bring greater uncertainty to my investment decisions", and "Using intelligent advisors exposes me to greater risks compared to human advisors" ($\alpha = 0.934$).

Results and Discussions

To test the effectiveness of decision speed manipulation, participants were asked to answer the following question: "To what extent do you agree that the decision speed of the intelligent advisor is faster than that of the human advisor?" The results of a one-way ANOVA indicated that participants in the high decision speed group perceived the decision speed of the intelligent advisor to be faster than those in the low decision speed group ($M_{high} = 6.37$, $SD = 0.42$; $M_{low} = 3.13$, $SD = 1.36$; $F(1, 80) = 207.515$, $p < 0.001$), demonstrating the successful manipulation.

	Sample size	Users' AI adoption Intention		Perceived AI intelligence		Perceived AI risk	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Low Speed	40	3.76	1.68	4.37	1.48	4.46	1.45
High Speed	40	5.12	1.45	5.38	0.84	3.44	1.48

Table 2. Results of Descriptive Analysis

Table 2 summarizes the descriptive statistics of the groups. First, a one-way ANOVA was conducted to examine the effect of decision speed on perceived intelligence and perceived decision risk. The results showed that participants in the high decision speed group perceived the intelligence of the AI ($M = 5.38$) to be significantly higher than those in the low speed group ($M = 4.37$; $F(1, 80) = 65.94$, $p < 0.001$). At the same time, participants in the high decision speed group perceived the decision risk of the AI ($M = 3.44$) to be significantly lower than those in the low speed group ($M = 4.46$; $F(1, 80) = 21.012$, $p = 0.002$). Besides, a one-way ANOVA was used to test the effect of decision speed on AI adoption willingness. The results showed a significant difference in AI adoption willingness between the two experimental groups ($F(1, 80) = 14.982$, $p < 0.001$), with participants in the high decision speed group ($M = 5.12$) having a significantly higher adoption willingness than those in the low decision speed group ($M = 3.76$).

To examine the mediating role of perceived intelligence and perceived decision-making risk in the relationship between decision speed and AI adoption intention, we conducted mediation analysis using the PROCESS program in SPSS (model 4, sample size = 5000). Decision speed was used as the independent variable (low decision speed = 0, high decision speed = 1), AI adoption intention as the dependent variable, and perceived AI intelligence and perceived AI risk as the mediating variables. Results showed that the decision speed group had a significant positive effect on perceived intelligence (β=1.94, t=8.12, p<0.001), which in turn had a significant positive effect on AI adoption intention (β=0.69, t=6.46, p<0.001). Additionally, decision speed had a significant negative effect on perceived decision-making risk (β=-1.03, t=-3.12, p=0.003), which in turn had a significant negative effect on AI adoption intention (β=-0.54, t=-6.94, p<0.001). After controlling for the direct effect of decision speed on AI adoption intention (β=-0.52, t=-2.23, p=0.029), the mediating effect of perceived AI intelligence on the relationship between decision speed and AI adoption intention was significant (indirect path effect=1.33, LLCI=0.69, ULCI=2.18), as was the mediating effect of perceived decision-making risk (indirect path effect=0.55, LLCI=0.18, ULCI=1.05). Hypotheses 1a and 1b were supported. Adding gender, age, and investment experience as control variables did not change the significance of the results.

The results of Study 1 showed that when AI decision speed was high (vs. low), users had a higher intention to adopt AI. Perceived AI intelligence and perceived AI risk played a mediating role in this process. Considering the universality of historical decision quality in practical decision tasks, study 1 introduced clues about AI's historical decision quality based on Study 1 to investigate how decision speed and historical decision quality jointly affect user adoption.

Study 2

The purpose of study 2 was to examine the impact of historical decision quality on AI adoption (H2) and the mediating role of perceived intelligence and perceived decision risk in the aforementioned impact (H2a and H2b).

Procedures and Measures

The experiment employed a between-group design with historical decision quality (high vs. low) as the independent variable. A total of 120 participants (61 males, 59 females) from an online survey platform (Credamo) took part in this experiment. The average age of the participants was 32 years.

