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RESEARCH ARTICLE

Time is shrinking in the eye of AI: AI agents influence intertemporal choice

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Abstract
Agents help consumers make decisions. While agents have traditionally been human (e.g., sales associate, real estate agent, financial advisor), artificial intelligence (AI) agents are becoming more prevalent. We find that the type of agent, AI versus human, has an influence on intertemporal judgment. Specifically, when an agent is identified as AI, the concept of fast processing becomes more accessible, which makes time delays seem subjectively longer and encourages impatient behavior. These results have implications for how to conceptualize the influence of AI agents on judgment, the impact of time perception on intertemporal choices, and the sources of impatient behavior.

KEYWORDS
intertemporal choice, judgment and decision making, preference and choice, time perception

INTRODUCTION

Consumers are experiencing a new era of technology. An evolving technology is the artificial intelligence (AI) agent. AI agents help consumers make decisions (De Bellis & Johar, 2020; Longoni & Cian, 2022; Tong et al., 2021). The beauty brands Curology, Function of Beauty, and Proven use AI agents to help consumers make decisions about haircare, skincare, and makeup (Longoni & Cian, 2022). Porsche offers an AI-driven Porsche Car Configurator that helps consumers design their car without the assistance of a sales associate. Danelfin (tagline: "AI-powered stock picking") uses an AI to identify relevant stocks and assist investors in building a successful stock portfolio. Several dating apps and websites, including DatingAI.pro, IrisDating, Yourmove.ai, claim to reduce "time spent swiping" by using AI to curate better matches. Amazon allows customers to chat with Rufus—a generative AI-powered shopping assistant that can answer questions about products and make recommendations based on customer needs. LendingTree uses an AI tool that curates a consideration set of auto loans that vary in APR and duration. Collectively, these examples illustrate how an AI agent can assist consumers during decision making, just as human agents have done so in the past.

In this paper, we focus on how the source of a decision aid (human agent vs. AI agent) influences intertemporal decision-making. Experts have proposed that consumers associate AI with fast and efficient data processing (Bughin et al., 2017; Cukier, 2021; Häubl & Trifts, 2000). If this is indeed so, associations to fast and efficient processing could influence consumers' subjective perception

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of time, so that a temporal delay (e.g., the time until a rebate is received, a loan duration) feels subjectively longer when consumers receive information about products from an AI agent (vs. a human agent). Consequently, temporal delays associated with negative utility (e.g., delaying a reward) could exert a higher cost which, in turn, lead consumers to prefer more immediate gains.

Our paper contributes to the literature in four important ways. First, we contribute to the work on consumers' reactions to AI agents in business contexts by examining the consequences of adopting AI agents on intertemporal decision-making. Second, we provide evidence that people associate AI agents with fast, efficient information processing which, consequently, shapes their judgments. Third, we identify a new antecedent (i.e., an AI agent) that influences the subjective perception of time. Fourth, we add to the growing body of research on intertemporal choices by exploring the influence of receiving choice sets from an AI agent.

CONCEPTUAL BACKGROUND

The perception of subjective time

Time is measured objectively but experienced subjectively. An objective time interval can be perceived as subjectively shorter or longer than its actual length. Antecedents that influence the perception of subjective time include arousal (Kim & Zauberman, 2013; Shalev & Morwitz, 2013), emotion (Droit-Volet & Meck, 2007), motivation (Gable & Poole, 2012), construal level (Wang et al., 2018), the recall of a nostalgic experience (Huang et al., 2016), and the spatial distance associated with a time-duration judgment (Kim et al., 2012).

One explanation of how cognitive factors influence the perception of subjective time is the "internal clock" hypothesis (Allman et al., 2014; Gibbon et al., 1984; Treisman, 1963). The hypothesis assumes people have a cognitive timer (i.e., an "internal clock") that is used to represent subjective time. When the internal clock runs faster than an objective clock, more subjective time passes than objective time, and a time interval feels longer than its objective duration. Conversely, when the internal clock runs slower than the objective clock, less subjective time passes than objective time, and a time interval feels shorter than its objective duration.

The speed of the internal clock depends on factors such as one's arousal, mood, and the characteristics of environmental stimuli. For example, high-arousal emotions (e.g., fear) have been shown to increase perceived time duration by speeding up the internal clock (Droit-Volet et al., 2004; Fayolle et al., 2015) while lowering arousal (e.g., relaxation) has been shown to reduce subjective time duration by slowing down the internal clock (Gorn et al., 2004; Wearden, 2008). More related to the current research, studies have demonstrated that one's internal clock can be affected by characteristics of environmental stimuli, such as their speed and rate of change. For example, observing stimuli moving at high speeds results in a faster internal clock, leading to an increase in subjective time duration (Brown, 1995; Kaneko & Murakami, 2009). Similarly, when an environment has frequent changes (e.g., fast-changing objects, visual flickers, frequent occurrence of sensory events), a time duration is judged as longer (Droit-Volet & Meck, 2007; Herbst et al., 2013; Kanai et al., 2006; Linares & Gorea, 2015; Poynter & Homa, 1983). Similar effects have been observed for auditory stimuli: music or metronome sounds with a fast tempo speed up the internal clock and make a time interval seem longer (Kim & Zauberman, 2019b; Treisman et al., 1990; Zakay et al., 1983).

The speed of the internal clock can also influence the perception of future time intervals. When the lapse of current time feels long, suggesting the internal clock is running faster than the objective clock, an anticipated time delay seems longer. For example, fast tempo music (as compared to slow tempo music) makes the lapse of current time feel longer and upcoming delays seem longer, so that people want sooner, smaller rewards (Kim & Zauberman, 2019b). Similarly, thinking about a nostalgic experience makes current time feel shorter and an upcoming time delay seem shorter, so that people want larger, later rewards (Huang et al., 2016). In each of these cases, it could be argued that the internal clock used to assess the passage of time in the present can also be used to estimate how much subjective time will pass in a future time interval (Allman et al., 2014).

Consumer perception of algorithms

Artificial intelligence is manifested by programs, algorithms, systems, and machines that exhibit aspects of human intelligence (Huang & Rust, 2018). Early AI consumer research focused on documenting consumer aversion to algorithms and tried to understand the reasons for this aversion (e.g., Burton et al., 2020; Dietvorst et al., 2015). More recent research has found that algorithm aversion and algorithm appreciation exist in different contexts (e.g., Bakpayev et al., 2022; Longoni et al., 2019). For example, people believe that algorithms are better at objective tasks and utilitarian decisions, while humans are better at subjective tasks and hedonic decisions (Castelo et al., 2019; Longoni & Cian, 2022; Luo et al., 2019).

A prevalent perception of AI relates to its operational characteristics. Given the advanced information processing capability of AI, algorithms are believed to be faster and more efficient than humans at processing information (Wathieu et al., 2002; Xiao & Benbasat, 2007). Such perceptions should be salient when people are interacting with an AI agent and waiting for its response, as this is the time people are likely to attend to an AI agent's processing speed. Indeed, people view slowly generated predictions from algorithms as less accurate and, thus, are less likely to rely on them (Efendić et al., 2020). If an AI agent is associated with fast and efficient processing, it is likely to influence people's subjective perception of time. Building on prior findings that the speed and rate of change of environmental stimuli affect one's internal clock, we propose that perceptions of the superior processing speed (e.g., works fast, can do a lot of tasks) of an AI agent, compared to a human agent, will speed up one's internal clock, and as a result, current and future time intervals will feel longer.

Subjective time perception and intertemporal choice

People often need to choose from outcomes distributed across multiple points in time (Loewenstein & Prelec, 1992; Soman et al., 2005; Urminsky & Zauberman, 2015). These choices reflect intertemporal preferences. A common form of intertemporal choice involves a trade-off between a smaller, sooner reward and a larger, later reward, such as receiving a small amount of money now or a larger amount of money in the future, making discretionary purchases in the present or saving money for retirement (i.e., delay spending to the future), and deciding whether to spend now or pay down debt (Chen et al., 2005; Frederick et al., 2002; Strathman et al., 1994).

The psychological processes that account for intertemporal preferences can be grouped into two broad streams of research: investigations of outcome effects and investigations of time effects (Kim & Zauberman, 2019a; Malkoc & Zauberman, 2018). First, prevalent in the intertemporal literature but unrelated to the current investigation, intertemporal choice can be influenced by the type of outcome and the construal of that outcome. Examples of outcome effects include hedonic outcomes (e.g., beer, candy, soda) resulting in more impatience than monetary outcomes (e.g., money) (Estle et al., 2007) and experiential outcomes (e.g., movies) resulting in more impatience than material outcomes (e.g., books) (Goodman et al., 2019). Examples of construal effects include becoming more impatient when goal activation (Shaddy & Lee, 2020) or reward motivation (Loewenstein, 1996; Skrynka & Vincent, 2019; Van den Bergh et al., 2008) increases.

