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ChatGPT for Trip Planning: The Effect of Narrowing Down Options

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Abstract

ChatGPT is expected to have significant implications for trip planning from a traveler's perspective. ChatGPT has the potential to be a revolutionary search tool, enabling travelers to bypass an often complicated and disturbing process with a simple conversation with ChatGPT. This research aimed to explain the impact of ChatGPT on travelers' trip planning behavior; specifically, it examined how travelers perceive ChatGPT when they narrow down multiple travel options. Based on the choice overload effect, we conducted five experimental studies to determine the negative effect of reducing options from the initial recommendations using ChatGPT. The results showed the importance of a hybrid decision-making process involving both humans and ChatGPT. Using our empirical results, we provide significant theoretical and practical implications for travelers' trip planning behavior incorporating ChatGPT.

Keywords

ChatGPT, Chatbot, hybrid choice, AI recommendation, choice overload, travel decision-making process, option recommendation

Introduction

ChatGPT (which stands for Chat Generated Pre-trained Transformer) has attracted huge attention worldwide: recently, it appeared on the cover of the international news magazine, *Time* (Chow & Perrigo, 2023). As a dialog-based artificial intelligence (AI) tool developed by OpenAI, ChatGPT can understand natural human language and generate human-like written text (Lock, 2022). While what ChatGPT can do is technically the same as an existing chatbot, its remarkable ability to interact with users by providing sophisticated answers to their queries has led millions of people to adopt it for tasks ranging from writing an essay in a specific tone, to creating music about a certain topic, debugging programing codes, and getting ideas for producing an artwork (Marr, 2023). ChatGPT reached 100 million users within 2 months of its launch (November 30, 2022), making it the fastest-growing application in history (Milmo, 2023). Given the rapid adoption of ChatGPT, many fields are adapting to its potential impact: educational institutions banned the use of ChatGPT for course work (Roose, 2023); hundreds of books either wholly or partly written by ChatGPT have been published (Cuthbertson, 2022); the editors-in-chief of Nature and Science require researchers to not give authorship to ChatGPT (Stokel-Walker, 2023); and a top software forum, Stack Overflow, does not allow uploading of content created by ChatGPT (Cowen, 2022).

In the hospitality and tourism field, ChatGPT is expected to have significant implications for recommending travel ideas from a traveler's perspective (J. Kim et al., 2023; Whitmore, 2023). While travelers currently have to access multiple websites (e.g., search engines, maps, online travel agencies, online review websites, and blogs) to find listings for possible destinations or activities, they can bypass such complicated and disturbing processes through a simple conversation with ChatGPT (Mogelonsky & Mogelonsky, 2023). Since ChatGPT can recommend

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possible destinations or activities within a few seconds, in accordance with travelers' requests (e.g., dates, company, preferred activities, and time budget), a list of options recommended by the tool could be a valid initial reference for trip planning (Hayhurst, 2023). Furthermore, as ChatGPT gives more than 10 options in most cases (usually 15 according to our observations), it could help travelers consider various versions of trip itineraries. While travelers need to narrow down the multiple options to finalize their trip planning, the option reduction can be also conducted by ChatGPT by typing only a few words (e.g., please narrow down to four destinations or activities).

Although it would be convenient for travelers if ChatGPT was also effective for the option reduction, some limitations of the tool could be obstacles. First, ChatGPT cannot provide real-time information because it provides answers based on online data up to 2021 (Reuters, 2023). Even if travelers ask ChatGPT to narrow down more than 10 options to three or four, the filtered options may not be viable if they have closed since 2021. Second, ChatGPT cannot provide any images or pictures because it is solely text-based. Since visual information is important for travelers to compare multiple alternative destinations or activities (e.g., pictures, videos, location on a map) (C. W. Park et al., 2021), text-based responses from ChatGPT may be insufficient for travelers to narrow down multiple options. Last but not least, ChatGPT is not always correct, because it generates responses by finding the logical next word in a sentence (Sundar, 2023). In fact, seemingly convincing, but actually wrong responses from ChatGPT have been reported in various media (Brainard, 2023; Glorioso, 2023; Tayeb, 2023). While suggesting one or two invalid options out of more than 10 destinations or activities would not be critical for travelers, recommending the invalid options for inclusion in a final trip itinerary would be. These limitations of ChatGPT might make travelers unwilling to fully trust and be satisfied with its ability to narrow down multiple options.

Several researchers and practitioners have suggested that ChatGPT could enhance the trip planning process (Carvalho & Ivanov, 2023; Gursoy et al., 2023; J. Kim et al., 2023; Sorrells, 2023). However, while ChatGPT may assist travelers by generating multiple destination or activity options during the early stages of trip planning, it may not be completely reliable or satisfactory for narrowing down those alternatives later on. The impact of ChatGPT on travelers' planning behavior may be contingent upon a specific stage of the trip planning process (Dobravsky, 2023; Whitmore, 2023). The extent to which travelers trust and adopt ChatGPT for their planning is likely contextual. There is currently a lack of research exploring how travelers perceive ChatGPT's role in their trip planning behavior, particularly in the context of generating a list of alternatives versus narrowing down those alternatives. Furthermore, empirical studies investigating ChatGPT in the hospitality and tourism field appear to be scarce. This research aims to address this gap by examining how travelers evaluate ChatGPT's recommendations, depending on whether the recommendations are narrowed down by ChatGPT or not. Given the limited effectiveness of ChatGPT identified earlier, this study investigates how travelers perceive ChatGPT when it is used to reduce multiple options. Drawing on the choice overload effect (Simon, 1955; Toffler, 1970), we hypothesize a negative impact of reducing options from the initial recommendations provided by ChatGPT. We further explore this negative effect through an experimental approach. Additionally, we identify perceived trustworthiness as a mediator for travelers' negative evaluations of the reduced recommendations by ChatGPT, supported by experimental findings. Finally, we propose a boundary condition for travelers' negative evaluations and suggest a potential approach to address this negative effect, wherein travelers actively engage in narrowing down the options (referred to as a hybrid choice mode in this study).

This study examines the interactive capabilities of ChatGPT and its impact on travelers' behavior, providing valuable insights into the perception and adoption of advanced interactive technology in the context of travel. Unlike previous research that generally assumes a high level of trust in interactive search technology (Loureiro et al., 2022), this study demonstrates that travelers' trust in the technology's recommendations is contingent upon the type of task (i.e., exploring multiple alternatives vs. narrowing down options) and their level of engagement (i.e., suggestions provided and options narrowed down by ChatGPT vs. suggestions provided by ChatGPT but narrowed down by travelers themselves). The findings of this research make significant contributions to the existing literature in the field of hospitality and tourism, shedding light on the acceptance and trust-driven behavior of travelers toward information technology (Xiang et al., 2015). Moreover, this study not only focuses on the emerging and underexplored AI tool but also provides a detailed understanding of how the trust in and acceptance of the technology vary under different conditions (Hua et al., 2020).

The paper is organized as follows. Firstly, the theoretical background and relevant literature are discussed and the hypotheses and research model are proposed. The research methodology is then explained, followed by the results of the five empirical studies. In the last section, a general discussion is presented, including theoretical and practical contributions, limitations, and future research directions.

Literature Review and Theoretical Frameworks

Choice Overload Effect

Contrary to traditional research that has demonstrated the multiple benefits of larger options (Deci & Ryan, 1985; Taylor, 1989), various researchers in the consumer behavior field have discussed the negative effect of a large assortment of choices, known as the choice overload effect (Simon, 1955). The choice overload effect, analogous to the over-choice effect, is generally understood to mean a situation in which the intricacy of the decision problem facing a person transcends his or her cognitive capacity (Toffler, 1970). Initial studies on choice overload primarily attributed it to the sheer number of choices, concluding that consumers presented with a limited set of options are more inclined to make a purchase compared to those faced with numerous alternatives (Iyengar & Lepper, 2000). The main pitfall of choice overload is explained by some reasonable assumptions concerning the time and effort required when faced with a large choice set (Scheibehenne et al., 2010).

Firstly, having a multitude of choices leads to dissatisfaction as customers struggle to make the optimal decision, because of the near-impossibility of exhaustively comparing all available alternatives (Iyengar et al., 2006). The regret stemming from the inability to select the best choice enhances the attractiveness of other options, potentially resulting in unfavorable outcomes such as switching decisions or opting for no decision at all (Schwartz & Schwartz, 2004). Secondly, the presentation of numerous options raises customers' expectations that they can discover an ideal choice that perfectly aligns with their preferences (Diehl & Poynor, 2010). From this perspective, the negative effects of choice overload arise from the fact that an increasing number of options shifts consumers' ideal points, rendering satisfaction more difficult to achieve. These logical discourses concur with two important decision-making goals: minimizing cognitive effort and maximizing accuracy (Payne et al., 1993) to explain the process of decision-making.

