Journal of Retailing and Consumer Services 75 (2023) 103494

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Decisions with ChatGPT: Reexamining choice overload in ChatGPT recommendations

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ARTICLE INFO

Keywords:
AI versus human recommendations
Artificial intelligence
ChatGPT
Choice overload
Recommendation agents

ABSTRACT

This research examines how individuals respond differently to recommendation options generated by ChatGPT, an AI-powered language model, in five studies. In contrast to previous research on choice overload, Studies 1 and 2 demonstrate that people tend to respond positively to a large number of recommendation options (60 options), revealing diverse consumer perceptions of AI-generated recommendations. Studies 3 and 4 further illustrate the moderating effect of recommendation agents and indicate that choice overload elicits distinct patterns of consumer reactions depending on whether the recommendations are from a human or AI agent. Lastly, Study 5 directly measures consumer preferences for recommendation agents, revealing a general preference for ChatGPT, particularly when a large number of options are available. These findings have significant implications for recommendation system design and user preferences regarding AI-powered recommendations.

1. Introduction

Recent years have seen rapid development in artificial intelligence (AI) and machine learning (ML) technologies, transforming the way we interact with our surroundings and revolutionizing many aspects of our lives, including consumer decision-making (Hu and Pan, 2023; Jan et al., 2023; Mariani et al., 2022; Melumad et al., 2020; Ruan and Mezei, 2022). The popularity of chatbots and conversational agents, one of the most prevalent forms of recommendation systems, can be attributed to their ability to mimic human-like conversations while providing users with personalized recommendations. As a result, chatbots have gained widespread adoption in many industries, including retail, customer service, and education, to enhance customer engagement and support.

Chatbots powered by GPT (Generative Pre-trained Transformer) models have become increasingly popular due to their advanced language processing capabilities. ChatGPT can understand the context of the conversation and provide more accurate and relevant recommendations (Dwivedi et al., 2023; Stokel-Walker and Van Noorden, 2023; Zhai, 2022). The GPT model is pre-trained on a vast amount of data, making it capable of generating natural-sounding responses that are virtually indistinguishable from those of a human. Moreover, ChatGPT's recommendations are highly personalized, based on the user's interests, browsing history, and preferences. This level of personalization allows for more targeted and relevant recommendations, thereby increasing the chances of users accepting the recommendations and making a purchase.

In addition, ChatGPT can provide a large option size in recommendations because of its advanced NLP and machine learning techniques. The ChatGPT model is pre-trained on massive amounts of text data, which enables it to understand natural language in a highly sophisticated manner. Additionally, ChatGPT is capable of generating highly diverse recommendations, which means that it can provide a large number of options without sacrificing quality or relevance. Furthermore, the cost of generating many options in ChatGPT is relatively low after the program has been developed following sampling and diversity-promoting objectives during training. In summary, the advanced capabilities of ChatGPT allow it to provide a large option size in highly personalized, accurate, and diverse recommendations. This is a significant advancement in the field of recommendation systems, as it enables users to make more informed decisions and find products or services that better match their needs and preferences.

Despite the advantages of ChatGPT, our understanding of the impact of ChatGPT on the change in consumer decision-making is quite limited in theoretical and empirical investigations. This paper focuses on the

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https://doi.org/10.1016/j.jretconser.2023.103494
Received 17 June 2023; Received in revised form 5 July 2023; Accepted 6 July 2023
Available online 13 July 2023

choice overload problem in decision-making. In this research, we answer the following research questions: (i) How do customers respond to a large number of options suggested by ChatGPT? (ii) What is the underlying mechanism for the positive effect of a large option suggestion by ChatGPT? and (iii) How do recommendation agents moderate the impact of the number of options on the customers' responses?

Specifically, we investigate consumers' responses to a relatively large number of options suggested by ChatGPT. In traditional decision-making, 24 or 30 options are typically categorized as choice overload (see, Chernev et al., 2015; Scheibehenne et al., 2010 for the review). However, we argue that the negative effect of providing 30 or more options in decision-making will be reduced significantly when the recommended options are generated by ChatGPT. This is because ChatGPT possesses the unique characteristic of providing personalized and accurate suggestions (Dwivedi et al., 2023; Gursoy et al., 2023; Paul et al., 2023). Based on this premise, we argue and demonstrate that people prefer a large number of options, such as 60 or 70, in recommendations from ChatGPT. As the number of recommendations increases, users' satisfaction or purchase intention will also increase. We also demonstrate that the above effect is explained by the perceived accuracy of information provided by ChatGPT. We further show the moderating role of recommendation agents in that while people prefer a larger number of options when receiving recommendations from ChatGPT, they do not necessarily prefer a large number of options when receiving recommendations from a human.

This research has several theoretical and practical implications. First, the study sheds light on the impact of recommendation agents on consumers' decision-making processes. By focusing on the impact of ChatGPT on choice overload, the research contributes to our understanding of how advanced recommendation systems can alleviate some of the negative effects of providing a large number of options. Second, the study shows that the effect of providing many options is moderated by the type of recommendation agent used. This finding has important implications for the design of recommendation systems and emphasizes the need to consider the characteristics of the recommendation agent when designing systems for optimal user experience. Practically, the findings of the study can inform the design of recommendation systems, especially those with a large number of options, to create more effective and user-friendly systems. This can improve user satisfaction and purchase intention for businesses. By leveraging ChatGPT's advantages and focusing on the perceived accuracy of information, businesses can provide more options without negatively affecting users' decision-making processes.

2. Theoretical background

2.1. Choice overload effect in consumer choice behavior

Based on the theory of choice overload (Guillet et al., 2020; Guo and Li, 2022; Ketron et al., 2016; Mittal, 2016), choice overload can be conceptualized as a situation in which consumers confront many similar alternatives or options, causing complexity and difficulty in their decision making. It occurs when consumers are not able to easily deal with the complexity of the decision-making because their cognitive resources are overwhelmed and overloaded with available choices. As consumers are often puzzled by too many choices in various contexts, such as tourism products (Park and Jang, 2013), online hotel bookings (Guillet et al., 2020), consumer boycotts (Yuksel et al., 2020), free gifts (Kumari et al., 2022), fast casual restaurants (Park and Kang, 2022), and food products (Turri and Watson, 2022), studies on choice overload have consistently highlighted that more is not always better. Information overload, referring to consumers' limited cognitive abilities in adequately processing given information, is closely connected and sometimes confused with choice overload. While the amount of information emphasizing the attributes of alternatives causes information overload, choice overload is primarily caused by the number of available choices (Guillet et al., 2020; Ketron et al., 2016; Park and Jang, 2013).