Experiment 2 adopted the same scenario as Experiment 1, involving intelligent investment advisors. Historical decision quality was manipulated by presenting the investment return rates of human advisors and intelligent advisors over the past three years. Annual investment return rate is an important indicator for evaluating the investment decisions and capabilities of fund managers, with higher return rates indicating higher profitability of the funds operated and recommended. Taking into account real investment practices and consulting professional managers in the relevant investment field, the average annual investment return rate for human advisors in the high historical decision quality group was set at 10.60%, while for intelligent advisors it was set at 12.72%. In the low historical decision quality group, the average annual investment return rate for human advisors was 10.60%, and for intelligent advisors it was 8.48%.

In the experiment, participants were randomly assigned to one of the two experimental groups. They were asked to provide specific numerical values regarding the annual return rates of human advisors and intelligent advisors to ensure their careful reading. The measurement of variables used the same scales as in Experiment 1, with Cronbach's alpha values for AI recommendation adoption, perceived intelligence, and perceived decision risk being 0.959, 0.879, and 0.933, respectively. These values exceeded the threshold of 0.7, indicating the reliability of variable measurement.

Results and Discussions

In order to test the effectiveness of manipulating historical decision quality, participants were asked to answer the following item: "To what extent do you agree that the investment return rate of the intelligent advisor is higher than that of the human advisor?" The results of a one-way ANOVA indicated that participants in the high decision quality group perceived the decision quality of the intelligent advisor to be higher compared to participants in the low decision quality group ($M_{\text{high quality}}$ = 5.75, SD = 1.19; $M_{\text{low quality}}$ = 2.20, SD = 1.38; $F(1, 120)$ = 226.634, $p < 0.001$), confirming the success of the manipulation.

Table 2 summarizes the descriptive statistics for each group. Firstly, a one-way ANOVA was conducted to examine the influence of historical decision quality on perceived intelligence and perceived decision risk.

The results revealed that participants in the high decision quality group perceived higher intelligence in AI ($M = 5.58$) compared to participants in the low decision quality group ($M = 3.80$; $F(1, 120) = 73.161$, $p < 0.001$). Additionally, participants in the high decision quality group perceived lower decision risk in AI ($M = 3.03$) compared to participants in the low decision quality group ($M = 4.79$; $F(1, 120) = 48.071$, $p < 0.001$). Subsequently, a one-way ANOVA was conducted to examine the effect of historical decision quality on AI recommendation adoption. The results showed a significant difference in AI recommendation adoption between the two experimental groups ($F(1, 120) = 117.597$, $p < 0.001$), with participants in the high decision quality group ($M = 5.73$) displaying a significantly higher intention to adopt AI recommendations compared to participants in the low decision quality group ($M = 3.02$). This finding supported hypothesis H2.

	Sample size	Users' AI adoption Intention		Perceived AI intelligence		Perceived AI risk	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Low Quality	60	3.02	1.64	3.80	1.37	4.79	1.47
High Quality	60	5.73	1.02	5.58	0.83	3.03	1.31

Table 3. Results of Descriptive Analysis

To test the mediating role of perceived intelligence and perceived decision risk in the relationship between historical decision quality and AI adoption, a mediation analysis was conducted using the PROCESS macro in SPSS (Model 4, sample size = 5000). Historical decision quality was treated as the independent variable (low decision quality = 0, high decision quality = 1), AI adoption as the dependent variable, and perceived intelligence and perceived decision risk as the mediator variables. The results indicated that historical decision quality had a significant positive effect on perceived intelligence ($\beta = 1.77$, $t = 8.55$, $p < 0.001$), and perceived intelligence further had a significant positive effect on AI adoption ($\beta = 0.72$, $t = 9.87$, $p < 0.001$). Historical decision quality had a significant negative effect on perceived decision risk ($\beta = -1.76$, $t = -6.93$, $p < 0.001$), and perceived decision risk had a significant negative effect on AI adoption ($\beta = -0.34$, $t = -5.65$, $p < 0.001$). After controlling for the direct effect of historical decision quality on AI adoption ($\beta = 0.83$, $t = 4.80$, $p < 0.001$), the mediating effect of perceived intelligence in the relationship between historical decision quality and AI adoption was significant (indirect path effect = 1.28, LLCI = 0.83, ULCI = 1.77). Similarly, the mediating effect of perceived decision risk in the relationship between historical decision quality and AI adoption was significant (indirect path effect = 0.59, LLCI = 0.26, ULCI = 1.05). These findings provided support for hypotheses H2a and H2b. The significance results remained unchanged after including gender, age, and financial investment experience as control variables in the model.