Over the past decade, there has been a growing recognition in the literature that the concept of choice overload is influenced by various factors beyond just assortment size, which has traditionally been regarded as the primary moderator influencing customers' decision-making. Departing from the conventional perspective, Chernev et al. (2010) emphasize the importance of identifying specific conditions under which choice overload is more likely to occur, rather than focusing on its occurrence across all conditions. In line with this research, many studies investigated other moderators' ability to increase, decrease or reverse the effect of choice overload, such as familiarity (Lee, 2017; Sthapit, 2018), time pressure (Godinho et al., 2016; Haynes, 2009), categorization (Sharma & Nair, 2023), and who the decision is being made for (Pizzi et al., 2021). By redirecting attention toward understanding the elements and contextual conditions that contribute to choice overload, researchers can acquire more profound insights into this phenomenon and identify significant patterns and associations.

In the hospitality and tourism literature, there have been several investigations of the negative outcomes of choice overload, mainly focusing on determining moderators to reduce the choice overload effect. J. Y. Park and Jang (2013) provided empirical evidence that many options increase the probability of making "no choice" in the tourism context. They also demonstrated the insignificant result of familiarity (a typical moderator for reducing the negative effect of choice overload) because of the uniqueness of travel products compared to ordinary retail products. Recently, Guo and Li (2022) also verified the choice overload effect in the online hotel booking context with experimental results from different choice set sizes. In particular, they focused on finding moderators to reduce the choice overload effect, such as the amount of information or the method of presentation. Other researchers in the hospitality and tourism field found that reducing perceived uncertainty (X. Hu & Yang, 2020) or building travelers' self-confidence (Thai & Yuksel, 2017) also helped to mitigate the negative effects of large numbers of options at multiple stages in the decision-making process. During the decision-making process, individuals often seek to reduce the size of their option set to counteract the negative consequences associated with choice overload.

This phenomenon is influenced by various contextual factors that can either exacerbate or alleviate the effects of a large option size. Choice overload theory also suggests that in this reduction process, decision makers also consider how to maximize the accuracy of choices or minimize the effort (Bettman et al., 1998). In other words, we can investigate which potential moderators make the negative effect of large options increase by reducing the accuracy of option sets, or decrease by adding effort to the choice process. While numerous efforts have been made to identify moderators that mitigate or increase the adverse impacts of choice overload in tourism and hospitality contexts, an important aspect frequently overlooked pertains to the information source (e.g., AI or human) as a potential moderator to increase the accuracy of choices. Given the unique characteristics of travel decision-making (e.g., intuitive and emotional), by adopting a comprehensive approach, researchers may obtain deeper understanding of the contextual factors that contribute to choice overload, facilitating a more nuanced comprehension of decision-making processes in the domains of tourism and hospitality. This shift in focus enables a comprehensive exploration of the conditions that amplify or alleviate choice overload, ultimately leading to a more profound understanding of the underlying mechanisms in the decision-making processes in the tourism and hospitality sectors.

AI and ChatGPT Recommendation in Travel

In the past few years, AI's exceptional quantitative, computational, and analytical capabilities have enabled it to outperform humans in complex tasks. Algorithmic decision-making has created novel prospects for managing complexity and provides more efficient methods of equipping human decision-makers with comprehensive data analytics. AI is generally defined as "programs, algorithms, and machines that demonstrate intelligence" (Shankar, 2018, p. 6). Russell (2010) also emphasized that AI can be defined as an agent that thinks or behaves like a human, based on two dimensions: thinking-process-action and human-performance-rationality. In other words, the concept of AI focuses on the extent to which machines can imitate or replicate human behavior and abilities. Academic discourse on the use of AI continues to focus on how the roles of humans and emerging AI can complement each other in the decision-making process. Despite evidence that AI surpasses human capabilities, consumers still have opposing views about algorithmic recommendations.

Prior studies examining algorithm preference have highlighted that consumers perceive algorithms and human decision-makers to have distinct strengths and weaknesses. Jarrahi (2018), for instance, underscored the advanced problem-solving capabilities of artificial intelligence (AI), which are particularly beneficial for supporting analytical decision-making involving conscious reasoning and logical deliberation. However, AI is often perceived to have limitations in understanding commonsense situations (Guszcza et al., 2017) and may exhibit reduced effectiveness in uncertain or unpredictable environments, especially outside predefined domains of knowledge, in comparison to human decision-makers (Brynjolfsson & McAfee, 2011).

Moreover, consumer reservations regarding AI's ability to replace jobs involving emotions (Waytz & Norton, 2014), perform tasks with high subjectivity (Castelo et al., 2019), and consider individuality (Granulo et al., 2021) contribute to consumers' hesitancy in trusting AI recommendations. Consumers perceive algorithms as more objective but less intuitive than humans, leading to variations in their preferences for AI depending on the specific situation. Another psychological mechanism explaining the avoidance of AI recommendations is "algorithm aversion" (Dietvorst et al., 2015, p. 114), which denotes the inclination of consumers to rely more on human advice than on AI-based recommendations. Similarly, Promberger and Baron (2006) argued that individuals tend to rely on human advice in decision-making to avoid assuming responsibility for decisions made by algorithms and to shift that responsibility onto others.

Recently, with the advances in AI technology, ChatGPT has significantly impacted human society (Jackson, 2023). ChatGPT is an extensive language model developed by OpenAI that can perform various natural language processing tasks learned from large datasets. Specifically, it can perform tasks such as generating answers to questions, generating conversations, translating, and summarizing, and it has the characteristic of high interactivity with computers, like having a conversation in natural language. ChatGPT's application in hospitality and tourism is very valuable because of the industry's focus on information-intensive characteristics (I. Tussyadiah, 2020; Whitmore, 2023). Specifically, ChatGPT can be used for tasks such as overcoming barriers in translating information about attractions, providing responsive services through chatbots based on ChatGPT at destinations and hotels, and offering various recommendation services based on the learning of massive datasets. These capabilities enable ChatGPT to serve as an effective tool for delivering tourism information and helping travelers efficiently plan their trips. Considering the unique characteristics of tourism and hospitality as service products, the adoption of ChatGPT in the process of travel decision-making indicates how potential travelers perceive and use the new technology in their decision-making processes.

Hypothesis Development and Research Model

Main Predictions (H1a & H1b)

Expanding upon the choice overload theory, our proposal posits that as ChatGPT streamlines a multitude of options into a more concise selection, it may lead to a reduction in travelers' satisfaction with the recommendations and their intention to visit the recommended destination. While the theory presupposes that diminishing the quantity of options can alleviate the negative impact on decision-makers, it also contends that the positive influence of such reduction hinges on situational factors (Scheibehenne et al., 2010). More precisely, the efficacy of option reduction in alleviating choice overload is contingent on whether the appealing choices are retained or the unattractive ones are excluded during the reduction process—in essence, the effectiveness of the reduction itself (Oppewal & Koelemeijer, 2005). Considering that AI is often perceived as less reliable in uncertain or unpredictable scenarios (Brynjolfsson & McAfee, 2011), travelers may harbor uncertainty regarding AI's proficiency in reducing options for their travel destination decisions, which necessitate the consideration of a multitude of factors, including travelers' preferences. Consequently, it is reasonable to anticipate that when ChatGPT narrows down the number of recommended options from a relatively large set to a more limited one, travelers' satisfaction with the recommendations and their intention to visit the recommended destinations will decrease. ChatGPT, therefore, has the potential to serve as a moderating factor, amplifying the impact of choice overload on travel decision-making. Our arguments led to the following two hypotheses.

> ***H1a:*** *Travelers' satisfaction with a recommendation will be lower when ChatGPT reduces large numbers of options to smaller numbers.*
> ***H1b:*** *Travelers' visit intentions to recommended destinations will be lower when ChatGPT reduces large numbers of options to smaller numbers.*

Mediating Effect of Perceived Trustworthiness (H2)

As previously discussed, the effectiveness of option reduction in mitigating choice overload can be elucidated by the level of trust that decision-makers place in the reduction process (Oppewal & Koelemeijer, 2005; Scheibehenne et al., 2010). Trust, in this context, is defined as one party's willingness to make themselves vulnerable to the actions of another party, grounded in the expectation that the other party will undertake a specific action that is crucial to the trustor (McAllister, 1995). Our comprehension of trust predominantly stems from research centered on interpersonal relationships, encompassing both the confidence in and the willingness to depend on a business partner (M. J. Kim et al., 2014). In simpler terms, trust is established when there is confidence in an entity and a readiness to rely on it. In the context of our study, the reduction of options performed by ChatGPT may adversely affect the dependent variables, namely satisfaction and the intention to visit. This could be attributed to the fact that the AI tool might not be fully trusted when asked to filter destination options. Given that the process of trip planning is subjective, intuitive, and emotional (J. Kim et al., 2021), travelers may opt to bypass option reduction by ChatGPT. The lack of perceived trustworthiness here arises from the widespread belief that AI has limited capabilities in handling tasks requiring intuition and empathy, such as decision-making in travel-related contexts (Huang & Rust, 2018). Consequently, travelers are inclined not to trust information that has been curated by ChatGPT, as trustworthiness serves as a mediator between their satisfaction with the recommendation and their intention to visit. Building upon these arguments, we propose the following hypothesis:

> ***H2:*** *Perceived trustworthiness mediates the impact of option reduction by ChatGPT on travelers' (a) recommendation satisfaction and (b) visit intention.*

Boundary Conditions (H3, H4, & H5)

According to the choice overload theory, although customers tend to avoid excessive choices when making decisions, they may also be driven by a desire for accuracy (Payne et al., 1993). While customers attempt to streamline their choices, especially when the initial selection is extensive, in order to minimize the effort required, they also weigh the importance of making an accurate decision (Bettman et al., 1998). This objective is directly linked to the risk of losing optimal options during the narrowing-down process. When consumers are concerned about potentially missing out on optimal choices during this reduction process, their response may be negative (Oppewal & Koelemeijer, 2005; Scheibehenne et al., 2010). This suggests that consumers' adverse reactions to the reduction process could be alleviated by addressing their apprehensions regarding the loss of potential options. Building on this insight, we concentrate on a solution to counteract the negative impact of reducing choices through ChatGPT recommendations in this section.