The prior literature on the theory of choice overload has demonstrated how relatively large numbers of options compared to medium and small numbers of options influence perceived choice overload (i.e., choice overload hypothesis), resulting in 'making no choice' (30 vs. 20 vs. 10 vs. 3 vs. 1 travel product option(s), Park and Jang, 2013), reduced decision confidence (30 vs. 9 vs. 3 room rate/type choices, Guillet et al., 2020), decision to sign a petition to support a boycott call (15 vs. 3 brands, Yuksel et al., 2020), satisfaction with customization (perceived number of choices, Park and Kang, 2022), and gift attractiveness (9 vs. 3 vs. 1 gift(s), Kumari et al., 2022). It happens because extensive options are significantly linked to perceived uncertainty and decision task difficulty (22 vs. 6 hotel choice sets, Guo and Li, 2022), regret, feeling overwhelmed, and small-agent rationalization (Yuksel et al., 2020).

For this reason, studies have also paid attention to plausible solutions that minimize the adverse effects of choice overload by investigating possible boundary effects: technological filters such as online recommendation agents and situational involvement with a gift for someone vs. a purchase for themselves (Turri and Watson, 2022); constraint of time and money resources (Kumari et al., 2022); amount (i.e., less vs more) and presentation (mono- vs multi-colored text) of information (Guo and Li, 2022); low vs high customer hedonic and utilitarian values (Park and Kang, 2022); presentation format as an information filtering mechanism (Guillet et al., 2020); and brand familiarity (24 options associated with familiar vs. unfamiliar brand names, Misuraca et al., 2019).

However, although recent literature has supported arguments in favor of the choice overload hypothesis, not all studies claim detrimental impacts for relatively large assortments or options because of the effects on consumers' overall utility maximization (Mittal, 2016). As two meta-analytic studies (Chernev et al., 2015; Scheibehenne et al., 2010) have comprehensively summarized, the prior literature on traditional economic and psychological theories argues against the choice overload hypothesis, as consumers can benefit from a large variety of choice options because they provide a close match to their purchase goals; enhanced option value; freedom of choice; or enhanced possibilities of meeting consumer preference. This implies that the choice overload hypothesis may occur depending on certain conditions or circumstances.

It is therefore also worth further examination of the threshold for choice overload that can explain a two-pronged effect (i.e., positive vs. negative) on choice. For example, while Park and Jang (2013) demonstrated that more than 22 choices raised the possibility of consumers 'making no choice' regardless of destination types (Park and Jang, 2013), the effect of a large number of options (i.e., choice overload) seems to vary with the research context. However, in traditional decision-making and prior studies on choice overload as discussed above, 24 or 30 options are typically categorized as choice overload (see Chernev et al., 2015; Scheibehenne et al., 2010). Consequently, the prior literature has stressed that while the likelihood of the choice overload hypothesis decreases as more options are given, it is likely to increase at a certain point.

2.2. AI recommendation in decision

Recommendation systems refer to the techniques that offer suggestions for a user and can function as a personalized information provider (Burke, 2007; Ricci et al., 2010). Resnick and Varian (1997) point out that individuals often need to make choices without sufficient knowledge or experience. Consequently, people rely on the recommendations of others. Recommendation systems in this context help by aggregating and directing large amounts of data and directing the refined information to the appropriate recipients (Resnick and Varian, 1997).

The development of AI-based recommendation systems began by observing that individuals rely on others' recommendations in everyday decision-making (Jan et al., 2023; Mahmood and Ricci, 2009; McSherry and Mironov, 2009). To perform the same task, early recommendation systems, known as collaborative filtering, applied algorithms that could produce recommendations by a community of users demonstrating similar preferences (Ricci et al., 2010). Recommendations are personalized and are presented as a "ranked list of items" (Ricci et al., 2010, p.2). To perform the task of ranking the items, recommendation systems use knowledge about the preferences and constraints of the user to predict the product that is most suitable for the user (Ricci et al., 2010).

Supporters of AI recommendations argue that the technology can help to improve consumers' decision quality, as it helps them to choose products or services quickly and at a lower cost (Chen et al., 2022). On the other hand, some critics believe that AI technology may facilitate information cocooning and deprive consumers of opportunities to be exposed to other information (Aksoy et al., 2011; Sunstein, 2006; Zuiderveen Borgesius et al., 2016). Furthermore, the development of the internet, along with the explosion of information available online, has resulted in users feeling overwhelmed. As a result, there is an increasing need for recommendations that can filter choices and alternatives (Chen et al., 2022). This led to the idea that although choice is often associated with positive terms such as freedom and autonomy, excessive choice may lead to diminished freedom (Schwartz, 2004). Recommendation systems have emerged as a way of addressing this issue of information overload.

Academic interest in recommender systems began in the mid-1990s (Anand and Mobasher, 2005; Goldberg et al., 1992; Mahmood and Ricci, 2009) in response to increasing interest, with much potential for practical and commercial implications in the domains of entertainment, content, e-commerce, and services. For example, in the travel context, recommendation systems can be adopted by an online travel agency (OTA) or a destination management organization (DMO) to increase turnover rates and visitor numbers. According to early investigators (Hu and Pan, 2023; Jan et al., 2023; Ricci et al., 2010; Ruan and Mezei, 2022), there are numerous roles that AI-based recommendation systems can play as follows. From a service provider's perspective, a recommendation system can increase the number of items sold; sell a greater variety of items; increase user satisfaction; increase user fidelity; and better understand users' needs. From a user's perspective, a recommendation system can aid in finding some good items, all good items, a bundle of items, or a sequence of items, and can be a credible recommender. Furthermore, users may simply want to browse, express themselves, help others, and influence others with the help of a recommendation system.

More recently, increasing interest emerged in the field of conversational recommender systems (CRS) and interactive recommendation agents (IRAs), which allow natural conversations with a human-like AI and provide enhanced personalization (Jannach and Chen, 2022). In addition, the advances in technology are expected to increase the benefits of AI by providing and collecting information, which in turn can enhance the quality of decision-making (Kim, 2020). Overall, there is no doubt that AI recommendation has much potential for both academic and practical application, and much remains to be discovered.

2.3. Recommendations under information overload

Decision-makers typically increase their usage intention for recommendation agents when they face information overload (Aljukhadar et al., 2012; Maes, 1994; Xiao and Benbasat, 2007). For example, Xiao and Benbasat (2007) suggested that recommendation agents could reduce decision-makers' information overload. Aljukhadar et al. (2012) provided empirical evidence that the preference for using recommendation agents was higher under information overload as option numbers and attributes information increased. In summary, prior literature predicted that recommendation agents could reduce decision-makers' information overload. However, research on human reaction to recommendation agents creating choice overload remains limited. This can be explained by the fact that previous recommendation agents had difficulty generating or suggesting many options with low operational costs. However, ChatGPT has changed the situation dramatically in that it can easily provide various numbers of recommendations. This research investigates the impact of a relatively large number of options on decision outcomes, including recommendation satisfaction and purchase intention relating to one option from the recommendations.

3. Hypotheses development

3.1. Main effect of ChatGPT recommendations

Consumers frequently refer to online recommendations to make decisions. Extensive research has examined the process, in which individuals purposefully engage in using information, such as accepting online word of mouth or recommendations (Matute et al., 2016). Because the comprehensiveness and relevance of information determine its usefulness (e.g., Cheung et al., 2008), the amount of information could determine consumers' likelihood of using such information (Filieri, 2015).