The above results indicate that in the context of AI-assisted decision-making, users' AI intention does not necessarily exhibit the algorithm aversion and preference for human decision-making proposed by Dietvorst et al. Therefore, when AI demonstrates higher historical decision quality than human experts, people still show a higher willingness to adopt AI recommendations.

Study 3

The purpose of Study 3 is to examine the interaction effect of the quality of AI historical decisions on the relationship between AI decision speed and users' AI adoption intention (H3).

Procedures and Measures

This experiment employed a 2 (decision speed: high vs. low) × 2 (historical decision quality: high vs. low) between-subjects design. A total of 389 participants (170 males and 219 females) from the Credamo platform participated in this experiment. The average age of the participants was 29 years. All participants had not taken part in Study 1.

We adopted the same scenario of an intelligent investment advisor as in study 1 but added the investment return rate of both the human and intelligent advisors over the past three years (similar to study2) to manipulate their historical decision quality. The annual investment return rate is an important indicator for evaluating the investment decisions and abilities of fund managers, with higher rates indicating greater returns from the funds operated and recommended by them. Participants were randomly assigned to one of four experimental groups. They were asked to fill in specific values for the decision speed and annual return rate of the human and intelligent advisors to ensure that they read the scenario carefully. Measurements of other variables followed the same scales as in Study 1.

Results and Discussions

After excluding 8 participants who failed the attention tests, 381 valid samples were included in the statistical analysis. To test the effectiveness of the experimental manipulation, participants were asked to respond to the following two items: "To what extent do you agree that the decision speed of the intelligent advisor is faster than that of the human advisor?" and "To what extent do you agree that the investment return rate of the intelligent advisor is higher than that of the human advisor?". The results of the one-way ANOVA showed that participants in the high decision speed group perceived the decision speed of the intelligent advisor to be faster than those in the low decision speed group ($M_{high\ speed}$=6.56, SD=0.61; $M_{low\ speed}$=2.84, SD=1.70; F(1,381)=802.033, p<0.001). Additionally, participants in the high historical decision quality group perceived the investment return rate of the intelligent advisor to be higher than those in the low decision quality group ($M_{high\ quality}$=6.03, SD=0.89; $M_{low\ quality}$=2.21, SD=1.12; F(1,381)=1363.200, p<0.001). These results suggest that both the decision speed and historical decision quality of the AI were successfully manipulated.

To further examine the effects of decision speed and historical decision quality on the perceived AI intelligence, a one-way ANOVA was performed. The results showed that the main effects of decision speed (F(1,381)=203.522, p<0.001) and historical decision quality (F(1,381)=298.785, p<0.001) were significant, and the interaction effect between decision speed and historical decision quality was also significant (F(1,381)=15.818, p<0.001). Specifically, when the historical decision quality of the AI was low, participants in the high decision speed group perceived AI intelligence (M=4.40) to be significantly higher than those in the low speed group (M=2.64, p<0.001). Similarly, when the historical decision quality of the AI was high, participants in the high decision speed group perceived the intelligence of the AI (M=5.69) to be significantly higher than those in the low speed group (M=4.69, p<0.001).

Moderator	Independent variables	Simple size	Users' AI adoption intention		Perceived AI intelligence		Perceived AI risk	
			Mean	S.D.	Mean	S.D.	Mean	S.D.
Low historical decision quality	Low decision speed	94	2.48	0.12	2.64	1.12	5.32	1.07
	High decision speed	93	3.44	0.12	4.40	1.09	4.53	1.46
high historical decision quality	Low decision speed	99	5.61	0.11	4.69	0.84	3.24	1.36
	High decision speed	95	5.88	0.12	5.69	0.64	3.41	1.35

Table 4. Results of Descriptive Analysis

Next, a one-way ANOVA was conducted to examine the effects of decision speed and historical decision quality on perceived AI risk. The results indicated that the main effects of decision speed (F(1,381)=5.456, p=0.020) and historical decision quality (F(1,381)=140.220, p<0.001) were significant, and the interaction effect between decision speed and historical decision quality on perceived decision risk was also significant (F(1,381)=12.629, p<0.001). When the historical decision quality of AI was low, the high decision speed group perceived AI risk (M=4.53) significantly lower than the low speed group (M=5.32, p<0.001). When the historical decision quality of AI was high, there was no significant difference between the perceived decision risk of the high decision speed group (M=3.41) and the low speed group (M=3.24, p=0.385).