Second, and most relevant to this research, intertemporal choices can be influenced by factors that alter how people construe time (Kim et al., 2012; Kim & Zauberman, 2019a; Zauberman et al., 2009). For instance, the further away people perceive retirement to be, the less willing they are to save (Zauberman & Kim, 2012). Similarly, when the temporal distance between options is perceived as subjectively long, people will prefer a sooner, smaller outcome (e.g., prefer a small box of chocolates in 5 days over a large box of chocolates in 35 days), but will reverse their preference when the temporal distance between options is perceived as subjectively short (e.g., prefer a large box of chocolates in 45 days over a small box of chocolates in 15 days) (Dai & Fishbach, 2013). The metric used to express time also contributes to the distortion of time duration and, subsequently, influences intertemporal choice (LeBoeuf, 2006; Read et al., 2005). For example, when the timing of a future option is described using a small metric (e.g., 14 days) versus a large metric (e.g., 2 weeks), consumers tend to perceive the future to be further away and show a steeper discounting curve (i.e., greater impatience) (Siddiqui et al., 2018). In general, these factors influence the subjective perception of the temporal distance between the two options.

THE CURRENT RESEARCH

We propose that interacting with an AI agent, as compared to a human agent, makes future delays feel longer because interacting with an AI agent activates a "fast processing" belief, which speeds up one's internal clock. Consequently, this will encourage the choice of a smaller, sooner reward over a larger, later reward. This hypothesis is shown in Figure 1 (AI agent → "Fast

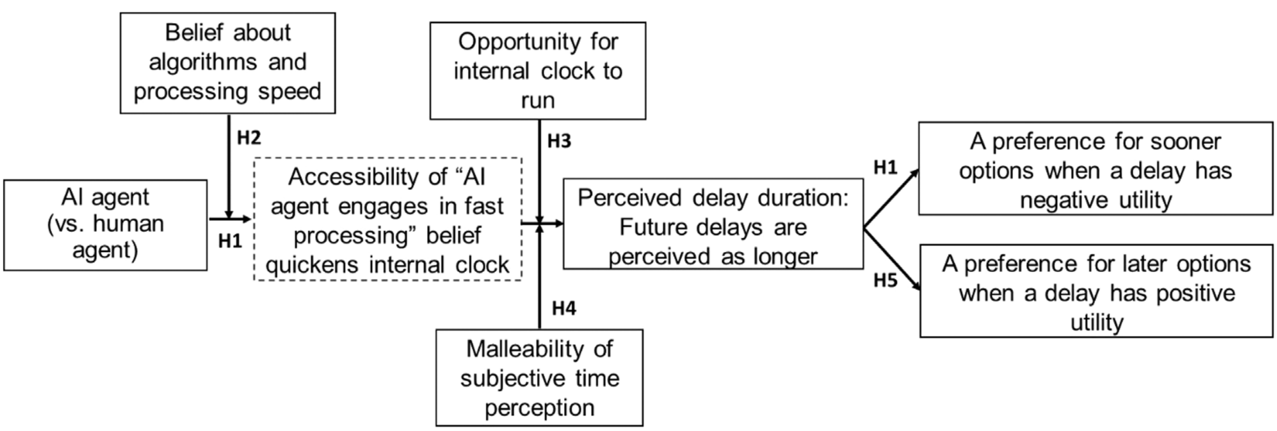

FIGURE 1 Conceptual model.

Processing" beliefs quicken internal clock → Future delays perceived as longer → Preference for sooner options). We bound H1 to situations where a delay has negative utility because choice options can reflect a delay of a reward (e.g., the timing of a rebate) or an extension of a stream of losses (e.g., a longer set of loan payments).

> **H1.** *Assistance from an AI agent (vs. a human agent) will result in preference for sooner options, owing to future delays being perceived as longer, when a delay has negative utility.*

Next, we propose three moderators based on H1. The first moderator involves manipulating the underlying process responsible for the effect (Spencer et al., 2005). In our case, we sought to manipulate the implicit beliefs about AI agents being fast. The "manipulate the beliefs" approach has been used in other domains, including self-control (Vohs et al., 2012), affect regulation (Labroo & Mukhopadhyay, 2009), motivated behavior (Zheng et al., 2023), and socially responsible decisions (Kwan et al., 2023). In our case, the proposed effect of an AI agent on intertemporal choice should be attenuated when an AI agent is not believed to be fast. For example, this could happen when consumers learn that an AI agent is not characterized as being fast, but instead by its ability to solve hard problems at the cost of processing speed (e.g., OpenAI's o1 model).

> **H2.** *The influence of an AI agent (vs. a human agent) on the preference for sooner options will be attenuated when beliefs supporting the "AI agent → fast processing" association are weakened.*

Second, the H1 effect should be attenuated when there is no opportunity for the internal clock to run. A consumer's internal clock runs when they are waiting for an agent to respond to a request. If getting information from the agent does not involve a wait time (e.g., a response is delivered immediately), then the internal clock should be unable to run and, thus, the identity of the agent should not affect time perception and intertemporal choice.

> **H3.** *The influence of an AI agent (vs. a human agent) on the preference for sooner options will be attenuated when there is no wait for the agent's response.*

Third, the H1 effect should be attenuated when judgments about time delays are less malleable (i.e., it is hard for the internal clock to influence the perception of a time interval). To illustrate, when people were asked how long it would be until they did laundry, they estimated a shorter time when using a number-of-days metric (e.g., "x days") than a date metric (e.g., "MM/DD") (LeBoeuf, 2006). Estimates of the number of days to an event are more sensitive to bias (e.g., bias from a "zero day" anchor, bias from an internal clock) than estimates made using a date because the number of days estimate puts more emphasis on the time interval (i.e., current time to future time) (LeBoeuf, 2006). When consumers construct a time estimate using a date, "the date may be construed as a relatively abstract point in time, and consumers may not even compute the interval's length" (LeBoeuf, 2006, p. 61). Thus, we propose that the influence of the identity of the agent on intertemporal choice will be present when a time duration is indicated using a time interval but attenuated when a time duration is indicated using a specific end-date.

> **H4.** *The influence of an AI agent (vs. a human agent) on the preference for sooner options will be attenuated when subjective time perception becomes less malleable.*

Finally, we investigate how an AI versus human agent influences a different type of intertemporal choice. H1 can be tested using a trade-off between a smaller, sooner reward and a larger, later reward. In this case, the temporal delay between the sooner and later reward is associated with negative utility (i.e., waiting for the later reward creates a negative feeling, and the reward has a diminishing utility over time), and thus, a longer future delay should lead to a preference for the smaller, sooner reward (H1). However, a delay is not always associated with negative utility. For example, when choosing between receiving (1) a larger, recurring stream of rewards over a shorter period of time (e.g., receive $20 per week for 9 weeks, starting now) vs. (2) a smaller, recurring stream of rewards over a longer period of time (e.g., receive $15 per week for 15 weeks, starting now), the temporal "delay" between the shorter and longer reward streams can be associated with positive utility because the "delay" refers to an additional time period of rewards. If the delivery of these options by an AI (vs. a human) agent makes people feel that the additional period of rewards is longer, the lower-longer reward stream (e.g., $15 per week for 15 weeks) should become more attractive.

> **H5.** *Assistance from an AI agent (vs. a human agent) will result in a preference for a lower, longer reward stream, owing to future delays being perceived as longer, when a delay has positive utility.*

The same logic can be applied to the streams of recurring payments in the loss domain. This often occurs in loan decisions. Consumers need to make trade-offs between a shorter-term loan with a higher monthly payment and a longer-term loan with a lower monthly payment. Contrary to the reward streams discussed in H5, the temporal delay between the shorter- and longer-term loans should be associated with negative utility because people have to continuously make payments during the delay period, which is a negative experience (see H1). In other words, the temporal delay makes people feel that they have to experience the losses for a longer time. Thus, if an AI (vs. a human) agent makes a future delay feel longer, it will lead to preference for a shorter recurring payment stream (e.g., shorter-term loan) (H1).