First, we anticipate that concerns about forfeiting the best options will be more pronounced when the initial number of choices is substantial. For instance, if decision-makers are left with four options after whittling down from an initial pool of 16 choices, it implies that 12 options from the original set will be eliminated during the reduction phase. Consequently, we can anticipate a more pronounced negative impact in such a scenario. However, when decision-makers are left with four choices after narrowing down from an initial set of eight options, only four options from the original choice set will be lost in the reduction phase. In the literature, the complexity of the initial choice set, such as the number of alternatives or the presence of dominant options, has been explored as a contextual factor affecting the choice overload effect (Chernev, 2006; Chernev & Hamilton, 2009). In this situation, the negative impact of the desire for accuracy is expected to be mitigated. Based on this rationale, we propose that the number of initial options recommended will serve as a moderating factor. Specifically, we predict that the adverse impact of narrowing down options will be less pronounced when the initial set of options is not extensive. Thus, our formal hypothesis is as follows:

> ***H3:*** *The negative effect of reducing options using ChatGPT will be reduced when the number of initial options is small (*vs. *large).*

Second, we focus on the agents responsible for option reduction, considering the extensive literature exploring moderators of the choice overload effect. When ChatGPT assumes the role of reducing options, it inevitably results in the exclusion of certain potential choices. In response to this concern, decision-makers have the option to take charge of the option reduction themselves, thereby minimizing concerns about forfeiting the best possible alternatives. Through active participation in the reduction process, decision-makers can mitigate the perceived

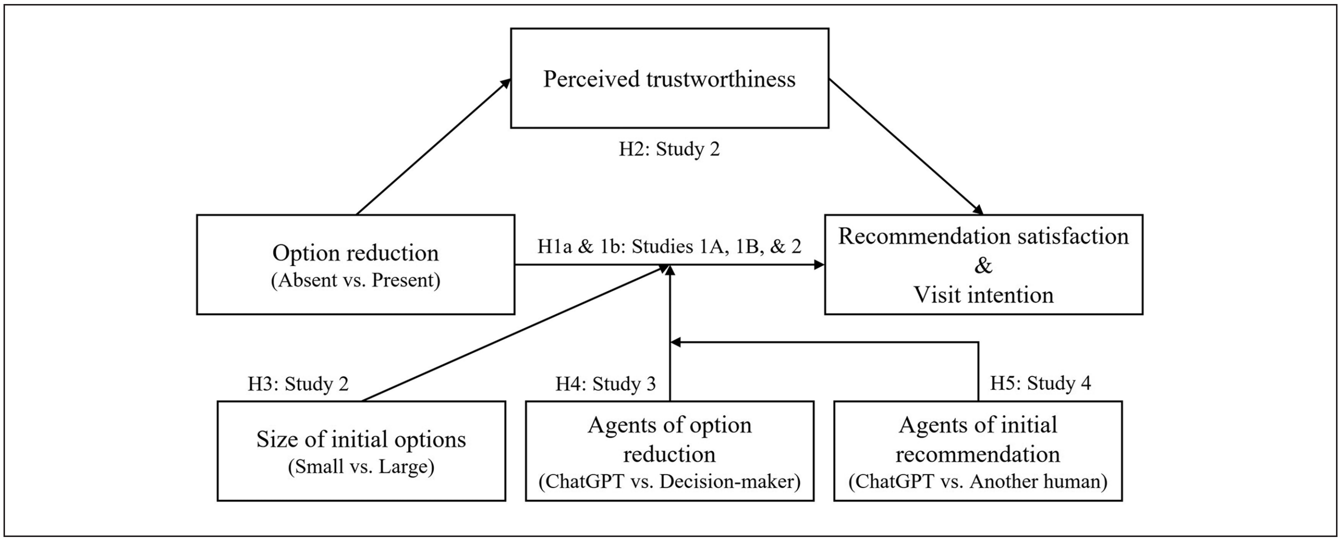


Figure 1. Overall theoretical framework and empirical studies.

negative consequences and bolster their confidence in the decision-making process. This concept aligns with Polman's (2012) findings, which highlight how the choice overload effect varies depending on whether consumers narrow down options independently or make choices on behalf of themselves or others. Based on this rationale, we propose the following hypothesis:

H4: *The negative effect of reducing options using ChatGPT will be reduced when the option reduction is done by the human decision-maker (rather than by ChatGPT).*

Regarding H4, we have also introduced a boundary condition. Drawing inspiration from the contextual influence of agents on choice overload, as demonstrated by Polman (2012), our investigation centers on recommendation agents. As suggested in the hypothesis, a negative effect is expected when the recommendation and option reduction is done by ChatGPT. We might expect different patterns when the recommendation and option reduction is done by human agents. For example, travelers frequently ask for travel information from people they know, such as friends or experienced travelers. In this situation, travelers' concerns about losing valuable potential options during the option reduction will be lower, since travelers are likely to be aware that the human agent already knows their preferences. In summary, we expected a moderating effect from the recommendation agents on the negative effect. The formal hypothesis is:

H5: *The types of recommendation agents will moderate the negative effect of option reduction. When initial options are generated by ChatGPT, there is a negative effect of option reduction by the ChatGPT (*vs. *by the travel decision-maker). When initial options are generated by another human, there is no negative effect of option reduction by the other human (*vs. *by the travel decision-maker).*

The overall theoretical frameworks and the five experimental studies are summarized in Figure 1. These studies were conducted to test five hypotheses. Study 1A, focusing on H1a, investigates the negative impact of ChatGPT's option reduction on travelers' satisfaction with recommendations. Study 1B, which replicates Study 1A with some refinements in experimental design, serves to reinforce and complement the initial findings. Study 2 is designed to assess another primary hypothesis, H1b, which explores the adverse effects of ChatGPT's option reduction on travelers' intentions to visit recommended destinations. Additionally, it examines the mediating role of perceived trustworthiness (H2) and the moderating influence of the size of the initial options (H3). Study 3 delves into a different aspect by scrutinizing the potential moderating effects of the agents responsible for option reduction. Finally, Study 4 explores the repercussions of agents' initial recommendations on the moderating role of these agents in option reduction.

All empirical studies were conducted in February 2023. Participants in this study were recruited from an Amazon Mechanical Turk (MTurk) online panel via a CloudResearch qualified sample. No participants were enlisted for multiple studies in this empirical investigation. All participants were recruited from the US to control for country-specific factors relating to ChatGPT availability and environment. The profiles of all participants are described in Table 1. In previous research examining the quality of data obtained through Amazon MTurk, it was determined that the samples of U.S.

Table 1. Profiles of Participants in Studies 1 to 4.