Finally, a one-way ANOVA was conducted to analyze the interactive effects of decision speed and historical decision quality on users' AI adoption intention, as shown in Figure 1. The results indicated that the main effects of decision speed (F(1,381)=29.177, p<0.001) and historical decision quality (F(1,381)=585.743, p<0.001) were significant, and the interaction effect between decision speed and historical decision quality was also significant (F(1,381)=9.093, p=0.003). When the historical decision quality was low, the high-speed group showed a significantly higher intention to adopt AI (M=3.44) than the low-speed group (M=2.48, p<0.000). However, for the high historical decision quality group, there was no significant difference between the high-speed group (M=5.88) and the low-speed group (M=5.61, p=0.089). Hypothesis H3 was supported.

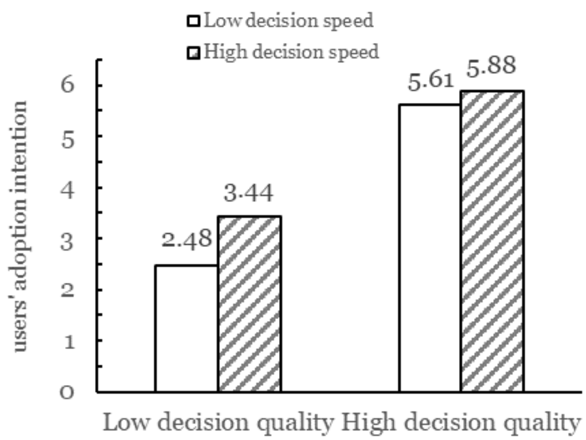

Figure 1 The Interaction of AI Speed and Historical Decision Quality

To further investigate the interactive effects of perceived decision speed and historical decision quality on users' adoption of AI recommendations, we employed the PROCESS procedure in SPSS (Model 8) with a sample size of 5000. Perceived decision speed (low = 0, high = 1) served as the independent variable, historical decision quality (low = 0, high = 1) as the moderator, and adoption of AI recommendations as the dependent variable. Perceived intelligence and perceived decision risk were included as mediating variables. The results revealed that when historical decision quality was low, the mediating effect of perceived intelligence was significant (indirect effect = 1.76, LLCI = 1.489, ULCI = 2.030). Even when historical decision quality was high, the mediating effect of perceived intelligence remained significant (indirect effect = 0.99, LLCI = 0.726, ULCI = 1.258). However, there was a significant difference in the size of the mediating effect of perceived intelligence between the two historical decision quality groups (effect size = -0.49, LLCI = -0.75, ULCI = -0.24). This suggests that the mediating role of perceived intelligence is stronger when historical decision quality is low.

Regarding perceived decision risk, the mediating effect was significant when historical decision quality was low (effect size = 0.18, LLCI = 0.092, ULCI = 0.297). However, when historical decision quality was high, the mediating effect of perceived decision risk was not significant (indirect effect = -0.038, LLCI = -0.127, ULCI = 0.056). There was a significant difference in the mediating effect of perceived decision risk between the two historical decision quality groups (effect size = -0.22, LLCI = -0.372, ULCI = -0.093). This indicates that the mediating effect of perceived decision risk is weakened when historical decision quality is high. The results remained unchanged when controlling for gender, age, and financial investment experience. In summary, the findings demonstrate an interactive effect between perceived decision speed and historical decision quality. The mediating roles of perceived intelligence and perceived decision risk in users' adoption of AI are more pronounced when historical decision quality is low. However, these mediating effects become less significant when historical decision quality is high.

Conclusions and Discussions

This research focuses on the AI-assisted decision-making context and conducts 3 experiments to examine the effects of AI decision speed on user decision adoption. The main findings are as follows: 1) AI decision speed positively affects users' adoption intention; 2) AI historical decision quality positively affects users' adoption intention. 3) the perceived intelligence and perceived risk play a mediating role in the effects of AI decision speed/historical decision quality on users' decision adoption; 3) the historical decision quality moderates the effects of AI decision speed.

Theoretical Contributions

This research contributes to theory in three ways. Firstly, it extends the current understanding and knowledge on AI adoption. Unlike ordinary IT components, AI applications possess both the "algorithmic" instrumentality and the "human-like" agency (Efendić et al. 2020; Gnewuch et al. 2022). Previous research mainly explored the effects of internal quality characteristics of AI algorithms, such as prediction accuracy, transparency, and explainability, on user adoption from the perspective of algorithmic and human-like characteristics (You et al. 2022; Zhang et al. 2021; Wu et al. 2020), while ignoring the external features of AI presentation. By examining the effects of AI decision-making speed on user adoption, this research shows that in addition to the internal quality characteristics of AI, the external features that users directly experience and perceive can also influence user adoption.