We present eight studies that test our conceptual model. As for the dependent variable, Studies 1–4 examine intertemporal choices between a smaller, sooner reward and a larger, later reward. Studies 5 and 6 investigate choices of recurring reward or payment streams. In Studies 1a and 1b, we show that an AI agent, as opposed to a human agent, encourages people to choose a smaller, sooner reward because the delay between the two rewards is perceived as longer (H1). Studies 2–4 show that the effect of agent on intertemporal choice is attenuated when the association between AI agent and fast processing is made less accessible (Study 2; H2), there is no time delay before receiving assistance (Study 3; H3), and when time duration is not easily malleable (Study 4; H4). Studies 5a and 5b examine the effect of agent type on a choice between two streams of recurring rewards or two streams of recurring payments, respectively. Study 5a shows that an AI agent, as opposed to a human agent, leads to preferences for long-term over short-term reward streams (i.e., allowance plan) because the difference between two timeframes is perceived as greater (H5). Study 5b shows that an AI agent leads to preferences for short-term over long-term payment streams (i.e., loan plan) because the difference between two timeframes is perceived as greater (H1). Study 6 reports industry data that are consistent with the findings of Study 5b and shows that people select shorter length loans when a consideration set of loans is curated by an AI agent as opposed to a human agent.

The details of the procedure, the data, and the SPSS analysis code for the studies are posted at OSF (https://osf.io/vzrhn/?view_only=bd77b6aebf9c484c96cc80bef3147b69).

STUDY 1A

The goal of Studies 1A and 1B was to investigate how interacting with an AI agent, compared to a human agent, influences time perception and choice in two different contexts. We predicted that interacting with an AI (vs. human) agent would increase the perceived length of a future delay and thus encourage the choice of a smaller, sooner reward over a larger, later reward (H1).

Method

Design

The study was preregistered (https://aspredicted.org/79pj-4jwd.pdf). Three hundred participants were recruited from Prolific (UK) (M_{age} = 36.57; 58.80% female). Participants were randomly assigned to one of two conditions (agent: human vs. AI). Sixteen participants did not pass a preregistered attention check, leaving a final sample of 284 participants.

Procedure

Participants read that they were planning a summer vacation for their family and wanted to visit some travel websites for vacation ideas (see Appendix S1 for full text of study materials). During their search, they visited TripAway.com and sought advice on vacation options. Participants in the AI (human) agent condition were told:

> You learned that if you are not sure where to go for vacation, you can chat with an AI-powered chatbot [travel specialist] and get some personalized recommendations through the chatbox on the lower right of the screen.

A chatbox then opened on the screen and invited the participant to list their vacation preferences (e.g., places/activities of interest, people who will be traveling, ideal length of the vacation). After the information was submitted, the participant was told to wait while the AI Bot [travel specialist] curated a list of travel options. After a wait of 20s, participants were told, "The AI bot [travel specialist] has created a list of recommended destinations for you. Before you check the list, you see a pop-up window with cashback offers from TripAway (see below)." The offers were $30 cash back immediately or $35 cash back in 4weeks, if a trip was booked today. Participants were asked which offer they would select if they were to book a trip. This was the dependent measure.

The anticipated mediator, perceived time duration, was measured with, "When you were choosing between getting $30 cashback instantly and getting $35 cashback in 4weeks, how far away did you feel 4weeks from today was?" (1 = close, 7 = far away). Additional measures were used to rule out alternative explanations: trust in the agent's recommendation (1 = not at all, 7 = very much), attractiveness of the agent's recommendation (1 = not at all, 7 = very much), and attitude toward TripAway (dislike-like, unfavorable–favorable, negative–positive, 7-point Likert scales). The attention check was a multiple-choice question assessing if the participant could remember the trip was a summer vacation with family.

Pretest

A pretest was run to confirm that an AI agent was more strongly associated with fast processing than a human agent. Ninety-nine participants were recruited from Prolific (UK) (M_{age}=37.07; 52.53% female). The participants were asked to assess the speed of either a human travel specialist or an AI-powered chatbot (between-subjects) using a three-item scale consisting of "processing speed," "calculation speed," and "recommendation speed" with endpoints labeled "very slow" (1) and "very fast" (7). As expected, the AI-powered chatbot (M=5.81, SD=0.95) was perceived as faster than the human travel specialist (M=4.58, SD=0.97), F(1, 97)=40.54, p<0.001, η^2=0.30.

Results

Intertemporal preference

In line with our predictions, participants were more likely to choose the smaller, sooner reward (i.e., getting $30 cashback instantly) when the agent was an AI Bot (72.92%) rather than a human travel specialist (55.71%, χ^2=9.17, p=0.002, φ=0.18, a small to medium effect size).

Perceived time duration

As predicted, 4 weeks was perceived to be longer in the AI Bot condition (M=4.78, SD=1.54) than in the human condition (M=4.39, SD=1.63), F(1, 282)=4.33, p=0.038, η^2=0.02.

Mediation analysis

A mediation analysis using Process Model 4 (Hayes, 2022) found that perceived time duration mediated the effect of the type of agent (0=human, 1=AI) on intertemporal choice (0=larger, later option, 1=smaller, sooner option; β=0.38, SE=0.20, 95% CI=[0.02, 0.81]).

Alternative accounts

The alternative mediators were not influenced by the type of agent manipulation: trust (M_{AI}=4.15, SD=1.35; M_{human}=4.26, SD=1.34, F(1, 282)=0.55, p=0.46), attractiveness (M_{AI}=4.42, SD=1.27; M_{human}=4.41, SD=1.35, F(1, 282)=0.004, p=0.95), attitude toward business (M_{AI}=4.88, SD=1.14; M_{human}=4.97, SD=1.19, F(1, 282)=0.38, p=0.54).

Posttest

The explanation of the effect depends on the assumption that the presence of the AI agent speeds an internal clock, so that present and future time durations feel longer. In Study 1A, the perceived time duration mediator measured future time. This posttest (N=201) measures present time. The procedure was identical to Study 1A except for the dependent measure. After the participant waited 20 s for the agent to respond, they were told "The AI bot [travel specialist] has created a list of recommended destinations for you. Before you see the list, we want to know how long you felt the wait for the AI bot's [travel specialist's] response was" (1=the wait felt short, 7=the wait felt long). Consistent with the internal clock assumption, the wait was perceived to be longer in the AI Bot condition (M=4.56, SD=1.36) than the travel specialist condition (M=3.94, SD=1.60, F(1, 199)=8.68, p=0.004, η^2=0.04).

STUDY 1B: REPLICATION

Method

Design

Three hundred participants (M_{age}=27.02, SD=6.28; 59.00% female) were recruited from Credamo. Participants were randomly assigned to one of two conditions (agent: human vs. AI).

Procedure

Participants imagined that they wanted to buy a laptop computer (see Appendix S1 for full text of study materials). They were going to use an app to make this purchase. Depending on condition, they were told that the app relied on the expertise of an algorithm or the expertise of a salesperson. To take advantage of the expertise of the algorithm/salesperson, participants were told they had to list attribute preferences for a laptop (open-ended). After listing their attribute preferences, participants waited 20 s for the app to process the information. Participants were then told the app had a laptop recommendation, but that it came with two promotions and the participants had to select one of the promotions prior to seeing the recommendation (adapted from May & Monga, 2014). Participants were instructed to indicate their preference between two options: A: RMB15 in 1 week, B: RMB20 in 3 weeks (1=definitely prefer A, 9=definitely prefer B; reverse coded so sooner option has a higher score). Participants were then told the app had identified a second laptop and that also had two rebate options. Participants again indicated their preferences between the two options (A: RMB15 in 1 week vs. B: RMB25 in 1 month; 1=definitely prefer A, 9=definitely prefer B; reverse coded so sooner option has a higher score). After making the choices, all participants answered two questions that measured perceived time duration mediator: "How far away three weeks (one month) seemed to you" on 7-point scales (1 = not at all, 7 = very much) (Bradford et al., 2019).

Results

Intertemporal preference

There was no agent by repeated measure interaction, $F(1, 298) = 0.03$, $p = 0.86$, so we averaged participants' responses for the two pairwise choices as the main dependent measure. As predicted, participants had a higher preference for the smalleraa-sooner option when the agent was an AI agent ($M = 5.14$, SD = 2.85) rather than a human agent ($M = 4.36$, SD = 2.63), $F(1, 298) = 6.08$, $p = 0.014$, $\eta^2 = 0.02$.

Perceived time duration

There was no agent by repeated measure interaction, $F(1, 298) = 0.002$, $p = 0.96$, so we averaged participants' responses for the 3-week and the 4-week perceived time duration measures. Time duration was perceived longer when the agent was an AI ($M = 4.97$, SD = 1.31) versus a human ($M = 4.61$, SD = 1.32), $F(1, 298) = 5.73$, $p = 0.017$, $\eta^2 = 0.02$.

Mediation analysis

A mediation analysis was conducted with agent as the independent variable (0 = human, 1 = AI), intertemporal preference as the dependent variable (9 = smaller, sooner option, 1 = larger, later option), and perceived time duration as the mediator (PROCESS model 4, 5000 bootstrap; Hayes, 2022). The analysis revealed a significant mediation effect of perceived time duration ($\beta = 0.44$, SE = 0.19, 95% CI = [0.08, 0.81]).