A stream of research has consistently suggested that offering an extensive assortment can benefit consumer choice. A larger number of options allow consumers to find a close match to their preferences (Baumol and Ide, 1956) and have flexibility in light of uncertain future tastes (Kahn and Lehmann, 1991; Kahneman and Snell, 1992). Furthermore, more extensive assortments may lower the uncertainty about whether the choice set at hand adequately represents all available options. Consumers tend to delay their purchase when they are unsure about whether the available choice set adequately represents the entire set of available options (Greenleaf and Lehmann, 1995). Therefore, consumers feel more confident when choosing from a larger assortment (Chernev, 2006; Sela et al., 2009).

Compared with recommendations from an OTA, ChatGPT provides consumers with high-quality data at a low cost (in terms of time) as it learns a set of scenarios by training on massive datasets (Wang et al., 2023). Unlike using an OTA, consumers input specific requests or criteria reflecting their preferences when using ChatGPT. Because of its advanced features, ChatGPT can promptly generate a large amount of customized information based on the requests or criteria (Dwivedi et al., 2023; Paul et al., 2023). Research suggests that detailed information can signal that recommendation agents care about the users and act in their interests, increasing perceived trust toward the recommendation agents (Xiao and Benbasat, 2007). Interactive experience by anthropomorphic chatbots can even increase trust and consumer engagement (Konya-Baumbach et al., 2023; Paul et al., 2023). Besides, consumers might appreciate and positively evaluate the unique characteristic of this new technology (Kasneci et al., 2023). Together, building upon prior research, we posit that consumers are more likely to accept and be satisfied with recommendations by ChatGPT when it offers a larger number of options. Formally, we hypothesize that:

H1. People prefer a large number of options in recommendations from ChatGPT. Recommendation satisfaction and purchase intention will increase as the recommendation options increase.

Furthermore, we propose that perceived accuracy is the key underlying mechanism for the positive effect of a large recommendation from ChatGPT. This is because ChatGPT generates personalized information (Dwivedi et al., 2023), consumers tend to perceive recommendation information as precise and accurate when ChatGPT generates a sufficiently large amount of information (i.e., a large assortment). Research examining psychological factors that influence consumers' acceptance of AI-generated information suggests that the preciseness of the recommendation information will significantly influence consumers' perceived usefulness of information and acceptance of the AI recommendations (Kim et al., 2021; Riedel et al., 2022). In addition, perceived accuracy is one of the important factors for adapting to ChatGPT (Gursoy et al., 2023). Following these logics, we suggest that perceived accuracy serves as a mediator of the main prediction.

H2. Perceived information accuracy will mediate consumers' positive reactance to and acceptance of recommendations by ChatGPT.

3.2. Moderating effect of recommendation agents

As discussed earlier, large assortments can also hinder consumer choice, particularly when consumers find the information irrelevant. Iyengar and Lepper (2000) proposed the choice overload hypothesis, which suggests that a large number of options increases consumers' difficulty in choosing, because of increased confusion in the decision-making process or greater dissatisfaction with a chosen option (Chernev et al., 2015; Iyengar and Lepper, 2000). For example, when consumers are presented with too many recommendations, they may feel overwhelmed and find it difficult to make a choice, leading to frustration and abandonment of the platform. This would be more likely when a long list of recommendations includes options that are irrelevant to the consumer's needs or interests. Unlike actively inputting specific requests for recommendations, online retailers or platforms present recommendations based on one's search history or other consumers' shopping patterns (Lin, 2014). When recommendations are generated based on many other consumers with diverse preferences, the likelihood of including irrelevant options will increase as the number of recommendations increases, possibly causing choice overload (Guo and Li, 2022). Therefore, we predict that consumers would favor a large number of recommendations from ChatGPT but not from an online travel agency (OTA).

H3. The recommendation agents will moderate the impact of the number of recommendations on the acceptance of recommendation. People prefer a large number of options in recommendations from ChatGPT, but do not prefer a large number of options in recommendations from humans or from OTAs.

3.3. Overall conceptual framework and summary of empirical studies

A summary of the three hypotheses is presented in Fig. 1. We conducted five empirical studies. In Studies 1 and 2, we investigated the participants' responses to a relatively large number of recommendation options from ChatGPT and demonstrated a positive response to a large number of options from ChatGPT. In Studies 3 and 4, we compared the effect of a large number of recommendation options from ChatGPT to the effect of a similar number of options from a human or an OTA. Finally, in Study 5, we directly measured people's references for the recommendation agents. To reduce different technological accessibility and cultural background, we used US participants in the study. We conducted all studies in February and March 2023. Participants were invited to participate in only one study through CloudResearch.com.

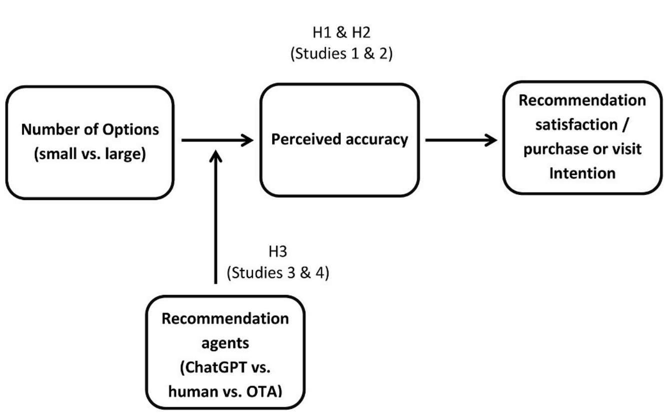

Fig. 1. Overall theoretical framework and empirical studies.

4. Study 1: investigating the evaluation of different numbers of recommendations from ChatGPT

This study investigated the impact of different numbers of recommended options from ChatGPT. We tested different numbers of options, ranging from 3 to 30 options, as examined in the current literature (e.g., Chernev et al., 2015).

4.1. Method: participants, procedure, and measurement

The participants in this study were 265 US adults (M_{age} = 39.51, SD = 11.79; 52.8% female) from Amazon MTurk, who participated in exchange for a nominal payment. Participants were randomly assigned to 4 (number of options recommended: 3 vs. 10 vs. 20 vs. 30 options) conditions in a between-subjects design.

Participants were instructed to imagine that they had asked ChatGPT to recommend a list of the most popular songs and were presented with a set of recommendations by ChatGPT with a screenshot from ChatGPT. The number of options across experimental conditions was different in that the number of recommended songs was 3, 10, 20, or 30. The recommendations are illustrated in Fig. 2.

All participants were then asked to rate the recommendations in terms of satisfaction (1 = not at all satisfied, 7 = very satisfied) and perceived accuracy (1 = not at all accurate, 7 = very accurate) on a 7-point scale. Participants then rated the number of options recommended on a 7-point scale (1= too small, 4 = optimal, 7 = too many).