		Study 1A ($n = 333$) (%)	Study 1B ($n = 326$) (%)	Study 2 ($n = 315$) (%)	Study 3 ($n = 130$) (%)	Study 4 ($n = 258$) (%)
Gender	Male	45.0	45.4	52.1	47.7	44.2
	Female	53.8	54.3	46.7	52.3	55.8
	Other	1.5	0.3	1.3	0.0	0.0
Age	18–29	18.3	18.4	18.1	21.7	20.2
	30–39	35.6	34.7	34.9	31.8	29.8
	40–49	25.2	22.7	21.9	27.0	23.3
	50–59	11.4	16.3	13.7	10.1	14.3
	60–	9.0	8.0	11.4	9.3	12.4
Family income	< $30,000	15.9	17.2	15.6	16.9	20.2
	$30,001–$60,000	27.3	28.2	28.6	29.2	34.1
	$60,001–$90,000	27.0	22.7	21.9	16.9	16.3
	$90,001–$120,000	15.0	16.9	16.5	16.9	15.5
	> $120,001	14.7	15.0	17.5	20.0	14.0
Education level	Did not complete high school	0.6	0.3	0.3	0.0	0.8
	High school graduate or some college	36.0	32.5	33.0	33.8	33.3
	College graduate (4 years)	45.9	42.6	45.7	44.6	46.1
	Postgraduate degree	17.4	24.5	21.0	21.5	19.8
Race	White/Caucasian	72.4	74.2	74.0	72.3	73.6
	African American	12.0	8.3	12.1	11.5	10.9
	Hispanic	6.0	7.4	3.8	3.8	4.7
	Asian	4.8	6.9	8.9	8.5	7.8
	Others	4.8	3.3	1.3	3.9	3.1

participants recruited via this platform effectively mirror the broader population (Merz et al., 2022). Furthermore, their representativeness was found to be superior to that of participants obtained from other survey platforms (Kimball, 2019). We assessed and confirmed the representativeness of our sample in relation to the U.S. population. Our findings indicate that our sample closely aligns with the demographic characteristics of the U.S. population, with a gender distribution of 50.5% male and 49.5% female. The largest age and racial/ethnic group in our sample is individuals aged 30 to 34, who identify as White, which is consistent with data from USAFacts (2022). The sample size was predetermined by the G*Power program (Faul et al., 2007). According to the given criteria (i.e., medium effect size $f = 0.25$ [medium], $\alpha = .05$, power $[1-\beta] = .80$, with four experimental groups), the minimum required total sample size was 128. However, in this study, our aim was to exceed this number and collect a larger sample.

Study 1A: Testing H1a

In Study 1A, we tested H1a to examine our expectation that travelers' evaluations of the reduced recommendations by ChatGPT would be lower. We chose Hong Kong as the target travel destination.

Participants, Design, and Procedure

This study used 333 US participants ($M\_{age} = 40.06$, $SD = 11.67$; 53.8% female), who received a nominal payment for their time. Participants were randomly assigned to 1 of 2 (initial recommendation set size: large I [15] versus large II [30]) ×2 (options reduction: absent vs. present) conditions with a between-subjects design.

First, participants were asked to read the following scenario: "Imagine you are planning a trip to Hong Kong and are seeking information on destinations/activities to enjoy while there. You turn to ChatGPT, an AI-based online chatbot developed by OpenAI, for recommendations. ChatGPT offers the following suggestions." Then, participants were exposed to either 15 or 30 destinations generated by ChatGPT,[1] as shown in Figure 2. Participants in the options reduction present conditions were further asked to imagine that they asked ChatGPT to narrow it down to four destinations,[2] and ChatGPT showed the four options, as shown in Figure 2. In contrast, participants in the options reduction absent conditions were not exposed to the reduced options set. All participants were then asked to evaluate their satisfaction with the recommendations made by ChatGPT, using a 7-point Likert scale (i.e., 1 = not satisfied at all, 7 = very satisfied). Participants evaluated the realism of this study, again using a 7-point scale (i.e., 1 = highly unrealistic, 7 = highly realistic). Then, participants were asked to describe their knowledge of and experience with ChatGPT (e.g., "Have you heard of ChatGPT?" or "Have you used ChatGPT?" (yes or no)), their experience of travel to Hong Kong travel (yes or no), and were asked to provide demographic information. All the meaurement scales are shown in the Appendix.

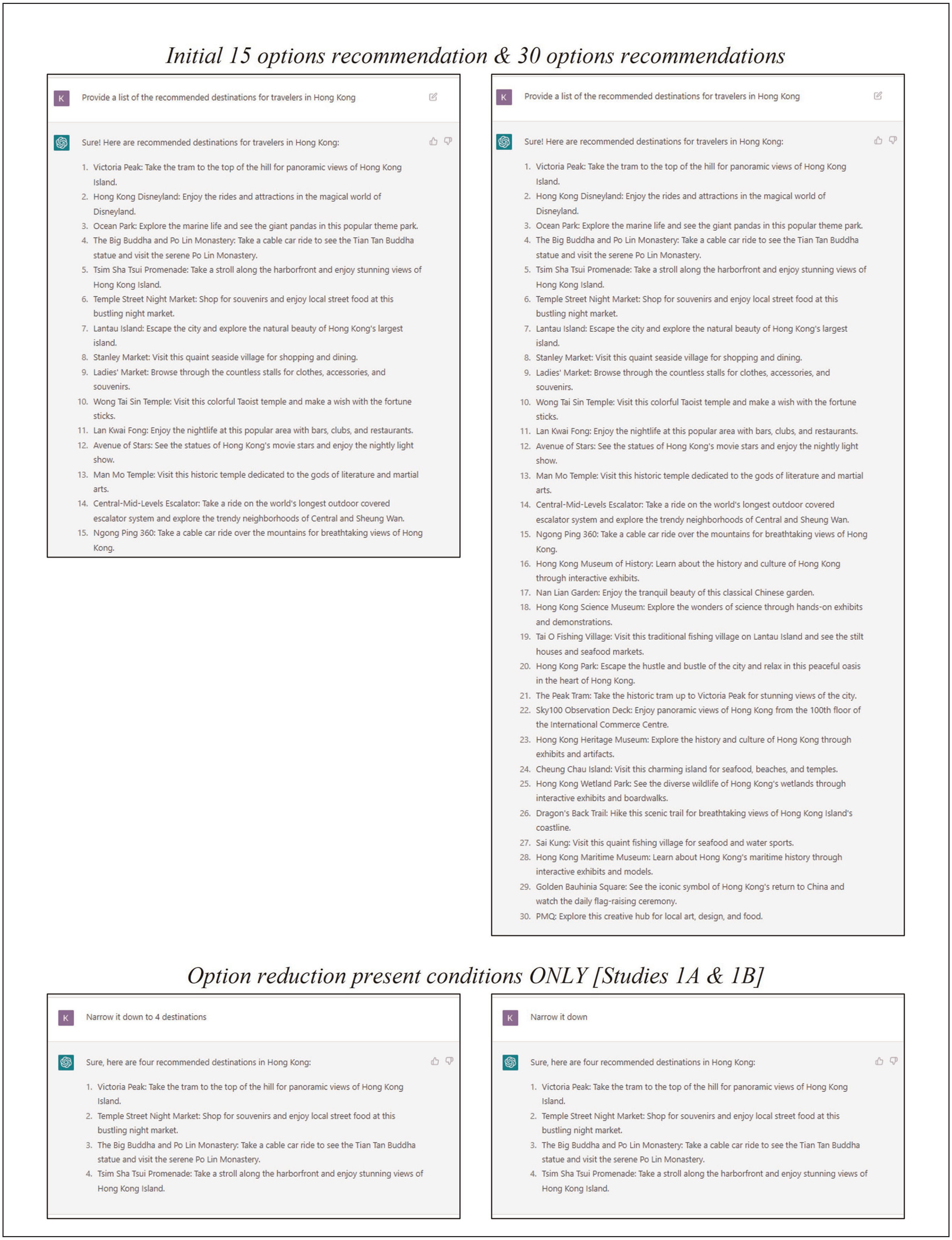


Figure 2. Stimuli for Studies 1A & 1B.