Posttest

In Study 1B, the perceived time duration mediator measured future time. This post-test measures present time ($N = 200$). The procedure was identical to Study 1B except for the dependent measure. After the participant waited 20 s for the agent to respond, they were told "According to your indicated preference, the algorithm [salesperson] has found a laptop that fits your needs. Before you see the laptop, we want to know how long you felt the wait for the algorithm's [salesperson's] response was" (1 = the wait felt short, 7 = the wait felt long). Consistent with the internal clock assumption, the wait was perceived to be longer in the algorithm condition ($M = 4.57$, SD = 1.72) than the salesperson condition ($M = 4.00$, SD = 1.84), $F(1, 198) = 5.03$, $p = 0.026$, $\eta^2 = 0.03$.

Discussion

The results of Studies 1A and 1B suggest that an AI agent, compared to a human agent, made people perceive the time point of the larger, later option as more distant, which consequently encouraged the choice of a smaller, sooner option as opposed to a larger, later option. In addition, Study 1A ruled out three alternative explanations: trust in the agent's recommendation, attractiveness of the agent's recommendation, and brand attitude.

STUDY 2

The goal of Study 2 was to examine the relationship between an AI (vs. a human) agent and intertemporal choice by manipulating the accessibility of the AI—fast processing association (Spencer et al., 2005). Inspired by OpenAI's description of their o1 model as "designed to spend more time thinking before they respond," we manipulated whether processing time was perceived as an indicator of the *speed of decision-making* or *providing a quality recommendation*. The *speed of decision-making* condition was the default condition, in that people assume the time it takes an agent to make a decision represents how efficiently the agent can do it. This assumption should allow the AI—fast processing association to exert an influence on intertemporal choice (see Studies 1A and 1B). In the *providing a quality recommendation* condition, participants were told the AI or human agent was trained to spend more time selecting the right options. This AI—time-is-quality association should interfere with the AI—fast processing association. We anticipated that the effect of an AI (vs. a human) agent on choice of the smaller, sooner option would be attenuated when participants were told that the agent (AI or human) was spending more time in order to select quality options (H2).

Method

Design

Four hundred and one participants were recruited from Prolific (UK) ($M_{age} = 37.00$, SD = 14.65; 63.59% female). The study design was a two (agent: human vs. AI) by two (time frame: time is an indicator of processing speed vs. time is an indicator of recommendation quality). Fifty-five participants did not pass an attention check, leaving a final sample of 346 participants.

Procedure

The procedure was similar to Study 1A except for two differences. First, due to the time the study was run (in November), participants imagined planning for a winter vacation instead of a summer vacation. Second, we manipulated how participants interpreted the time delay before receiving the recommendation. Participants in the time is an indicator of processing speed condition followed the same procedure as in Study 1A, so that the identity of the agent could influence associations about processing speed (i.e., AI—fast processing) and influence the internal clock. Participants in the time is an indicator of recommendation quality condition learned that the agent was trained to spend more time selecting the right destinations for them and that by spending more time, the agent refined the selection process, tried different strategies, and ultimately made better recommendations. This encouraged an AI—time-is-quality association that should interfere with the AI—fast processing association. The dependent measure was a choice between \$30 cash back immediately and \$35 cash back in 4 weeks, the same as in Study 1A. At the end of the study, participants completed a multiple-choice attention check question assessing if the participant could remember the trip was a winter vacation with their family.

Results

Intertemporal preference

We ran a logistic regression on choice (0 = \$35, 1 = \$30) with agent (0 = human, 1 = AI), time frame (0 = time indicates processing speed: fast, 1 = time indicates recommendation quality), and their interaction as independent variables (see Figure 2 for choice percentages). The model revealed a significant effect of agent (β = 1.06, SE = 0.33, Wald χ^2 (1, N = 346) = 10.15, p = 0.001, odds ratio = 2.89), no effect of time frame (β = 0.25, SE = 0.30, Wald χ^2 (1, N = 346) = 0.72, p = 0.40 odds ratio = 1.29), and a significant interaction (β = −1.12, SE = 0.46, Wald χ^2 (1, N = 346) = 5.94, p = 0.015, odds ratio = 0.33). In the time indicates processing speed condition, participants were more likely to choose the smaller, sooner option (i.e., getting \$30 cashback instantly) when the agent was an AI Bot (77.11%) rather than a human travel specialist (53.76%), Wald χ^2 (1, N = 346) = 11.36, p < 0.001, odds ratio = 2.89. When time indicated recommendation quality, however, there was no difference in choice between the two conditions (M_{AI} = 58.75%, M_{human} = 60.00%; Wald χ^2 (1, N = 346) = 0.027, p = 0.87).

Discussion

Study 2 manipulated the accessibility of the AI—fast processing association by manipulating whether the time an agent needed to make a recommendation was perceived as an indicator of the speed of decision-making or the quality of a recommendation. When time was an indicator of processing speed, an AI (vs. a human) agent increased the choice of a smaller, sooner reward. This result replicated the results in studies 1A and 1B. However, this effect was attenuated when participants learned that time was an indicator of a quality recommendation, suggesting that the effect of the agent on time perception and intertemporal choice is conditioned on the accessibility of the AI agent → fast processing association.

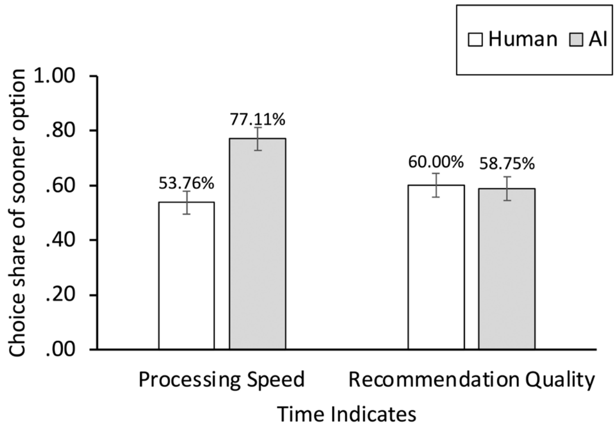

FIGURE 2 The influence of an AI agent on intertemporal choice depends on beliefs about time.

STUDY 3

Study 3 was designed with two goals in mind: (1) provide evidence for the internal clock explanation and (2) provide evidence against the alternative explanation that the AI agent's activation of the fast processing belief encourages increased accessibility of the concept impatience (Hardisty et al., 2013; Roberts et al., 2024). Our conceptualization (see Figure 1) proposes that an AI agent alters the perception of elapsed time in the present (i.e., the internal clock) and the perceived duration of a future delay because an AI agent activates beliefs about fast processing which, in turn, alters the speed of the internal clock. If an interaction with an AI agent does not involve a wait time (i.e., the agent responds immediately), then the internal clock cannot run and judgments about future time delays will not be influenced. Thus, Study 3 manipulated how long it took the AI/human to provide information (15 s vs. immediately). We anticipated that an AI (vs. a human) agent would increase the perceived length of a future delay and the choice of the smaller, sooner reward when there was a 15 s delay (the internal clock could run) but generate a null effect when there was no time delay.

An alternative process account is that an AI agent increases the accessibility of the concept "impatience." The accessibility of the concept of impatience should depend on the type of agent, not on the wait time for the agent's response. Thus, when the agent is an AI, as opposed to a human, people should prefer a smaller, sooner reward irrespective of the wait time to receive a response from the agent (i.e., a main effect of agent type). In addition, Study 3 ruled out other alternative accounts, including trust in the agent and perceived expertise of the agent.

Method

Design

The study was preregistered (https://aspredicted.org/24vd-r3by.pdf). The design was a two (agent: human vs. AI) by two (time to receive the response: 15 s vs. immediate).

Participants

Six hundred and two participants ($M_{age}=37.99$, SD = 13.84; 53.99% female) were recruited from Prolific. No attention check was used in the study, and all participants were retained in the analysis.

Procedure

Participants imagined that they had $5000 cash on hand and planned to invest it (see Appendix S1 for full text of study materials). They contacted their bank, trying to obtain professional suggestions for the investment. Depending on the condition, participants were told either a financial algorithm or a financial advisor had received their request and would look for promotional offers. To take advantage of the expertise of the financial algorithm/advisor, participants were told they had to answer some questions, including the number of family members, employment status, household income, and credit score. After participants responded to these questions, the financial algorithm/advisor spent 15 s [0 s] processing the information. Participants were then told the financial algorithm/advisor found two promotional offers from the bank, and both promotions were a one-time benefit for loyal customers without further requirements (adapted from May & Monga, 2014). Participants were asked to make a choice between two promotional options:

a. Receive a $50 bonus now
b. Receive a $55 bonus in 30 days

After making the choice, all participants answered a question that measured the perceived time duration mediator "In the two options generated by the financial algorithm / advisor, how far away did you feel 30 days from today was?" on a 7-point scale, anchored by "1 = close" and "7 = far away" (Bradford et al., 2019). Additional measures were used to rule out alternative explanations: familiarity with financial products, experience with financial investments as well as the perceived trust and expertise of the financial algorithm/advisor.