4.2. Results and implications

To analyze the manipulation of different numbers of options, we conducted an ANOVA for the perceived number of options. The results indicated significance (F (3, 261) = 32.50, p < .001, η^2 = .27). The perceived number of options was very low for the 3 songs recommendation ($M_{3\ songs}$ = 2.88, SD = 1.48), and the score increased as the number of options became larger ($M_{10\ songs}$ = 4.25, SD = 1.16; $M_{20\ songs}$ = 4.74, SD = 1.06; $M_{30\ songs}$ = 4.70, SD = 1.23).

First, we conducted an ANOVA with linear trend analysis for recommendation satisfaction. The simple main effect of the number of options was not significant (F (3, 261) = 1.59, p = .192, η^2 = .02). However, the linear trend analysis indicated significant results (F (1, 261) = 4.58, p = .033). Satisfaction with 3 recommended options was lowest ($M_{3\ songs}$ = 4.32, SD = 1.88), and the satisfaction score increased as the number of options became larger ($M_{10\ songs}$ = 4.45, SD = 1.84; $M_{20\ songs}$ = 4.76, SD = 1.47; $M_{30\ songs}$ = 4.86, SD = 1.35), as shown in Fig. 3.

Similar results were found for perceived accuracy. The simple main effect of the number of options was not significant (F (3, 261) = 1.53, p = .207, η^2 = .02). However, the linear trend analysis indicated marginally significant results (F (1, 261) = 3.26, p = .072). The perceived accuracy with 3 recommended options was lowest ($M_{3\ songs}$ = 4.56, SD = 1.60), and the perceived accuracy score increased as the number of options became larger ($M_{10\ songs}$ = 4.99, SD = 1.54; $M_{20\ songs}$ = 4.91, SD = 1.43; $M_{30\ songs}$ = 5.08, SD = 1.33), as shown in Fig. 3.

Finally, to test the mediation (IV [1: 3 songs vs. 2: 30 songs] → perceived accuracy → recommendation satisfaction), we conducted Hayes (2017)'s macro #4 with 5000 bootstrapping, comparing 3 versus 30 songs. The results indicated that the indirect effect was significant (index = .13, 95% Confidence Interval [CI] = [0.01, 0.26]), while the direct effect was insignificant (index = .05, 95% CI = [-0.09, 0.19]). In summary, the results supported the mediation hypothesis (H2).

5. Study 2: replication of the previous study

In study 1, we found a positive effect of providing up to 30 options from ChatGPT in terms of recommendation satisfaction, perceived accuracy and credibility. This study extended Study 1 with a few

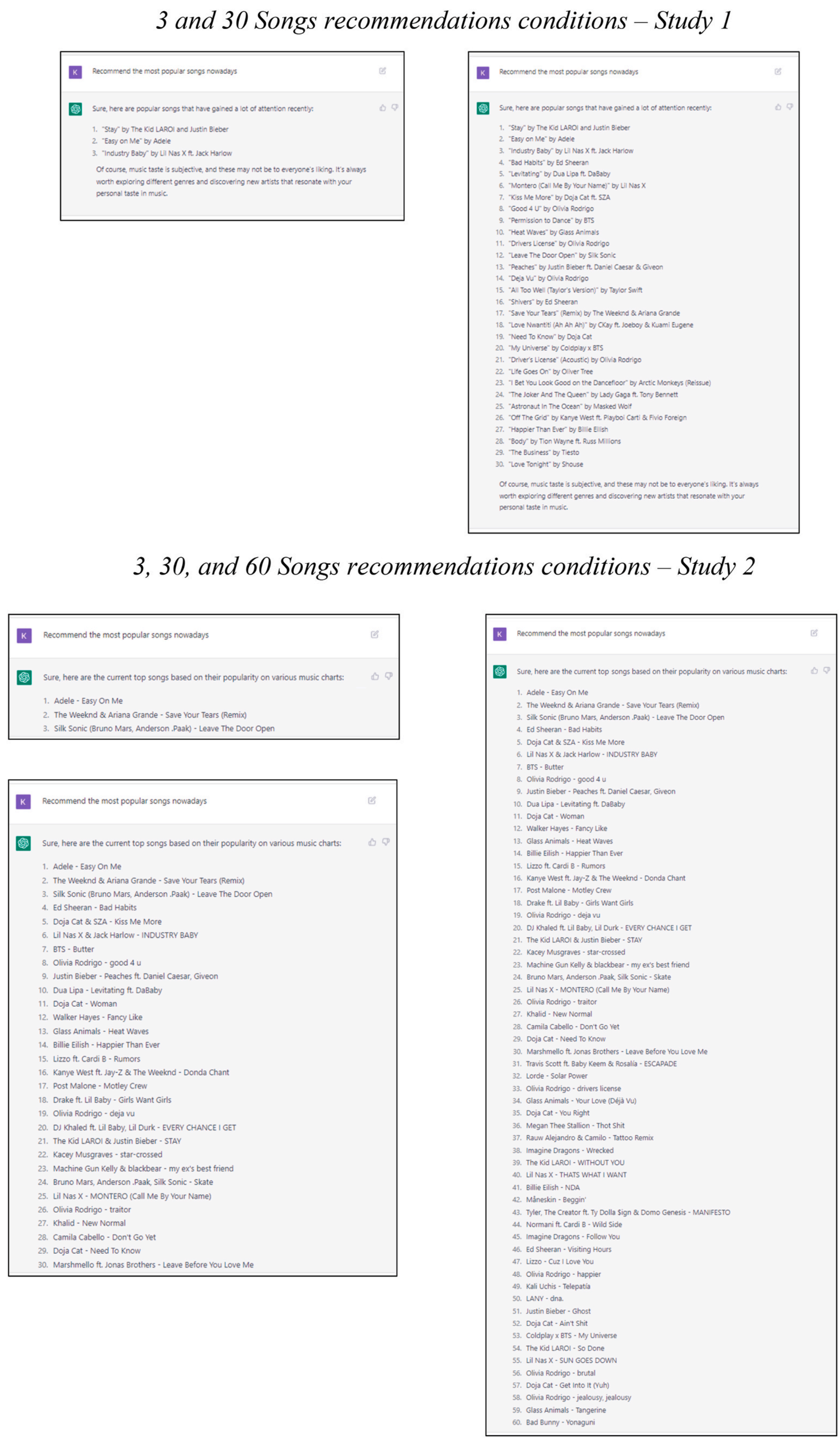

Fig. 2. Stimuli for studies 1 and 2.