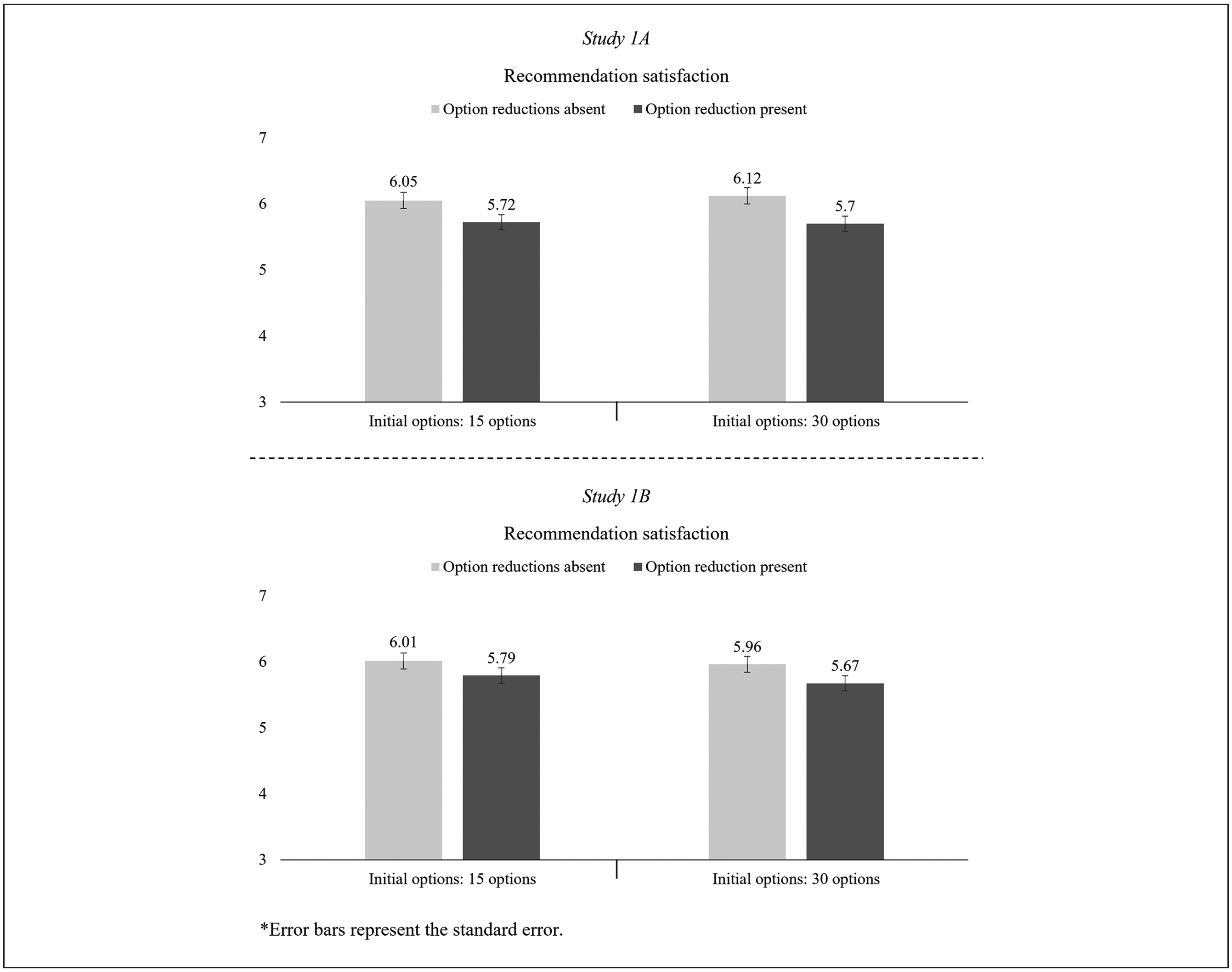


Figure 3. Results of Study 1.

Results and Discussion

The perceived realism was relatively high in that the value was above the neutral point (M = 5.84, SD = 1.12 vs. "4", t (332) = 29.92, p < .001).

For the main analysis, we conducted a 2 × 2 ANOVA (Analysis of Variance) for the recommendation satisfaction. The results indicated that the main effect of initial recommendation set size was not significant (F (1, 329) = 0.03, p = .859, η^2 < .001), as the recommendation satisfaction was very similar regardless of the initial recommendation size. The interaction effect of the two experimental factors was also non-significant (F (1, 329) = 0.13, p = .737, η^2 < .001). However, the main effect of the options reduction factors was significant (F (1, 329) = 8.11, p = .005, η^2 = .024): satisfaction with the recommendations was reduced significantly when the ChatGPT suggested narrowed-down options from the initial large option ($M_{\_reduction\ absent}$ = 6.08, SD = 1.16 vs. $M_{\_reduction\ present}$ = 5.71, SD = 1.23), supporting H1a. The detailed pattern is shown in Figure 3.

Finally, we also conducted 2 × 2 ANCOVA with the knowledge and experience of using ChatGPT, Hong Kong travel experience, perceived realism and demographic information on income, gender, and age. We found that gender (F (1, 321) = 5.05, p = .045, η^2 = .012), users' experience of ChatGPT (F (1, 321) = 3.00, p = .084, η^2 = .009), and perceived realism (F (1, 321) = 102.03, p < .001, η^2 = .241) significantly influenced recommendation satisfaction. Importantly, we found that the main effect of the options reduction factor was still significant (F (1, 321) = 14.26, p < .001, η^2 = .043), suggesting that the negative effect of reducing recommended options was robust regardless of these demographic and other factors.

Study 1B: Replicating Study1A With Modification

One weakness of Study 1A was that the options reduction number was explicitly provided to ChatGPT in the options reduction present condition. In this study, we did not mention four options to the participants in the option reduction present conditions. Otherwise, the study was very similar to Study 1A.

Participants, Design, and Procedure

This study involved 326 US adults who participated in return for a nominal payment (M_{age} = 40.67, SD = 11.99; 54.3% female). Participants were randomly assigned to one of 2 (initial recommendation set size: large I [15] versus large II [30]) ×2 (options reduction: absent vs. present) conditions with a between-subjects design.

Overall, the general procedure for this study was similar to Study 1A, apart from the narrowing-down request wording in the options reduction present condition. Specifically, participants in the options reduction present conditions were asked to imagine that they asked ChatGPT to narrow it down (without being told how many options ChatGPT should present), and ChatGPT showed four options, as shown in Figure 2. After that, participants were asked to state their recommendation satisfaction using the same scale as in Study 1A.

Results and Discussion

The perceived realism was relatively high in that the value was above the neutral point (M = 5.80, SD = 1.16 vs. "4", t (325) = 28.01, $p < .001$).

We conducted 2 × 2 ANOVA for the recommendation satisfaction. The results indicated that the main effect of initial recommendation set size was not significant (F (1, 322) = 0.39, p = .534, η^2 = .001). The interaction effect was also non-significant (F (1, 322) = 0.06, p = .810, $\eta^2 < .001$). However, the main effect of options reduction factors was significant (F (1, 322) = 4.03, p = .045, η^2 = .012) in that satisfaction with the recommendations was reduced significantly when ChatGPT suggested narrowed-down options from the initial large option set ($M\_{reduction\ absent}$ = 5.99, SD = 1.07 vs. $M\_{reduction\ present}$ = 5.73, SD = 1.23), supporting H1a. The detailed pattern is illustrated in Figure 3.

Finally, we also conducted 2 × 2 ANCOVA with perceived realism as a covariate. We found that perceived realism (F (1, 321) = 87.31, $p < .001$, η^2 = .214) significantly influenced recommendation satisfaction. The results indicated that the main effect of the options reduction factor was still significant (F (1, 321) = 4.07, p = .044, η^2 = .013), suggesting that the negative effect of reducing recommended options was robust above and beyond the perceived realism.

Study 2: Testing H1b, H2, and H3

Based on the findings of the previous studies, this study extended the investigation in several ways. First, we measured visit intention and perceived trustworthiness for the recommendations to test H1b and H2. Second, we tested the moderating effect of the number of initial destination recommendations to test H3. Specifically, we expected that the negative effect of narrowing down by ChatGPT would be reduced significantly when the size of the initial set of options was relatively small (vs. large).

Participants, Design, and Procedure

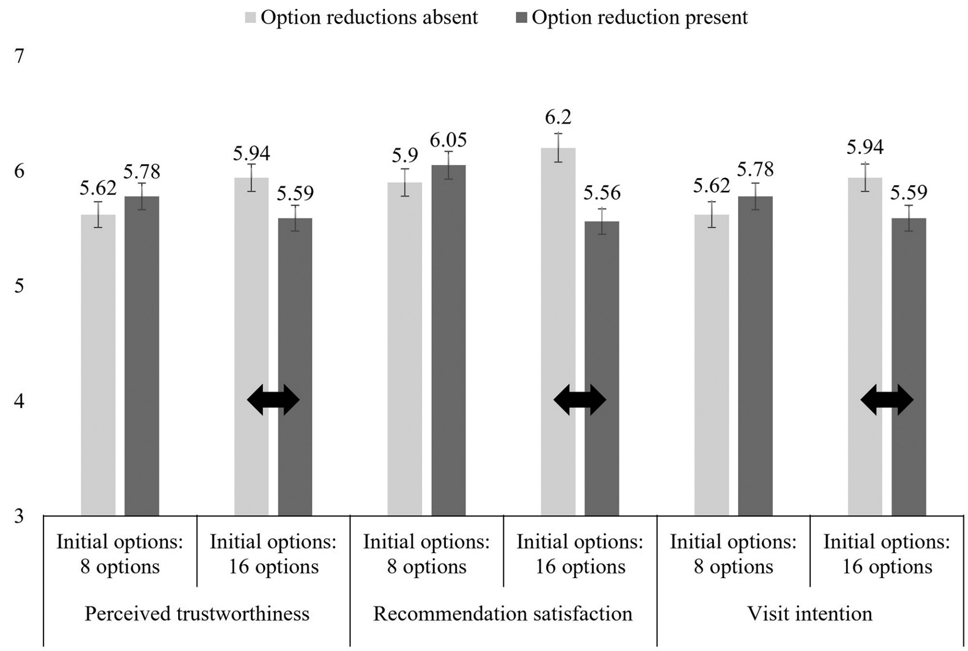
For this study, 315 US adults participated in return for a nominal payment (M_{age} = 41.45, SD = 13.05; 46.7% female). Participants were randomly assigned to one of 2 (initial recommendation set size: medium [8] vs. large [16]) ×2 (options reduction: absent vs. present) conditions with a between-subjects design.