Results

Intertemporal preference

The choice shares for the smaller, sooner reward are shown in Figure 3. Logistic regression was adopted, with agent (0 = human, 1 = AI), time to receive the response (0 = 15 s, 1 = immediate), their interaction as independent variables, and choice of the smaller-sooner reward as the dependent variable (0 = larger, later, 1 = small, sooner). The model revealed a significant effect of the type of agent ($\beta=0.86$, SE = 0.24, Wald χ^2 (1, $N=602$) = 12.63, $p<0.001$, odds ratio = 2.37), a significant effect of time to receive the response ($\beta=0.52$, SE = 0.23, Wald χ^2 (1, $N=602$) = 5.04, $p=0.025$, odds ratio = 1.69), and a significant interaction ($\beta=-0.88$, SE = 0.34, Wald χ^2 (1, $N=602$) = 6.67, $p=0.010$, odds ratio = 0.42). In the 15 s condition, there was a higher choice share for the smaller-sooner option when the agent was an AI ($M=70.63\%$, SD = 0.46) versus a human ($M=50.32\%$, SD = 0.50), Wald χ^2 (1, $N=602$) = 13.56, $p<0.001$. When the recommendation was delivered immediately, there was no difference in choice share between the two conditions ($M_{AI}=62.75\%$, SD = 0.49; $M_{human}=63.09\%$, SD = 0.48; Wald χ^2 (1, $N=602$) = 0.004, $p=0.95$).

Moderated mediation analysis

First, a two-way ANOVA analysis was adopted, with the type of agent (0 = human, 1 = AI) and the time to receive the response (0 = 15 s, 1 = immediate) as the two

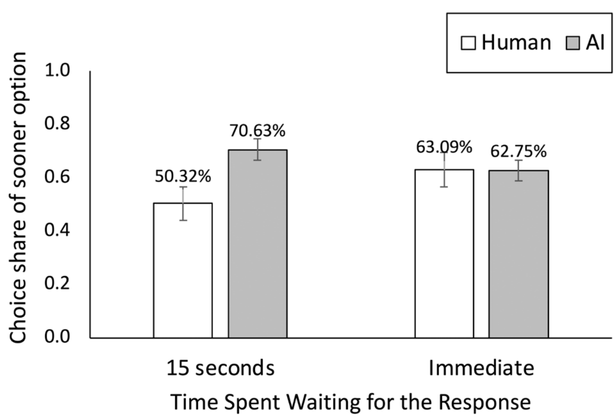

FIGURE 3 The influence of an AI agent on intertemporal choice depends on the time spent waiting to receive a response.

independent variables, and perceived time duration as the dependent variable. The main effect of agent on perceived time duration was significant (M_{AI}=4.77, SD=1.99; M_{human}=4.41, SD=2.03; F(1, 598)=4.78, p=0.029, η^2=0.01). Consistent with our prediction, the interaction between the type of agent and time to receive the response was significant, F(1, 598)=5.82, p=0.016, η^2=0.01. When there was a 15 s delay, the perceived time duration was longer when the type of agent was an AI (M=4.92, SD=2.05) versus a human (M=4.17, SD=2.08), F(1, 598)=10.52, p=0.001, η^2=0.02. However, when there was no delay, the perceived time duration did not differ between the two agent conditions (M_{AI}=4.63, SD=1.94, M_{human}=4.66, SD=1.95; F(1, 598)=0.03, p=0.87).

Second, a moderated mediation analysis was run with the type of agent as the independent variable (0=human, 1=AI), time to receive the response as the moderator (0=15 s, 1=immediate), intertemporal preference as the dependent variable (0=larger, later, 1=smaller, sooner), and perceived time duration as the mediator (PROCESS model 8, 5000 bootstrap; Hayes, 2018). The analysis revealed a significant moderated mediation effect of perceived time duration (β=−0.75, SE=0.32, 95% CI=[−1.37, −0.15]). Perceived time duration was a mediator in the 15 s condition (β=0.71, SE=0.23, 95% CI=[0.28, 1.18]), but not in the immediate condition (β=−0.04, SE=0.22, 95% CI=[−0.45, 0.40]).

Alternative accounts

Moderated mediation tests were not significant for familiarity with financial markets (β=0.03, SE=0.03, 95% CI=[−0.02, 0.11]), experience with financial investments (β=0.04, SE=0.04, 95% CI=[−0.02, 0.14]), trust in the agent (β=−0.01, SE=0.04, 95% CI=[−0.10, 0.07]), and the perceived expertise of the agent (β=−0.04, SE=0.04, 95% CI=[−0.14, 0.02]) (PROCESS model 8, 5000 bootstrap; Hayes, 2018).

Discussion

The results of Study 3 suggest that an AI agent, compared to a human agent, increases the perceived length of a future time delay and encourages the choice of the smaller, sooner reward when there is a time lag before the agent provides assistance, but not when there is no time lag. This result is consistent with our conceptualization that experiencing a time lag before receiving assistance allows the internal clock to run and, therefore, influences subjective time perception. This result is inconsistent with the alternative hypothesis that an AI agent increases the accessibility of the concept of impatience, which should have resulted in a main effect of agent type, not an interaction of agent type and the time it took to receive the recommendation.

STUDY 4

Study 4 was designed with two goals in mind: (1) provide insight into when the internal clock influences a judgment about future time (H4) and (2) provide evidence against a second alternative explanation concerning impatience—that waiting for an AI (vs. a human) to respond creates a feeling of impatience. Our favored explanation is that when an agent is an AI, as opposed to a human, it increases the accessibility of a "fast processing" belief that speeds an internal clock so that time intervals are experienced as longer. In Study 4, we used a procedure that allowed for the internal clock to exert an influence (i.e., allowed future time perception to be malleable) versus not (i.e., did not allow future time perception to be malleable). Prior work has found that subjective time duration estimates are more easily biased when the future time is expressed as a time interval (e.g., "1 month") rather than a date (e.g., "MM/DD/YYYY"; a date 1 month from today) (LeBoeuf, 2006; Malkoc et al., 2010; Rung & Madden, 2018). LeBoeuf (2006, p. 61) proposes that when date endpoints are used, "consumers may not even compute the interval's length." If this is so, then agent type (AI vs. human) should not influence intertemporal choice when duration is indicated using a date endpoint but should influence intertemporal choice when a duration is indicated using a time interval (H4). Support for this prediction is provided by Malkoc et al. (2010, Exp. 4), who found that discount rates are sensitive to attribute alignability (nonalignable vs. alignable) when delays were expressed as time intervals but not when delays were expressed as future dates. Similar to LeBoeuf (2006), Malkoc et al. (2010, pp. 121–122) explained their result as "date frames shift the focus to the future moment the outcome will occur without focusing the individual on the time frame they will need to wait." That is, a date frame should make the time interval non-salient.

An alternative explanation is that waiting for an AI (vs. a human) agent to respond creates a feeling of impatience (i.e., that the wait time was longer than expected). If this is so, then a preference for a larger, sooner option should occur whether the delay is expressed as a time interval or using a date endpoint. Impatience should not be sensitive to the format used to express the future option.

Method

Design

Two hundred ninety-nine participants (M_{age}=28.10, SD=6.14; 62.29% female) were recruited from Credamo. Two duplicate participants were excluded, resulting in a final data set of 297 responses. Participants were randomly assigned to one of four conditions in a 2 (agent: human vs. AI) by 2 (format of time delay: time interval vs. calendar date) between-subjects design. No participants were excluded from the analysis.

Procedure

Participants imagined that they wanted to buy a mobile phone (see Appendix S1 for full text of study materials). They were going to use an app to make this purchase. Depending on the condition, they were told the app relied on the expertise of an algorithm or a salesperson. To take advantage of the expertise of the algorithm/salesperson, participants were told they had to list attribute preferences for a mobile phone (open-ended). After listing their preferences, the app spent 30 s processing the information. The participant was then told the algorithm/salesperson made a mobile phone recommendation, but that it came with two promotions and the participant had to select one of the promotions prior to seeing the recommendation (adapted from May & Monga, 2014).

The description of the rebate options represented the experimental manipulations. In the time interval condition, the choice was between two interval options (A: RMB15 in 1 week vs. B: RMB20 in 1 month, 1 = definitely prefer A, 9 = definitely prefer B; reverse coded so the sooner option has a higher score). In the calendar date condition, the choice was between two date options that corresponded to the interval options (A: RMB15 rebate on September 23 vs. B: RMB20 rebate on October 17 (1 = definitely prefer A, 9 = definitely prefer B; reverse coded so the sooner option has a higher score); the data were collected on September 17).