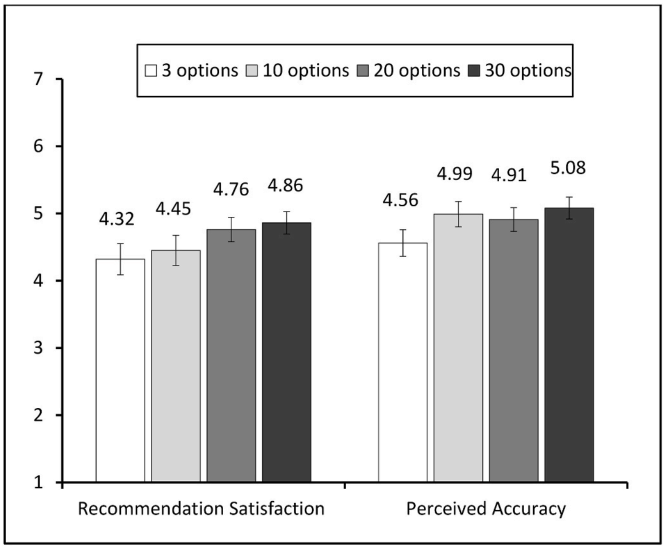

Fig. 3. Results of Study 1
* Error bars represent the standard error.

modifications. First, we measured the behavioral intention of buying one option from the recommendation. Second, we extended the number of options up to 60. Finally, we measured individual differences in general preference for music, as well as the ChatGPT usage experience.

5.1. Method: participants, procedure, and measurement

The participants in this study were 315 US adults (M_{age} = 41.45, SD = 13.05; 46.7% female) from Amazon MTurk, who participated in exchange for a nominal payment. Participants were randomly assigned to 3 (number of options recommended: 3 vs. 30 vs. 60 options) conditions in a between-subjects design.

The general procedure was similar to that of Study 1. Participants were instructed to imagine that they had asked ChatGPT to recommend the most popular songs and were presented with a set of recommendations with a screenshot figure from ChatGPT. The number of recommendation options across experimental conditions was different in that the number of recommended songs was either 3, 30, or 60. In addition, the specific song recommendation was slightly different from the previous study, as shown in Fig. 2.

All participants were then asked to state their purchase intention of buying one song from the recommendations on a 7-point scale (1 = not at all, 7 = very much). They also rated their recommendation satisfaction, perceived accuracy, and the perceived number of options using the same scale as Study 1. Next, participants were asked to rate their general preference for music on a 7-point scale (i.e., *How much do you like listening to music?* 1 = not at all, 7 = very much) and their ChatGPT usage experience on a 7-point scale (i.e., *How frequently do you use ChatGPT?* 1= not at all, 7 = very much).

5.2. Results and implications

To check the manipulation of different numbers of options, we conducted an ANOVA for the perceived number of options. The results indicated significance (F (2, 312) = 108.98, p < .001, η^2 = .41). The perceived number of options was very low for the 3 songs recommendation ($M_{3\ songs}$ = 2.81, SD = 1.53), and the score increased as the number of options became larger ($M_{30\ songs}$ = 4.63, SD = 1.17; $M_{60\ songs}$ = 5.41, SD = 1.20).

First, we conducted an ANCOVA with linear trend analysis for purchase intention for a song from a recommendation by ChatGPT. The covariate of ChatGPT usage experience was significant (F (2, 310) = 47.02, p < .001, η^2 = .13), but the covariate of preference for music was not (F (2, 310) = 2.53, p = .113, η^2 = .01). The simple main effect of the number of options was significant (F (2, 310) = 2.53, p = .042, η^2 = .03). In addition, the linear trend analysis produced significant results (contrast estimate = .46, p =.013). The purchase intention from 3 recommended options was the lowest ($M_{3\ songs}$ = 3.32, SD = 2.09), and the purchase intention increased as the number of options became larger ($M_{30\ songs}$ = 3.46, SD = 2.00; $M_{60\ songs}$ = 3.83, SD = 1.90), as shown in Fig. 4.

Second, we found similar results for recommendation satisfaction. The covariate of ChatGPT usage experience was only marginally significant (F (2, 310) = 2.95, p = .087, η^2 = .01), but the covariate of preference for music was significant (F (2, 310) = 6.97, p = .009, η^2 = .02). The simple main effect of the number of options was not significant (F (2, 310) = 2.18, p = .115, η^2 = .01). However, the linear trend analysis indicated significant results (contrast estimate = .33, p = .041). The purchase intention from 3 recommended options was the lowest ($M_{3\ songs}$ = 4.74, SD = 1.80), and the purchase intention increased as the number of options became larger ($M_{30\ songs}$ = 4.97, SD = 1.69; $M_{60\ songs}$ = 5.17, SD = 1.35), as shown in Fig. 4.

Third, we found similar results for perceived accuracy. The covariate of ChatGPT usage experience was significant (F (2, 310) = 12.89, p < .001, η^2 = .04), and the covariate of preference for music was significant (F (2, 310) = 5.87, p = .016, η^2 = .02). The simple main effect of the number of options was marginally significant (F (2, 310) = 22.76, p = .065, η^2 = .02). However, the linear trend analysis indicated significant results (contrast estimate = .38 p =.024). The purchase intention from 3 recommended options was lowest ($M_{3\ songs}$ = 4.47, SD = 1.99), and the purchase intention increased as the number of options became larger ($M_{30\ songs}$ = 4.53, SD = 1.71; $M_{60\ songs}$ = 4.94, SD = 1.53), as shown in Fig. 4.

Finally, to test the serial mediation (IV [1: 3 songs vs. 2: 60 songs] → perceived accuracy → recommendation satisfaction → purchase intention), we conducted Hayes (2017)'s macro #6 with 5000 bootstrapping with two covariates, only comparing 3 versus 60 songs. The results indicated that the indirect effect of serial mediation was significant (index = .14, 95% Confidence Interval [CI] = [0.01, 0.29]), while the direct effect was insignificant (index = .12, 95% CI = [-0.08, 0.33]).

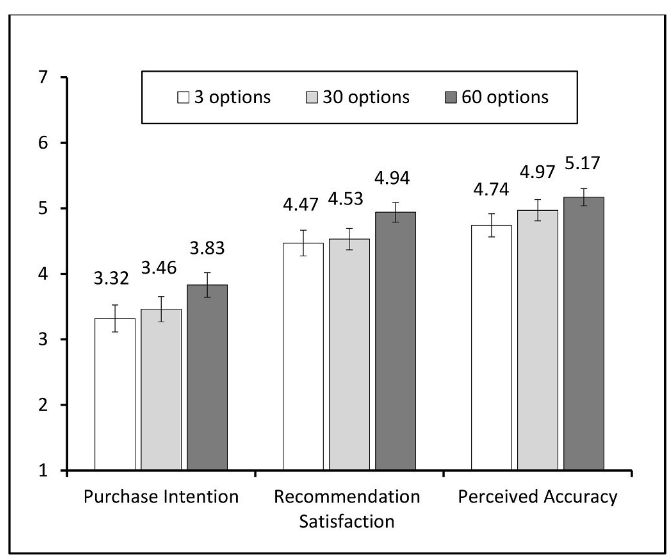

Fig. 4. Results of Study 2
* Error bars represent the standard error.

6. Study 3: testing the effect of recommendation agents (ChatGPT vs. human)

In the previous studies, we found a positive effect of providing relatively large options, such as 60 different options in the ChatGPT recommendation situation. In this study, we tested the effect of recommendations from two different agents: ChatGPT vs. human. We predicted that providing relatively large options would not generate positive responses when the recommendation agent was human (vs. ChatGPT). We also tested the expectation in different consumption situations, such as decisions involving travel destinations.