The overall procedure for this study was similar to Study 1B apart from a few modifications. All participants were asked to imagine that they planned to visit Hong Kong and asked ChatGPT for recommendations. The number of recommended options was either 8 or 16.[3] After either being told that ChatGPT would narrow down the options to 4, or not being told, participants were asked to rate their visit intention with two items on a 7-point scale (i.e., 1 = not at all/very low, 7 = very much/very high, r = .81, $p < .001$), and their recommendation satisfaction, using the same scale as the previous studies. Then, they rated the perceived trustworthiness of the recommendations with two items on a 7-point scale (i.e., 1 = not trustworthy at all/ not credible at all, 7 = very trustworthy/very credible, r = .91, $p < .001$, Luffarelli et al., 2021). Participants then evaluated the realism of this study and provided demographic information.

Results and Discussion

The perceived realism was relatively high in that the value was above the neutral point (M = 5.93, SD = 1.00 vs. "4", t (314) = 29.92, $p < .001$).

For the main analysis, we conducted a 2 × 2 ANOVA for recommendation satisfaction. The results indicated that the main effect of initial recommendation set size was not significant (F (1, 311) = 0.62, p = .432, η^2 = .002), whereas the main effect of options reduction was significant (F (1, 311) = 4.12, p = .043, η^2 = .013) in that satisfaction was reduced by narrowing down using ChatGPT ($M\_{reduction\ absent}$ = 6.05, SD = 0.98 vs. $M\_{reduction\ present}$ = 5.81, SD = 1.18). More importantly, the interaction



* Error bars represent the standard error. "↔" indicates significance at α =.05.

Figure 4. Results of Study 2.

effect of two experimental factors was significant (F (1, 311) = 10.72, p = .001, η^2 = .033),[4] as shown in Figure 4. Planned contrast confirmed that recommendation satisfaction was reduced significantly following narrowing down by ChatGPT (Contrast F (1, 311) = 13.84, p < .001, η^2 = .043; $M\_{reduction\ absent}$ = 6.20, SD = 0.93 vs. $M\_{reduction\ present}$ = 5.56, SD = 1.19) when the initial number of options was large, at 16. On the other hand, the recommendation satisfaction was similar regardless of narrowing down by ChatGPT (Contrast F (1, 311) = 0.79, p = .376, η^2 = .003; $M\_{reduction\ absent}$ = 5.90, SD = 1.01 vs. $M\_{reduction\ present}$ = 6.05, SD = 1.14) when the initial number of options was medium at 8, supporting H3.

We found similar results for visit intention. The results indicated that the main effect of initial recommendation set size was not significant (F (1, 311) = 0.60, p = .441, η^2 = .002). The main effect of options reduction was also not significant (F (1, 311) = 0.32, p = .574, η^2 = .001). More importantly, the interaction effect for the two experimental factors was significant (F (1, 311) = 4.43, p = .036, η^2 = .014). Planned contrast confirmed that visit intention for the recommended places was reduced significantly following narrowing down by ChatGPT (Contrast F (1, 311) = 4.07, p = .045, η^2 = .013; $M\_{reduction\ absent}$ = 5.94, SD = 0.85 vs. $M\_{reduction\ present}$ = 5.59, SD = 1.13) when the initial number of options was large, at 16. On the other hand, the visit intention was similar regardless of narrowing down by ChatGPT (Contrast F (1, 311) = 0.90, p = .342, η_2 = .003; $M\_{reduction\ absent}$ = 5.62, SD = 1.24 vs. $M\_{reduction\ present}$ = 5.78, SD = 1.07) when the initial number of options was medium at 8, as shown in Figure 4, supporting H1b and H3.

We also found similar results for perceived trustworthiness. The results indicated that the main effect of initial recommendation set size was not significant (F (1, 311) = 0.25, p = .618, η^2 = .001). The main effect of options reduction was marginally significant (F (1, 311) = 2.99, p = .085, η^2 = .010). More importantly, the interaction effect of the two experimental factors was significant (F (1, 311) = 5.83, p = .016, η^2 = .018). Planned contrast confirmed that the perceived trustworthiness of the recommendation was reduced significantly with narrowing down by ChatGPT (Contrast F (1, 311) = 8.45, p = .004, η^2 = .026; $M\_{reduction\ absent}$ = 5.88, SD = 1.16 vs. $M\_{reduction\ present}$ = 5.31, SD = 1.32) when the initial number of options was large at 16. In contrast, visit intention was similar regardless of narrowing down by ChatGPT (Contrast F (1, 311) = 0.24, p = .626, η^2 = .001; $M\_{reduction\ absent}$ = 5.62, SD = 1.19 vs. $M\_{reduction\ present}$ = 5.71, SD = 1.19) when the initial number of options was medium at 8, as shown in Figure 4.

Finally, we conducted a serial mediation (IV → perceived trustworthiness → recommendation satisfaction → visit intention) for the condition where the initial number

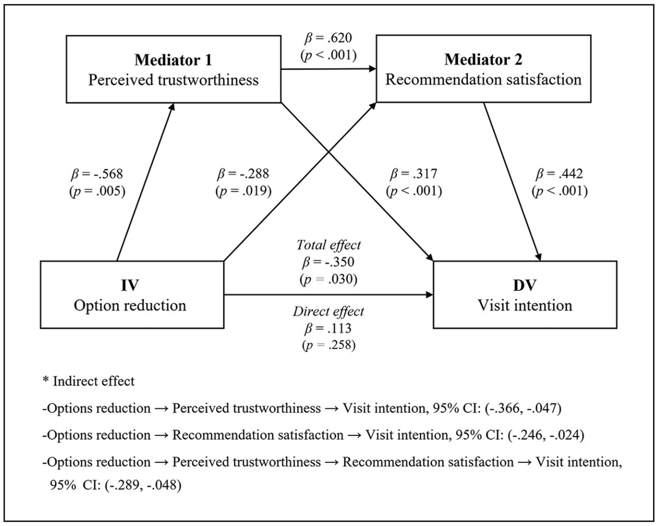


Figure 5. Serial mediation results of Study 2.

of options was large at 16, using Hayes (2017) macro with 5,000 bootstrapping. The results indicated that the indirect effect of serial mediation was significant (95% Confidence Interval [CI] [−0.289, −0.048]), supporting H2. The detailed results are presented in Figure 5. We also conducted the same analysis for the condition where the initial number of options was medium at 8 and found that the indirect effect of serial mediation was not significant (95% CI [−0.120, 0.197]).

Study 3: Testing H4

In the previous studies, we found that visit intention for the recommended places was reduced significantly by narrowing down by ChatGPT. In this study, we tried to suggest a condition that could reduce the negative effect to test H4. Specifically, we compared two conditions: narrowing down by ChatGPT versus narrowing down by the decision-maker. In addition, to increase the external validity, we used Key West in Florida as the final trip destination.

Participants, Design, and Procedure

In this study, 130 US adults (M_{age} = 39.66, SD = 12.76; 52.3% female) participated in exchange for a nominal payment. Participants were randomly assigned to one of 2 (initial recommendation agents: ChatGPT [8] vs. large [15]) ×2 (options reduction: absent vs. present) conditions with a between-subjects design.

The overall procedure of this study was similar to the previous studies apart from a few modifications. First, all participants were asked to imagine that they planned to visit Key West, Florida, and had asked ChatGPT for recommendation. They were then exposed to the 15 options recommended by ChatGPT, as shown in Figure 6. Participants in the options reduction by ChatGPT condition were further informed that they asked ChatGPT to narrow it down to three activities, as shown in Figure 6. In contrast, participants in the options reduction by decision-maker condition were asked to choose three activities from the 15-option list. Then, all participants were asked to rate their visit intention for the reduced three-choice set using the same scales that were used in the previous study, and rate their satisfaction with the recommendation using the 7-point scale applied in the previous study.

Results and Discussion

The perceived realism was relatively high in that the value was above the neutral point (M = 5.92, SD = 1.06 vs. "4", t (131) = 20.66, $p < .001$).

For the main analysis, we conducted one-way ANOVA for the visit intention for narrowing down to three options. The results indicated a significant effect of the experimental conditions. Visit intention was higher when the options reduction was done by the decision-maker ($M\_{decision\ maker}$ = 5.77, SD = 1.35) rather than by ChatGPT ($M\_{ChatGPT}$ = 4.99, SD = 1.67; F (1, 128) = 8.52, p = .004, η^2 = .062), supporting H4.

The results of the recommendation satisfaction survey were similar, in that the recommendation satisfaction was higher when the options reduction was done by the decision-maker ($M\_{decision\ maker}$ = 5.97, SD = 1.32) rather than by ChatGPT ($M\_{ChatGPT}$ = 5.05, SD = 1.69; F (1, 128) = 12.02, $p < .001$, η^2 = .086), also supporting H4.

Study 4: Testing H5

In the previous study, we demonstrated that the negative effect of options reduction by ChatGPT could be reduced significantly when the options reduction was conducted by the decision-maker. In this study, we empirically examined the moderating role of recommendation agents to test H5. We compared the ChatGPT and human recommendations. We expected that the negative effect of options reduction by the same recommendation agents would be reduced significantly when done by the human agents.