Afterwards, perceived time duration was measured by asking how far away the future date seemed on a 7-point scale (1 = extremely close, 7 = extremely far away; Bradford et al., 2019).

Results

Intertemporal preference

We submitted participants' responses to a 2 by 2 factorial ANOVA (see left panel of Figure 4). The main effect of type of agent, $F(1, 293) = 0.97$, $p = 0.32$, and time format, $F(1, 293) = 0.05$, $p = 0.83$, was not significant. As expected, the interaction between the type of agent and time format was significant, $F(1, 293) = 8.39$, $p = 0.004$, $\eta^2 = 0.03$. Specifically, when time delay was presented as a time interval, we replicated the previous finding that participants expressed a stronger preference for the smaller, sooner reward when the product was recommended by an AI agent ($M = 4.88$, $SD = 2.97$) than by a human agent ($M = 3.59$, $SD = 2.65$), $F(1, 293) = 7.57$, $p = 0.006$, $\eta^2 = 0.03$. However, when a time delay was presented as a calendar date, the type of agent had no effect on preference for the sooner reward ($M_{AI} = 3.99$, $SD = 2.82$; $M_{human} = 4.62$, $SD = 3.02$; $F(1, 293) = 1.82$, $p = 0.18$).

Moderated mediation

First, a 2 by 2 factorial ANOVA was conducted on perceived time duration (see right panel of Figure 4). The main effects of the type of agent, $F(1, 293) = 2.58$, $p = 0.11$, and time format, $F(1, 293) = 1.45$, $p = 0.23$, were not significant. Importantly, there was a significant interaction between the type of agent and time format, $F(1, 293) = 4.04$, $p = 0.045$, $\eta^2 = 0.01$. Specifically, when the time delay was presented as a time interval, the future was perceived as farther away if the product was recommended by an AI agent ($M = 5.55$, $SD = 1.94$) rather than by a human agent ($M = 4.71$, $SD = 2.08$), $F(1, 293) = 6.57$, $p = 0.011$, $\eta^2 = 0.02$. When the time delay was presented as a calendar date, there was no difference in perceived time duration between the AI agent ($M = 5.36$, $SD = 1.97$) and the human agent ($M = 5.46$, $SD = 2.08$) conditions, $F(1, 293) = 0.08$, $p = 0.78$.

Second, a moderated mediation analysis was run with the type of agent as the independent variable (0 = human advisor, 1 = algorithm), format of time delay as the moderator (0 = time interval, 1 = calendar date), intertemporal preference as the dependent variable (0 = larger, later, 1 = smaller, sooner), and perceived time duration as the mediator (PROCESS model 8, 5000 bootstrap;

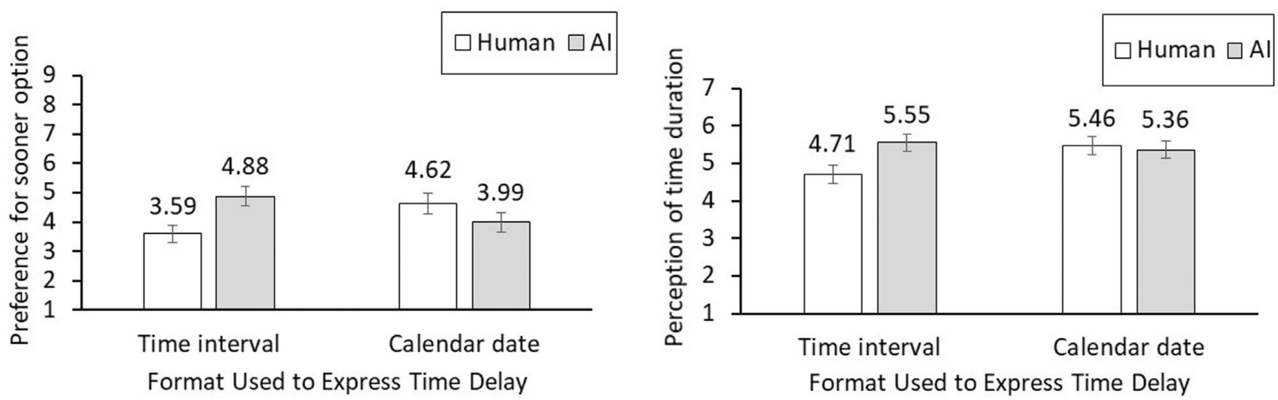

FIGURE 4 The influence of an AI agent on intertemporal preference depends on the format used to express the time delay.

Hayes, 2018). The analysis revealed a significantly moderated mediation effect of perceived time duration (β = −0.85, SE = 0.41, 95% CI = [−1.67, −0.05]). Perceived time duration was a mediator in the time interval condition (β = 0.76, SE = 0.29, 95% CI = [0.22, 1.38]), but not in the calendar date condition (β = −0.09, SE = 0.29, 95% CI = [−0.67, 0.49]).

Discussion

Study 4 replicates the findings observed in previous studies and provides further evidence for the underlying process. Specifically, we contend that the presence of an AI agent increases the perceived duration of a future delay which, in turn, shifts people's preferences toward smaller–sooner options. When future time is presented as a specific date, however, perceptions of future time duration are less malleable. Consequently, the effect of an AI agent on perceived time duration is mitigated and there is no effect on intertemporal choice.

There was one unexpected finding in Study 4. The perceived time duration estimate in the calendar date condition should have had means that were equivalent to the mean in the human—time interval condition. Only the AI agent—time interval condition should have been influenced by the "fast time" belief and the internal clock. We expect the perceived time duration in the calendar date conditions to be longer than expected because the interval included a change in month. Intervals that cross a time boundary are perceived to be longer than those that do not (Donnelly et al., 2022).

STUDY 5

We hypothesize that an AI agent, as compared to a human agent, increases the perceived length of a future delay. So far, we have examined its consequences on the choice between a smaller, sooner reward and a larger, later reward. Study 5 extends our findings to a different type of intertemporal choice: choosing between streams of recurring rewards (i.e., payments received over a shorter vs. a longer time period).

Study 5a examined a choice between receiving larger recurring rewards over a shorter time period versus receiving smaller recurring rewards over a longer time period (i.e., receive \$20 per week for 9 weeks vs. receive \$15 per week for 15 weeks). As discussed earlier, the temporal delay between the shorter and longer reward streams is associated with positive utility because people receive repeated rewards during the extended period. Thus, if an AI (vs. a human) agent makes a future delay seem longer, it should lead to a preference for the longer reward stream (H5).

Study 5b examined a choice between a shorter-term loan with a higher monthly payment and a longer-term loan with a lower monthly payment. As discussed earlier, the temporal delay between the shorter-term and longer-term loans should be associated with negative utility because people have to make repeated payments during the extended period. Thus, if an AI (vs. a human) agent makes a future delay seem longer, it will lead to a preference for the shorter loss streams (e.g., shorter-term loans).

Method study 5a

Design

The study was pre-registered (https://aspredicted.org/VB1_JG9). Three hundred and three participants were recruited from Prolific (UK) (M_{age} = 38.57; 58.42% female). Participants were randomly assigned to one of two between-subject conditions (agent: human vs. AI). No participants were excluded from the study.

Procedure

Participants read that the Treasury Department wants to promote a new SNAP program for families across the country (see Appendix S1 for full text of study materials). Different food assistance programs within SNAP have different eligibility criteria and payment schedules. An algorithm (vs. an advisor) from the Treasury's official website could help participants find a suitable program. Then participants were required to indicate their monthly spending on family's groceries, number of family members, employment status, and household income. After a 20-s wait, the agent (algorithm vs. advisor) generated two eligible SNAP programs. Participants had to indicate which program they preferred: (1) a "9-week benefit. For 9 consecutive weeks, you will receive a \$20/week benefit on your EBT card" and (2) a "15-week benefit. For 15 consecutive weeks, you will receive a \$15/week benefit on your EBT card." This choice was the dependent variable (0 = longer-term program, 1 = shorter-term program).

Next, the mediator was measured "When you were choosing between the two benefit options, how much shorter did 9 weeks feel than 15 weeks?" on a 7-point Likert scale anchored by "1—not that much shorter" and "7—very much shorter". Finally, demographic information including age, gender and education was collected.

Results study 5a

Intertemporal choice

A chi-squared analysis on choice with agent as the independent variable found that when the agent was an AI (vs. a human), participants were marginally less likely to select the shorter-term allowance (M_{AI} = 20.39%, M_{human} = 29.14%; χ^2 = 3.11, p = 0.08, φ = 0.18, a small to medium effect size).