6.1. Method: participants, procedure, and measurement

We recruited 440 US adults (M_{age} = 41.31, SD = 12.53; 54.1% female) from Amazon MTurk, who participated in exchange for a nominal payment. Participants were randomly assigned to 2 (recommendation agents: ChatGPT vs. human) X 3 (number of options recommended: 3 vs. 20 vs. 70 options) conditions in a between-subjects design.

First, participants were instructed to imagine that they were planning a trip to Kyoto, Japan and seeking information on destinations to enjoy while there. Then the recommendation agents were manipulated so that participants in the ChatGPT conditions were asked to imagine that they turned to ChatGPT and ChatGPT provided recommendations for places to visit. In contrast, participants in the human conditions were asked to imagine that they turned to a friend who was an experienced traveler to Kyoto to provide recommendations for visiting places. In addition, the numbers of recommended options were different across the experimental conditions in that the number of recommended places was 3, 20, or 70. The stimuli are illustrated in Fig. 5.

All participants were then asked to rate their visit intention to the recommended place(s) on a 2-item 7-point scale (1 = not at all/very low, 7 = very much/very high, ; α = .96). Next, participants were asked to rate the perceived realism for the study on a 7-point scale (1 = highly unrealistic, 7 = highly realistic).

6.2. Results and implications

The perceived realism of the scenarios above was high (M = 5.06, SD = 1.59), compared to a neural point of 7-point scale (i.e., '4'; t(439) = 13.91, $p < .001$).

For the main analysis, we conducted 2 X 3 ANOVA for the visit intention. The main effect of the recommendation agents was significant (F (1, 434) = 15.92, $p < .001$, $\eta^2 = .04$) in that the visit intention was higher when the recommendation was from a human (vs. ChatGPT) (M_{human} = 5.56, SD = 1.39 vs. $M_{ChatGPT}$ = 5.06, SD = 1.30). The main effect of the number of options recommended was not significant (F (1, 434) = .43, p = .430, $\eta^2 = .01$). More importantly, the interaction effect was significant (F (1, 434) = 4.53, p = .011, $\eta^2 = .03$), as shown in Fig. 6. Further analysis indicated that the visit intention in ChatGPT recommendation conditions increased as the number of recommendations also increased. The highest value was obtained when the recommendation included 70 options ($M_{70\ options}$ = 5.28, SD = 1.25). The visit intention was higher when the number of recommended places was 70 options (vs. 3 options) ($M_{3\ options}$ = 4.84, SD = 1.38 vs. $M_{70\ options}$ = 5.28, SD = 1.25; Contrast F (1, 434) = 3.79, p = .052, $\eta^2 = .01$). The visit intention following exposure to 20 options ($M_{20\ options}$ = 5.05, SD = 1.24) lay between that for 3 options and that for 70 options. In contrast, the visit intention in human recommendation conditions demonstrated a different pattern. The highest value was when the recommendation provided 20 options ($M_{20\ options}$ = 5.80, SD = 1.08). The visit intention was lower when the number of recommendations included 70 options (vs. three options) ($M_{3\ options}$ = 5.64, SD = 1.55 vs. $M_{70\ options}$ = 5.24, SD = 1.46; Contrast F (1, 434) = 3.23, p = .073, $\eta^2 = .01$). The visit intention with 20 options was higher than that with 70 options ($M_{20\ options}$ = 5.80, SD = 1.08 vs. $M_{70\ options}$ = 5.24, SD = 1.46; Contrast F (1,

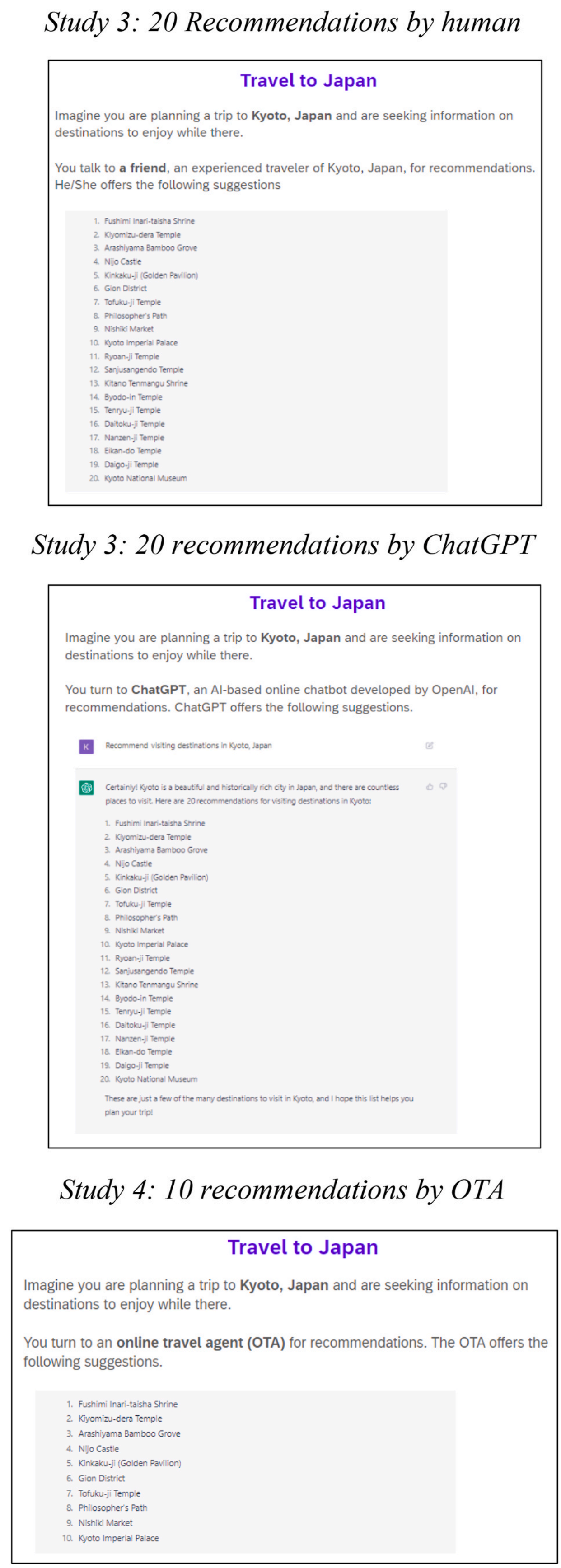

Fig. 5. Stimuli for Studies 3 & 4.