Participants, Design, and Procedure

For this study, 258 US adults (M_{age} = 41.45, SD = 13.05; 55.8% female) participated in exchange for a nominal payment. Participants were randomly assigned to one of 2 (initial recommendation agents: ChatGPT vs. human) × 2 (options reduction: by recommended agent vs. by decision-maker) conditions with a between-subjects design.

Figure 6. Stimuli for Studies 3 & 4.

The overall procedure of this study was similar to study 3 apart from a few modifications. First, participants were asked to imagine that they planned to visit Key West, Florida and that they asked either ChatGPT or a friend who was an experienced traveler for Key West recommendations, based on the first factor of initial recommendation agents' conditions (i.e., human vs. ChatGPT). The initial recommendation destinations involved 15 options. Then, participants either had recommended agents reduce the options to 3, or they were asked to narrow down the options by themselves, based on the second factor of options reduction. Finally, participants were asked to choose one option and rate their perceived satisfaction with the decision using 7-item scales (i.e., 1 = not satisfied at all/not confident at all/not certain at all, 7 = very satisfied/very confident/very certain, Cronbach's $\alpha = .902$, Bodur et al., 2016; Sainfort & Booske, 2000).

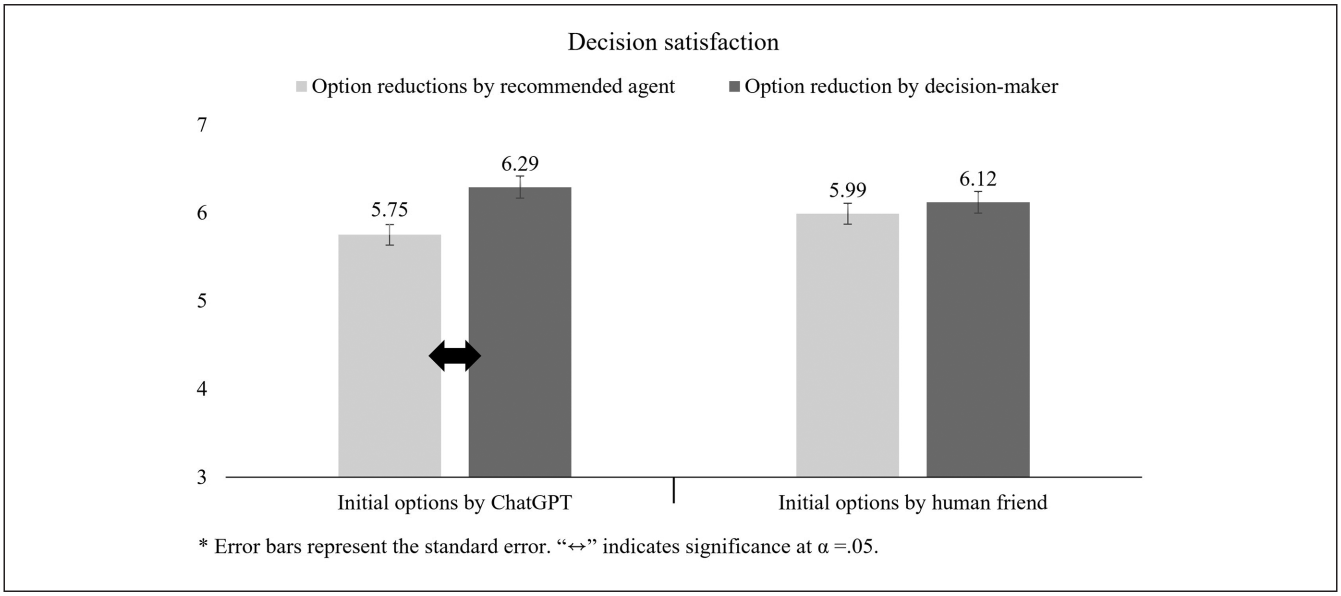


Figure 7. Results of Study 4.

Results and Discussion

The perceived realism was relatively high in that the value was above the neutral point (M = 6.01, SD = 1.15 vs. "4", t (397) = 28.14, $p < .001$).

For the main analysis, we conducted two-way ANOVA for the decision satisfaction. The main effect of the initial recommendation agents was not significant (F (1, 254) = 0.08, p = .774, η^2 = .001). However, the main effect of options reduction was significant (F (1, 254) = 7.71, p = .006, η^2 = .029) in that the decision satisfaction was higher when the options reduction was done by the decision-maker ($M\_{decision\ maker}$ = 6.20, SD = 0.92) rather than by the recommended agent ($R\_{recommended\ agent}$ = 5.88, SD = 1.02). More importantly, the interaction effect was marginally significant (F (1, 254) = 2.82, p = .095, η^2 = .011), supporting H5. Further planned contrast indicated that the decision satisfaction was higher when the options reduction was done by the decision-maker ($M\_{decision\ maker}$ = 6.29, SD = 0.79) rather than by the recommended agent or ChatGPT ($R\_{recommended\ agent}$ = 5.88, SD = 1.06, Contrast F (1, 254) = 9.55, p = .002, η_2 = .036) when the initial options were recommended by ChatGPT. In contrast, when the initial options were recommended by a human friend, the decision satisfaction was the same regardless of the options reduction by the decision-maker ($M\_{decision\ maker}$ = 6.12, SD = 1.00) or by the recommended agent, who in this case was human ($R\_{recommended\ agent}$ = 5.99, SD = 0.98, Contrast F (1, 254) = 0.63, p = .429, η^2 = .002), as shown in Figure 7.

General Discussion

Given the potential for ChatGPT to serve as a tool for travelers' trip planning, we examined the influence of ChatGPT as a recommendation agent on the planning process. Our research findings, drawn from four experimental studies, offer guidance on the potential uses of ChatGPT within the hospitality and tourism context. Based on the results of Studies 1A and 1B, we found that when ChatGPT provided reduced recommendations from the set of initial options, it led to negative evaluations (i.e., recommendation satisfaction) compared to situations where reduced recommendations were absent. In Study 2, we found that similar to the mechanisms identified in Studies 1a and 1b, when ChatGPT provided reduced recommendations (vs. the option reduction absent condition), it had a significantly negative impact on the behavioral responses (i.e., visit intention) of decision makers, which was mediated by perceived trustworthiness and recommendation satisfaction. Our findings confirmed that option reduction by ChatGPT had a negative impact on decision-maker's emotional reactions and behaviors. Additionally, our research results demonstrated that ChatGPT's option reduction's negative effect was magnified when the initial decision size was relatively large (vs. small). To explore suggestions to mitigate the negative effects, in Study 3, we found that recommendation satisfaction and visit intention were significantly higher when the options were narrowed down by decision-makers (rather than ChatGPT). Finally, in Study 4, we showed that the decision satisfaction was higher when options reduction was made by the decision-maker (vs. ChatGPT) when the initial options were recommended by ChatGPT (vs. a human agent).

Theoretical Contributions

Our research sheds light on the comparative effects of ChatGPT and humans as recommendation agents in the context of tourism information search and decision-making processes, which has theoretical implications. The specific theoretical contributions are as follows.

First, this research contributes to the hospitality and tourism literature on the development of information technologies. When a technological development occurs, the hospitality and tourism literature has attempted to clarify how the new technology, such as social media and smart devices, will affect travelers' perceptions or behaviors (Xiang et al., 2015). Although ChatGPT is expected to significantly change travelers' searching and trip planning (Dobravsky, 2023; Sorrells, 2023; Whitmore, 2023), the AI tool's potential impact has seldom been discussed in the hospitality and tourism literature. By examining how ChatGPT can be perceived and used by travelers for trip planning, this research provides an empirical reference for future studies on the impact of ChatGPT on travelers' behavior. Furthermore, given the scarcity of research on perception of ChatGPT in other academic fields, this study can serve as an important empirical baseline for future research in general.

Second, this research expands upon previous studies on choice overload effect on consumer behaviors; it provides academic value by examining the perception and behavior response toward ChatGPT as an effective tool for delivering tourism information. Our research findings showed that the evaluation of ChatGPT by decision-makers was focused on "maximizing accuracy" in pre-travel situations. While the marketing and tourism literature displays conflicting perspectives on the effectiveness of information overload, many studies have emphasized the need for providing simple and summarized information, as information overload often results in decision-making complexity (H. F. Hu & Krishen, 2019; J. Y. Park & Jang, 2013; Zhang et al., 2022). However, we confirmed that when ChatGPT was involved in travel recommendations, decision-makers tended to distrust the reduction of options by the AI tool, leading to a negative impact on their behavioral responses. In other words, when ChatGPT has reduced the options excessively, decision-makers may cognitively construe it as a loss of choice. Our findings can be interpreted from two different perspectives. First, regarding perceptions of AI, prior research has shown a skeptical response to AI's capability, particularly in decision-making situations where high uncertainty, contextual information, and emotional evaluations are involved (Jarrahi, 2018). Second, the emphasis on maximizing accuracy versus minimizing effort in decision-making can vary depending on the situation (Affonso et al., 2021). In the context of hospitality and tourism, where purchasing intangible products is based on uncertainty (Litvin et al., 2008), the decision-making process can be oriented toward maximizing accuracy by willingly accepting a large amount of information in order to enhance satisfaction with the tourism experience from the traveler's perspective. In summary, based on the understanding of contrasting perspectives on the choice overload effect, our research can be considered an initial exploratory study of the manner in which tourism information is presented through ChatGPT.