Perceived time duration

A one-way ANOVA was conducted on perceived time duration. The time difference between 9 weeks and 15 weeks was perceived to be marginally larger in the AI agent (M = 4.80, SD = 1.67) condition than in the human agent condition (M = 4.48, SD = 1.49), F(1, 301) = 2.95, p = 0.09, η^2 = 0.01.

Mediation

A PROCESS analysis with the type of agent as the independent variable (0 = human, 1 = AI), perceived time duration as the mediator, and intertemporal preference as the dependent variable (0 = larger, later, 1 = smaller, sooner) (Model 4, 5000 bootstrap; Hayes, 2022) revealed a marginally significant mediation effect at a 90% confidence level (β = −0.10, SE = 0.07, 90% CI [−0.23, −0.00]).

Method study 5b

Design

The study was pre-registered (https://aspredicted.org/kdqr-g8pj.pdf). Three hundred and ninety-nine participants were recruited from Prolific (UK) (M_{age} = 39.48; 58.40% female). Participants were randomly assigned to one of the two between-subject conditions (agent: human vs. AI). No participants were excluded from the analysis.

Procedure

Participants imagined that they were buying a new car. They planned to finance $18,000 of the cost and were considering a 5–7 year loan (see Appendix S1 for full text of study materials). They imagined logging into their bank account and checking potential loan options offered by their bank. They learned they needed to answer a few questions about their needs from [a loan officer/an AI] who would help them find the best loan options. After answering the questions, participants waited 15 s for the agent to find the loan options. Then, all participants saw the following two options and indicated which option they would choose. This was the dependent variable.

Option 1:
5-year loan
60 monthly payments
Monthly payment: $354.30 (APR: 6.75%)

Option 2:
6-year loan
72 monthly payments
Monthly payment: $307.31 (APR: 7.05%)

Next, participants responded to the mediator measure on a 7-point scale: "When you were choosing between the two options, how much shorter did 5 years feel than 6 years?" (1 – not that much shorter, 7 – very much shorter). We also measured trust, attractiveness of the recommendations, and brand attitude as in previous studies.

Results study 5b

Intertemporal preference

In line with our prediction (H1), participants were more likely to choose the shorter-term loan (i.e., 5-year loan) when the agent was an AI (78.28%) rather than a loan officer (68.66%, χ^2 = 4.74, p = 0.030, φ = 0.11).

Perceived time duration

As predicted, the perceived time difference between the 5-year loan and 6-year loan was marginally larger in the AI condition (M = 4.42, SD = 1.49) than in the human condition (M = 4.15, SD = 1.44, F(1, 397) = 3.40, p = 0.07, η^2 = 0.01).

Mediation analysis

A PROCESS analysis with the type of agent as the independent variable (0 = human, 1 = AI), perceived time duration as the mediator, and intertemporal preference as the dependent variable (0 = 6-year loan, 1 = 5-year loan), (Model 4, 5000 bootstrap; Hayes, 2022), revealed a marginally significant mediation effect at a 90% confidence level, β = 0.13, SE = 0.08; 90% CI = [0.02, 0.27].

Alternative accounts

The type of agent did not affect the attractiveness of the recommendations (M_{AI} = 4.34, SD = 1.45; M_{human} = 4.43, SD = 1.33, F(1, 397) = 0.41, p = 0.52). Trust in the agent's recommendations and brand attitudes were lower in the AI condition as compared to the human condition (trust: $M_{AI}=4.38$, SD = 1.48; $M_{human}=4.76$, SD = 1.34, $F(1, 397)=6.97$, $p=0.009$; brand attitude: $M_{AI}=4.79$, SD = 1.43; $M_{human}=5.11$, SD = 1.25, $F(1, 397)=5.74$, $p=0.017$). However, trust and brand attitudes were not correlated with loan choice ($ps>0.16$) and, thus, did not mediate the effect of agent on loan choice. Controlling for trust and brand attitudes did not change the findings.

Discussion

The results of study 5a and study 5b demonstrate that the effect of an AI (vs. a human) agent on time perception and intertemporal choice can be extended into the domain of recurring rewards/payments. Specifically, an AI agent, as compared to a human agent, increased the perceived length of a future time period, leading to preferences for longer-term recurring rewards (study 5a) but shorter-term recurring payments (study 5b). Importantly, these results provide further support that AI (vs. human) agents affect intertemporal choices by altering future time perceptions.

The results are inconsistent with the impatience mediators discussed in studies 3 and 4. First, the findings are inconsistent with the *impatience owing to uncertainty about the future* explanation that was investigated in study 3 (Hardisty et al., 2013; Patak & Reynolds, 2007; Takahashi et al., 2007). Uncertainty about the future would lead to a preference for gains now and losses in the future. Thus, if AI induces uncertainty about the future, it should encourage the choice of the short-term recurring rewards in Study 5a and long-term recurring payments in Study 5b, which is the opposite of what was found. Second, the findings are inconsistent with the general impatience (i.e., the desire to get things resolved immediately) explanation investigated in study 4 (Hardisty et al., 2013; Roberts et al., 2024). If an AI agent makes people want to get things done faster, then it should increase choices of the short-term recurring rewards in study 5a, which is the opposite of what we found.

STUDY 6

Study 6 replicates the findings of study 5b in the marketplace. The data were on choices of consumer auto loans by LendingTree. LendingTree is a U.S. financial services firm that uses AI to curate consideration sets of auto loan offers that vary by APR and length, with longer loans having higher APRs. LendingTree provides loan options in a format that makes it easy to compare APRs, loan durations, monthly payments, and total loan cost. The vast majority of LendingTree-originated loans are for used cars.

We predicted that consumers would select shorter loan durations when these loans were offered by LendingTree rather than financial service firms that do not use AI to generate a consideration set of financing offers.

Data

The loan data were for the third quarter of 2022. Americans take out approximately $62B in auto loans per month. In the third quarter of 2022, 38.32% of these loans were for new cars, and the remainder were for used cars. The factor that most influences loan APR and duration is credit worthiness. Credit worthiness segments consist of super-prime (credit score 781–850) (18.07% of loans), prime (661–780) (46.26%), near prime (601–660) (18.82%), subprime (501–600) (14.84%), and deep subprime (300–500) (2.00%). Additionally, loans are extended through different distribution channels: credit union (28.44%), bank (27.32%), captive finance (e.g., auto maker) (21.89%), finance company (11.75%), and Buy Here Pay Here (10.59%).

The data for the analysis were from two sources, segmented by type of loan and credit worthiness. The first data source was the State of Automotive Finance report provided by Experian. These data were for the entire auto finance market. The second data source was LendingTree. LendingTree has less than a 2% share of the auto loan market. LendingTree is known for having an AI app that curates loan offers. The data are shown in Table 1.

Analyses

The analysis can be performed in two ways because the distribution of loans by credit worthiness was different for the industry and LendingTree. LendingTree makes more loans to the prime segment and fewer loans to the remaining segments than the industry.

The first analysis ignored the difference in the distribution of loans by credit worthiness and compared the aggregate LendingTree loan duration to the aggregate industry loan duration. This analysis is biased because people with higher credit scores take shorter loans and the proportion of super-prime and prime loans differed between LendingTree and the industry. Despite this bias, an analysis of the raw data is informative for certain stakeholders (e.g., general public, industry participants). In this analysis, LendingTree had a shorter duration on all auto loans ($M_{Ind}=69.12$; $M_{LT}=67.45$, $SE=0.205$, $t=8.15$, $p<0.001$, $\eta^2=0.02$). Further, shorter durations were observed for used auto loans ($M_{Ind}=67.92$; $M_{LT}=66.55$, $SE=0.25$, $t=5.43$, $p<0.001$, $\eta^2=0.03$), but not new auto loans ($M_{Ind}=69.80$; $M_{LT}=69.25$, $SE=0.34$, $t=1.61$, $p=0.11$, $\eta^2=0.001$).

TABLE 1 Auto loan data.