Secondly, this research contributes to the research on the effects of AI decision-making speed. Previous research has mainly focused on the intelligent customer service context, where users and AI are interactive parties, and decision-making speed is treated as a type of humanization signal to explore how it affects user attitudes (Cheng et al. 2022; Gnewuch et al. 2022). In the AI-assisted decision-making context, little is known about whether and how AI decision-making speed affects user behavior. By examining the effects of decision-making speed on user AI adoption, this research indicates that in the AI-assisted decision-making context, AI decision-making speed also affects user behavior, and the effects are opposite to those observed in the intelligent customer service context. By examining the mechanisms of this effect, we found that previous research ignored the benefits and risk evaluations during user decision adoption (Hengstler et al. 2016). By examining the effects of AI decision-making speed on perceived intelligence and perceived decision risk, this research shows that AI decision-making speed not only affects users' perceived benefits but also their perceived risks.

Thirdly, this research introduces the classic theory of clue utilization into the emerging context of AI-assisted decision-making, expanding the application range and research scope of the theory. This research shows that AI decision-making speed affects the clue utilization and information search of users in the AI-assisted decision-making context. It also demonstrates that users' perceived intelligence and perceived decision risk mediate the effects of AI decision-making speed on user adoption, and the historical decision quality moderates the effects of AI decision-making speed.

Practical Implications

This article provides some insights for enterprise AI service providers and developers on adopting artificial intelligence applications. Firstly, in the past, intelligent customer service applications mainly emphasized the anthropomorphic characteristics of AI, by designing appropriate interaction delays to bring users closer psychologically, thereby promoting higher user satisfaction. However, in the increasingly common context of AI-assisted decision-making, when AI algorithms are embedded in ordinary web programs, app applications or other non-anthropomorphic products, presenting low AI processing speeds for decision-making tasks may hinder the delivery of services, resulting in a decrease in customer trust and an increase in perceived decision-making risk. Therefore, service providers and developers should consider the context and internal and external features of AI applications.

Secondly, in the absence of historical decision quality information or when historical decision performance is poor, AI decision-making speed will significantly affect users' willingness to adopt AI. Therefore, when unable to provide decision quality information or when historical decision performance is poor, service providers and developers can reduce users' perceived uncertainty and risk by designing responsive features to offset the impact of insufficient historical decision quality information. When AI's historical decision performance has consistently been at a high level (such as high return rates for financial applications, high click-through and purchase rates for intelligent push), users are more willing to “wait” for high-quality decision-making results. At this time, lower AI decision-making speeds will not hinder users’ willingness to use AI. Therefore, when facing the trade-off between decision speed and decision quality, service providers and developers should prioritize improving decision quality and displaying better historical decision quality information to users. This can avoid the negative impact that decision speed may produce.

Limitations

There are three shortcomings in this article. Firstly, the article mainly discusses how two types of user clues, AI decision speed and historical decision quality, affect individual decision-making from the perspective of user clue utilization, responding to current issues of low trust and weak adoption of AI among users. This research expands the relevant studies of user acceptance of AI product services and technology. However, in the context of human-machine collaborative decision-making, besides affecting users’ acceptance of AI services, whether AI decision speed has persuasive effects on other user cognition or behaviors, such as decision switching and service satisfaction, is worth further exploring, enriching the understanding of how AI decision speed affects user behavior.

Secondly, the experimental situation of this study is AI financial decision-making, and users may consider privacy risks and financial risks when adopting the decisions. Perception of other types of risks still lack examination. Subsequent research can examine the universality of the impact of AI decision speed on user risk perception and adoption willingness in more AI-assisted decision-making contexts, such as medical health and recruitment interviews.

Thirdly, this article examines the role of historical decision quality in the impact of AI decision speed from the dimensions of efficiency and effectiveness. Are there any other boundary conditions for the impact of AI decision speed? Literature indicates that design features such as AI’s anthropomorphic characteristics or relational interactions, users’ technological readiness attitudes or risk preferences, may affect user adoption willingness, and whether these factors can moderate the impact of decision speed needs further examination.

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