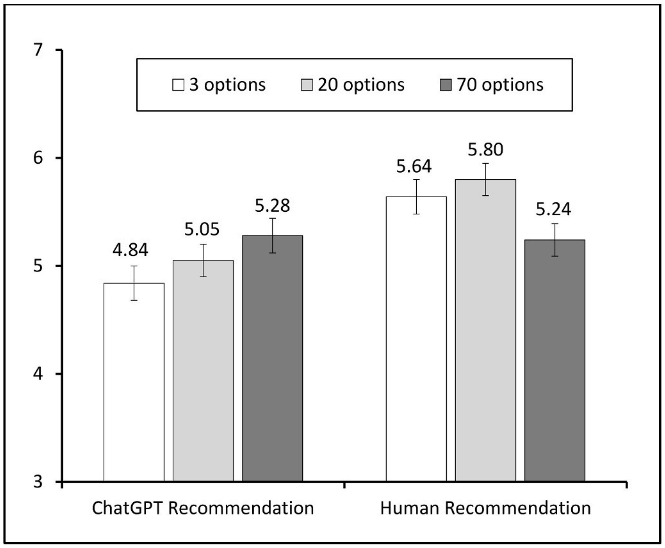

Fig. 6. Results of Study 3
* Error bars represent the standard error.

434) = 6.62, p = .010, η^2 = .02).

In summary, the results replicated the previous studies in the ChatGPT recommendation conditions. However, when humans recommended the options, choice overload was observed.

7. Study 4: testing the effect of recommendation agents (ChatGPT vs. OTA)

This study tested the difference between ChatGPT and an OTA for recommendations. We predicted that providing relatively large numbers of options would not generate positive responses when the recommendation agent was an OTA (vs. ChatGPT).

7.1. Method: participants, procedure, and measurement

We recruited 210 US adults (M_{age} = 41.38, SD = 12.92; 44.8% female) from Amazon MTurk, who participated in exchange for a nominal payment. Participants were randomly assigned to 2 (recommendation agents: ChatGPT vs. OTA) X 2 (number of options recommended: 10 [medium] vs. 60 [large]) conditions in a between-subjects design.

The overall procedure of this study was similar to that of Study 3, with a few modifications. Participants were instructed to imagine that they were planning a trip to Kyoto, Japan, and seeking information on destinations to enjoy while there. The recommendation agents were manipulated so that participants were asked to imagine asking either ChatGPT or an online travel agent (OTA) for recommendations. The number of recommended options was different across the experimental conditions in that the number of recommended places was either 10 or 60. The stimuli are illustrated in Fig. 5.

All participants were then asked to rate their satisfaction, perceived accuracy, intention to visit the recommended place(s) (α = .97), and perceived realism, using the same scale as the previous studies.

7.2. Results and implications

The perceived realism of the scenarios above was high (M = 5.41, SD = 1.41), compared to the neutral point on the 7-point scale (i.e., '4'; t (209) = 14.51, p < .001).

For the main analysis, we conducted a 2 X 2 ANOVA for the visit intention. The main effect of the recommendation agents was not significant (F (1, 206) = 1.29, p = .257, η^2 = .01). The main effect of the number of options recommended was marginally significant (F (1, 206) = 2.94, p = .088, η^2 = .01) in that the visit intention was higher when the number of recommendations was medium versus large ($M_{10\ options}$ = 5.05, SD = 1.32 vs. $M_{60\ options}$ = 4.70, SD = 1.61). More importantly, the interaction effect was significant (F (1, 206) = 5.27, p = .023, η^2 = .03), as shown in Fig. 7. The visit intention with a large number of recommendations was similar to that for the medium number of recommendations in the ChatGPT conditions ($M_{10\ options}$ = 4.93, SD = 1.34 vs. $M_{60\ options}$ = 5.05, SD = 1.45; Contrast F (1, 206) = .17, p = .684, η^2 < 0.01), whereas the visit intention with a large number of recommendations was significantly lower than that for the medium number of recommendations in the OTA conditions ($M_{10\ options}$ = 5.16, SD = 1.31 vs. $M_{60\ options}$ = 4.36, SD = 1.70; Contrast F (1, 206) = 8.20, p = .005, η^2 = .04).

Similar results were obtained for recommendation satisfaction. The main effect of the recommendation agents was marginally significant (F (1, 206) = 2.98, p = .086, η^2 = .01). The main effect of the number of options recommended was significant (F (1, 206) = 5.95, p = .016, η^2 = .03) in that the recommendation satisfaction was higher when the number of recommendations was medium versus large ($M_{10\ options}$ = 5.07, SD = 1.44 vs. $M_{60\ options}$ = 4.50, SD = 1.92). More importantly, the interaction effect was significant (F (1, 206) = 5.18, p = .024, η^2 = .03), as shown in Fig. 7. The recommendation satisfaction with a large number of recommendations was similar to that for the medium number of recommendations in the ChatGPT conditions ($M_{10\ options}$ = 5.00, SD = 1.46 vs. $M_{60\ options}$ = 4.96, SD = 1.70; Contrast F (1, 206) = .02, p = .909, η^2 < 0.01), whereas the recommendation satisfaction with a large number of recommendations was significantly lower than that for the medium number of recommendations in the OTA conditions ($M_{10\ options}$ = 5.13, SD = 1.44 vs. $M_{60\ options}$ = 4.04, SD = 2.03; Contrast F (1, 206) = 11.33, p < .001, η^2 = .05).

Similar results were found for perceived accuracy. The main effect of the recommendation agents was not significant (F (1, 206) = .07, p = .787, η^2 < .01). The main effect of the number of options recommended was also not significant (F (1, 206) = .75, p = .387, η^2 = .01). However, the interaction effect was significant (F (1, 206) = 7.88, p = .005, η^2 = .04), as shown in Fig. 7. The perceived accuracy of a large number of recommendations was similar to that of the medium number of recommendations in the ChatGPT conditions ($M_{10\ options}$ = 4.94, SD = 1.20 vs. $M_{60\ options}$ = 5.26, SD = 1.21; Contrast F (1, 206) = 1.85, p = .176, η^2 = .01), whereas the perceived accuracy of a large number of recommendations was significantly lower than that of a medium number of recommendations in the OTA conditions ($M_{10\ options}$ = 5.36, SD = 1.21

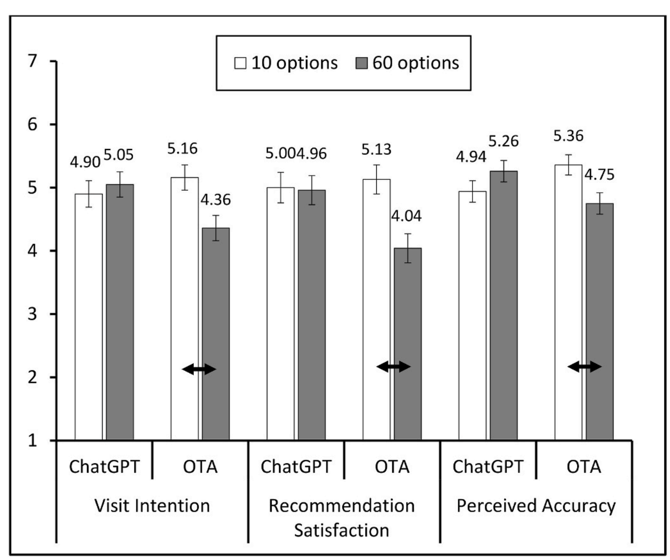

Fig. 7. Results of Study 4
* Error bars represent the standard error. '↔' indicates the significance at α =.05.

vs. $M_{60\ options} = 4.75$, SD = 1.22; Contrast $F(1, 206) = 6.88$, $p = .009$, $\eta^2 = .03$).