$ Volume and loan duration for new and used car loans 2022, Q3, industry

$ Volume	% Volume	Deep subprime (300–500)	Subprime (501–600)	Near prime (601–660)	Prime (661–780)	Super prime (781–850)	Industry Aggregate
New auto—industry	38.32%	0.24%	5.18%	13.24%	52.18%	29.17%	100.00%
Loan length (months)		72.79	74.25	74.73	71.25	64.14	69.80
Used auto—industry	61.68%	2.88%	19.65%	21.59%	43.32%	12.56%	100.00%
Loan length (months)		62.68	66.51	69.06	69.06	65.47	67.92
New and used auto—industry	100.00%	2.00%	14.84%	18.82%	46.26%	18.07%	100.00%
Loan length (months)		66.55	69.48	71.23	69.90	64.96	69.12

$ Volume and loan duration for new and used car loans 2022, Q3, LendingTree

Number of loans	% Volume	Deep Subprime (300–500)	Subprime (501–600)	Near Prime (601–660)	Prime (661–780)	Super Prime (781–850)	LendingTree Aggregate	LendingTree Weighted
New auto—LendingTree	33.27%	0.00%	11.89%	13.66%	66.63%	7.82%	100.00%	100.00%
Loan length (months)		N/A	71.39	72.22	68.58	66.52	69.25	68.61
Used auto—LendingTree	66.73%	0.11%	9.34%	9.06%	75.62%	5.88%	100.00%	100.00%
Loan length (months)			68.36	67.36	66.37	64.55	66.55	64.99
New and used auto—LendingTree	100.00%	0.07%	10.19%	10.59%	72.63%	6.52%	100.00%	100.00%
Loan length (months)			69.54	69.45	67.04	65.34	67.45	66.38

The second analysis adjusted for the bias introduced by different distributions of loans in the LendingTree and industry data. The LendingTree loan durations were weighted to match industry weights (i.e., we assumed 18.07% of LendingTree loans were super-prime, 46.26% were prime, 18.82% were near prime, 14.84% were subprime, and 2.00% were deep subprime). LendingTree had a shorter duration on the weighted average of all auto loans ($M_{\text{Ind}}=69.12$, $M_{\text{LT}}=66.38$, $t=13.36$, $p<0.001$, $\eta^2=0.06$). Industry weighted loan durations were also calculated in the new and used auto loan segments. Shorter durations were observed for new auto loans ($M_{\text{Ind}}=69.80$; $M_{\text{LT}}=68.61$, $t=3.50$, $p<0.001$, $\eta^2=0.01$) and used auto loans ($M_{\text{Ind}}=67.92$; $M_{\text{LT}}=64.99$, $t=11.55$, $p<0.001$, $\eta^2=0.07$).

Discussion

Consistent with the findings of study 5b, study 6 shows that consumers select shorter loan durations when the loan options are AI-curated versus non-AI-curated. Although secondary data cannot provide process evidence, the results are consistent with the idea that AI-curated loan options influence an internal clock, make loan durations feel subjectively longer and, consequently, encourage people to select shorter loan periods. Of course, there could be additional reasons why LendingTree customers select shorter loans, including (1) these customers are more price sensitive (i.e., want lower APR loans), (2) there is more time to compare loan options (i.e., the captive finance and the Buy Here Pay Here distribution channels tend to encourage quick decisions), and (3) APR and loan duration are more salient relative to the monthly payment.

GENERAL DISCUSSION

We show that a recommendation from an AI agent, as compared to a human agent, encourages people to have a faster internal clock so that future time delays are perceived as subjectively longer. This leads to a preference for sooner options when a delay generates negative utility (reduces access to a gain, increases access to repeated losses). Study 1 demonstrated that an AI agent, as opposed to a human agent, encouraged people to choose a smaller, sooner reward because the delay between the two discounts was perceived as longer (H1). Studies 2–4 provided evidence that the effect of agent on intertemporal choice depends on the accessibility of the association between AI agent and fast processing (H2), whether there is a time delay before receiving assistance (H3), and the malleability of time perception (H4). It is also the case that perceiving future time delays as subjectively longer leads to a preference for a later option when a delay generates positive utility (e.g., increases the experience of repeated gains; H5) but a sooner option when a delay generates negative utility (e.g., increases the experience of repeated losses; H1).

Theoretical contributions

The psychological processes that account for intertemporal preferences can be grouped into benefit effects and time effects (Kim & Zauberman, 2019a; Malkoc & Zauberman, 2018). Time effects tend to focus on the hyperbolic shape of the discount curve for time delays—that is, an equivalent time duration (e.g., 1 day) has much more value in the present (e.g., a delay from today to tomorrow) than the future (e.g., a delay from 30 to 31 days) (Ainslie & Haslam, 1992; Dai & Fishbach, 2013; Strotz, 1955). Our research extends this literature by showing that another source of discounting is subjective time perception. To illustrate, consider the Intertemporal Choice Heuristic model (Ericson et al., 2015). This model assumes that an intertemporal choice depends on the absolute and relative differences in the benefit attribute and the absolute and relative differences in the time attribute. We show that the relative differences in the time attribute are sensitive to changes in the speed of an internal clock that is created by the context, in this case an AI agent. When a person waits for an AI agent to make a recommendation, their internal clock runs faster, future delays are perceived as longer, and people want sooner (later) options with a delay that has negative (positive) utility. We anticipate that there are other contextual factors, beyond an AI agent, that alter a person's internal clock.

Our results also contribute to a growing literature about how people perceive algorithms. Research on algorithms tends to focus on identifying the willingness of a consumer to accept algorithmic assistance (Burton et al., 2020; Dietvorst et al., 2015); hence, identifying the types of decisions algorithms are best equipped to assist (Bakpayev et al., 2022; Longoni et al., 2019). We show that an algorithm is not simply a tool. An algorithm has personal attributes (e.g., speedy, objective, analytic) that cannot only alter the believability of information (Longoni et al., 2019) but also the interpretation of information (Longoni & Cian, 2022). In a sense, an algorithm is a contextual factor that can increase the accessibility of concepts that can frame judgments about information provided by the algorithm itself (Lempert & Phelps, 2016). We show that an AI agent can influence subjective time perception. By extension, it is possible that an AI agent might alter the subjective perception of an acceptable amount of error (i.e., constrict the error scale), so that product tolerances (e.g., minimum acceptable level of service in a restaurant, range of acceptable quality in an AI-generated consideration set, amount of an ingredient in a recipe) shrink when an AI agent is the source of the information. We note that such demonstrations need not be intertemporal, as a multi-attribute decision need not include a time attribute.

Finally, our results speak to research on impatience. Impatience has been attributed to two cognitive events. First, the value of a reward is discounted as it is delayed, so that a reward in the present has considerably more value than the same reward in the future (Ainslie & Haslam, 1992). Second, impatience has also been attributed to changes in the relative weight placed on product benefits versus time costs (i.e., people become more impatient when time delays become more important) (Ebert & Prelec, 2007). What most work on impatience fails to recognize is that the perception of time is malleable (see Jhang & Lynch Jr., 2015 for an exception). In our studies, we show how a source of information (as AI agent) can make time feel subjectively longer. There may be other contextual variables that make time feel subjectively longer or shorter.

Future research directions

The current research suggests several possibilities for future research. First, there may be other downstream consequences associated with the use of AI agents or algorithms. For instance, procrastination is bad for productivity and long-term success. More than half of college students indicate that they suffer from frequent procrastination (Gallagher et al., 1992). If homework is assigned by an algorithm rather than a human instructor, students might perceive time as more abundant and, thus, be less willing to start the assignment. In a similar vein, given the relationship between time pressure and choice deferral (Dhar & Nowlis, 1999), consumers might be less likely to defer their decisions when the agent is an AI (vs. a human).

Second, in our studies, associations to AI agent versus a human agent influenced the speed of the internal clock. The AI agent's associations to fast and efficient processing influenced the perception of time duration. It would be interesting to know when and where this effect generalizes. For example, consider the purchase of a sports car versus a family car. The sports car has associations to fast. Would a consumer prefer a shorter-term loan for a sports car as compared to a family car, all else equal? The answer to this question depends on the background factors that encourage adjustments to the internal clock. We found that experiencing a lapse of time in the present (H3, study 3), while the fast-processing associations were active, was necessary for the intertemporal choice effect to emerge. Additional research needs to assess antecedents and moderators that alter the speed of the internal clock in consumption situations.

Third, despite the evidence supporting the proposed mechanism underlying the effect in H1, there could be other potential processes contributing to the results. For example, AI agents may not only affect time perception, but they might also shape how people perceive the future. AI agents might be associated with other characteristics, such as "high adaptability," that make the future seem more uncertain. Consequently, there may be situations in which a recommendation by an AI agent encourages people to accept whatever is offered in the present.

Finally, although decisions in real life inherently involve trade-offs between costs and benefits, most of the research in the intertemporal literature has examined contexts in which people choose to receive pure gains in the present versus in the distant future. Consistent with the prior literature, the scenarios used in our paper also focus on decisions with pure gains (e.g., rebate, bonus, repeated monetary benefits), recurring gains, or recurring losses (e.g., repeated loan payments), while being silent on intertemporal choices involving trade-offs between costs and benefits in each time period. Future research could study the effect of AI agents on more complex intertemporal decisions (e.g., buying a used car now versus leasing a new car now and buying a new car in the future).

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DATA AVAILABILITY STATEMENT

The details of the procedure, the data, and the SPSS analysis code for the studies are posted at OSF (https://osf.io/vzrhn/?view_only=bd77b6aebf9c484c96cc80bef3147b69).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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