Third, our research reveals the underlying psychological mechanisms behind why decision-makers do not prefer a reduction in recommendations by AI agents, which has theoretical implications. In previous studies on AI in the hospitality and tourism fields, "trust" has been treated as a crucial mediator, leading to positive behavioral responses (e.g., S. Park, 2020; Shi et al., 2021; I. P. Tussyadiah et al., 2020). Many hospitality and tourism scholars have attempted to verify the effectiveness of the modality of information provision (Liu et al., 2022) or technology attributes (Chi et al., 2022), particularly with regard to chatbots and service robots. Continuing the research stream, however, we investigated the impact of ChatGPT, a more advanced technology than existing ones, on the negative impact of trustworthiness and behavioral reactions when it exhibits human-like capabilities, specifically travel recommendations. In other words, our research is significant because it engaged in the theoretical discourse of "the acceptance of advanced technology," which has been a sustained interest in the tourism and hospitality sectors, while emphasizing the importance of emotional responses in the formation of a relationship between technology (i.e., ChatGPT) and humans from the perspective of human-computer interaction.

Finally, the results presented in Study 4 enable an expansion of theoretical discourse on the use of AI technology. Interestingly, our research findings highlight the importance of a hybrid decision-making process that involves both ChatGPT and decision-makers as a means to enhance satisfaction during the pre-travel decision-making stage. This approach allows for the provision of initial information by AI agents, while also enabling decision-makers to exercise their discretion within a range of options. Considering the theoretical discussion on the theory of AI job replacement, our findings can be seen as a significant contribution to the hospitality and tourism industry while emphasizing the importance of human agents. Our results highlight the importance of decision-makers exercising their own discretion in making final decisions from initial options provided by AI agents. We regard our research findings as being relevant to critical facets of human capabilities, such as self-regulation (Molenaar, 2022) and capacity for information processing

(J. Kim et al., 2021) concerning the use of technology, including AI. In summary, our research outcomes underscore the criticality of leveraging AI agents to maximize the recognition of human autonomy in decision-making processes while delineating the role that AI should play.

Practical and Managerial Contributions

Currently, major OTAs plan to embed ChatGPT's functions in their websites to help travelers to create travel itineraries (Kong, 2023). The findings of this research may be useful guidelines for the embedding process. First, our findings indicated that ChatGPT can be useful for travelers to explore multiple destinations or activities at the early stage of trip planning, but it might not be helpful in narrowing them down to several options at a later stage because ChatGPT's narrowing-down ability was not perceived as trustworthy. According to our findings, OTAs should emphasize ChatGPT's ability to generate the initial pool of destinations or activities and deemphasize its narrowing-down ability. For example, OTAs could place a box for talking with ChatGPT in a conspicuous space on the main page (e.g., the center) where travelers start their search, but make the box less conspicuous to users on the following page (e.g., bottom-right) at the point where travelers narrow down the recommended options (Djamasbi, 2014).

Second, our findings showed that the benefits of using ChatGPT for trip planning can increase when its initial recommendations are narrowed down by travelers. Although ChatGPT can create final trip itineraries for travelers (Hayhurst, 2023), OTAs should enable travelers to be engaged in the creation to maximize their satisfaction with the itineraries. For example, OTAs could instruct ChatGPT to check with travelers every time when it completes a task (e.g., "15 destinations or activities have been located: do you want me to narrow them down or do you want to do it by yourself?"). Also, hospitality businesses (e.g., restaurants, hotels, or airlines) that plan to adopt ChatGPT can refer to these findings for the adoption (Dobravsky, 2023; Loten, 2023). Building on our findings that travelers prefer a hybrid choice mode when using ChatGPT, businesses could instruct their chatbots to give multiple possible alternatives to customers' inquiries, to lead them to make their own choices.

Lastly, while it was not our main focus, our research showed that travelers perceived choice overload when more than 15 options were proposed by AI tools. Specifically, we found that travelers considered choosing one out of eight options doable, but out of 15 psychologically demanding. In various hospitality business domains, AI tools have been adopted to provide customers with recommendations: concierge robots in hotels (Aue, 2023) or menu ordering devices in restaurants (Redmond, 2023). Based on our findings, hospitality businesses could adjust the default number of recommendations their AI tools provide, to enable customers to easily interact with them, and to have better experience with such tools.

Limitations and Future Study

Future research should address two limitations of this study. First, we conducted our studies using a scenario-based situation. Although the method has been widely applied in the tourism literature (J. Kim et al., 2019, 2023), future studies need to use real-world surveys, secondary data, or actual data to increase external validity. Second, we recommend including a wider variety of situations that lead to choosing tourism products using ChatGPT. This research only contained two situations for choosing a destination and activity for travel. A range of contexts for selecting various travel products (e.g., hotels and restaurants) would be helpful to widen the understanding of appropriate management strategies. Furthermore, the adoption of technology can be shaped by a range of user attributes, encompassing psychological characteristics and demographic backgrounds, such as age and gender. We also recommend investigating these factors in future studies. In addition, in this study, the amount of information varied based on the size of the recommendation. Future studies need to investigate the specific impact of the number of options while keeping the information amount constant. Prior research suggests that the preference for different decision-making processes is influenced by travelers' personalities (e.g., sensation seeking, absorptive capacity, self-efficacy, or trend affinity). Although the results of this research suggest the importance of a hybrid decision-making process between human and ChatGPT, future studies could explore whether our observed effect of hybrid decision-making process holds for travelers with different personality characteristics. Lastly, although the sample's representativeness of the population was checked and confirmed, it does not perfectly represent the whole US adults. Future studies should increase the sample size to improve the generalizability of our findings.

Appendix. Measurement Items

Recommendation satisfaction (Studies 1A, 1B, 3, & 4)

How satisfied are you with the recommendations provided above? (1 = not satisfied at all, 7 = very satisfied)

Visit intention (Studies 2, 3, & 4)

How much do you want to participate in the recommended destinations? (1 = not at all, 7 = very much/ 1 = very low, 7 = very high)

Perceived satisfaction with the decision (Study 5)

How satisfied are you with your decision? (1 = not satisfied at all, 7 = very satisfied)

How confident are you in your decision? (1 = not credible at all, 7 = very credible)

To what extent do you feel certain about your decision? (1 = not certain at all, 7 = very certain)

Perceived trustworthiness of the recommendations (Study 2)

How trustworthy do you find the recommendations provided by ChatGPT above? (1 = not trustworthy at all, 7 = very trustworthy/1 = not credible at all, 7 = very credible)

Perceived realism (Studies 1A, 1B, 2, 3, 4, & 5)

The scenario above is …. (1 = highly unrealistic, 7 = highly realistic)

Perceived number of option (Pre-test)

How do you evaluate the number of the recommended destinations above? (1 = very few options, 7 = too many options)

Declaration of Conflicting Interests

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Notes

1. We conducted a pre-test to verify the number of options in this study (n = 86). After exposure to one of the experimental conditions, participants were asked to evaluate the perceived size of the recommended options along a 7-point scale (1 = very few options, 7 = too many options). The result indicated that the perceived size of each condition was higher than the neutral point of the scale ($M_{\_large\ I}$ = 5.44, SD = 1.18 vs. "4", t (42) = 8.00, p < .001; $M_{\_large\ II}$ = 5.91, SD = 1.11 vs. "4", t (42) = 11.28, p < .001). The two means were not significantly different at the 0.05 level (F (1, 84) = 3.54, p = .063).
2. We chose four options since the size of the consideration set was typically estimated to 3 to 5 options (Ringel & Skiera, 2016).
3. We conducted a pre-test to verify the number of options in this study (n = 93). Participants were asked to evaluate the perceived size of the recommended options along a 7-point scale (1 = very few options, 7 = too many options) for either 8 or 16 options. The result indicated that the perceived size of the 16 choice set condition was higher than the neutral point of the scale ($M_{\_large\ I}$ = 5.58, SD = 0.99 vs. "4", t (47) = 11.13, p < .001), but the perceived size of the eight choice set condition was similar to the neutral point of the scale ($M_{\_medium}$ = 4.20, SD = 0.87, vs. "4", t (44) = 1.55, p = .130). The two means were significantly different (F (1, 91) = 51.28, p < .001).
4. This significant interaction effect (F(1, 308) = 9.63, p = .002, η^2 = 0.033) was robust in demographic variables of age, income, and gender as covariates.

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