In summary, the results indicated that suggesting a large number of options, such as 60, was evaluated positively in the ChatGPT (vs. OTA) recommendation conditions only.

8. Study 5: examining the preference for the recommendation agents

In this study, we directly measured the preference for the recommendation agents based on the different number of options in the information search. We predicted that when decision-makers wanted information on a large number of options, they would prefer ChatGPT to other agents such as a human or an online travel agent (OTA).

8.1. Method: participants, procedure, and measurement

We recruited 251 US adults ($M_{age} = 42.14$, SD = 12.37; 57.8% female) from Amazon MTurk in exchange for a nominal payment. Participants were randomly assigned to 2(number of options searching: 5 vs. 50 options) conditions in a between-subjects design.

First, participants were instructed to imagine that they were planning a trip to Kyoto, Japan, and seeking information on destinations to enjoy while there. Based on the experimental factor, they were further asked to imagine that they would like to know about (i) a few places to visit, with up to 5 destinations; or (ii) many places to visit, with up to 50 destinations during their stay. Then, all participants were given three sources of information: (i) *Chat*GPT, an AI-based online chatbot developed by OpenAI, (ii) *a friend* who is an experienced and recent traveler of Kyoto, Japan, and (iii) an *Online Travel Agent (OTA)* website, which aggregates information on prior travelers' experiences. Then, participants were asked to choose one for providing recommendations. Next, participants were asked to rate their perceived realism for the study on the same scale as that used in Study 3.

8.2. Results and implications

The perceived realism of the scenarios above was high ($M = 5.60$, SD = 1.29), compared to the neutral point of the 7-point scale (i.e., '4'; $t(250) = 19.61$, $p < .001$).

The overall selection for the recommendation was marginally different ($\chi^2(2) = 5.02$, $p = .081$, see Fig. 8. The selection of a ChatGPT recommendation agent was different ($\chi^2(1) = 3.76$, $p = .053$, $\varphi = .12$) in that participants chose it more frequently when the recommendation options were 50 rather than 5 ($M_{50\ options} = 14.96\%$ [19/127] vs. $M_{5\ options} = 7.26\%$ [9/124]). However, for the selection of human recommendations, the opposite pattern was found, in that participants chose a human recommendation less frequently when the options were 50 rather than 5 ($M_{50\ options} = 69.29\%$ [88/127] vs. $M_{5\ options} = 80.64\%$ [100/124]; ($\chi^2(1) = 4.30$, $p = .038$, $\varphi = .13$). The selection of OTA was not significantly different for the two option sizes ($M_{50\ options} = 15.75\%$ [20/127] vs. $M_{5\ options} = 12.10\%$ [15/124]; ($\chi^2(1) = .70$, $p = .404$, $\varphi = .05$).

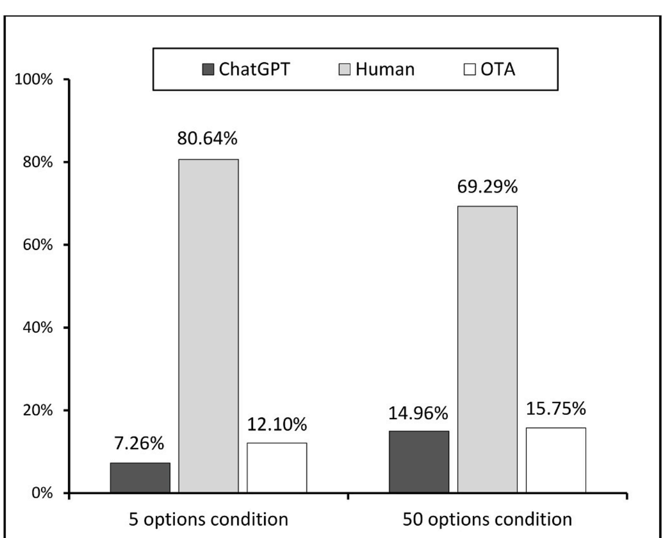

Fig. 8. Results of study 5.

9. General discussion

We conducted five empirical studies. Studies 1 and 2 focused on analyzing the responses of participants who were presented with a relatively large number of recommendation options generated by ChatGPT. These studies demonstrated the positive reception of a wide range of song recommendations provided by ChatGPT. In Studies 3 and 4, we empirically tested the moderating effect of recommendation agents. We found that typical choice overload problems occurred with human or OTA recommendations when presented with a relatively large number of options (e.g., 60 or 70 options). In contrast, different patterns emerged from ChatGPT recommendations for the same number of options. Lastly, Study 5 aimed to directly measure people's preferences for recommendation agents. We found that participants generally preferred ChatGPT, especially when they needed a large number of options for their decision-making process. In summary, the research involved conducting five empirical studies to examine participants' responses to recommendations generated by ChatGPT, comparing them with other sources, and measuring people's preferences for recommendation agents.

9.1. Theoretical implications

This research has several important theoretical implications. First, to the best of our knowledge, this was the first empirical investigation of the impact of ChatGPT on consumer decision-making. We investigated the phenomenon of 'choice overload,' which is one of the essential marketing theories in decision-making. Our empirical findings, demonstrating positive responses to relatively large numbers of options, such as 60 or 70, provided by ChatGPT, are provocative in that they change our understanding of the optimal number of options for decision-making.

Second, building upon the previous point, this study contributes to our understanding of the choice overload literature. Early investigators indicated that providing options such as 24 or 30 can increase cognitive load in decision-making and decrease decision confidence (e.g., Chernev et al., 2015; Guillet et al., 2020). In contrast to these findings, our empirical results suggest that recommending a larger number of options, such as 60 or 70, can generate positive consumer responses when the recommendation is made by ChatGPT. This challenges the prevailing assumption regarding the impact of a large number of options on consumer decision-making. In the current research, we explained the mechanism based on information accuracy. We hope that this research stimulates further investigations of product recommendations and information overload by taking into account the unique aspects of advanced technologies.

Third, we suggested perceived accuracy as the underlying mechanism for the positive effect and provided empirical evidence of significant mediations. Compared to the existing literature emphasizing the cost aspects of dealing with large numbers of options (e.g., decision difficulty or confusion) (Chernev et al., 2015; Iyengar and Lepper, 2000), this study found that the benefits of large numbers of options exceeded the costs, especially when ChatGPT provided the recommendations. This finding may be explained by the superiority of the new technology, including interactive functions of narrowing down large numbers of options in repeated interactions.

Finally, this research also extends our knowledge of online recommendation agents. Compared to prior studies that focused on specific help from online recommendation agents, such as a sorting function in information searching based on attributes or benefits (Su et al., 2008), this paper focuses on decision-making with ChatGPT using the options generated. While the technology preceding ChatGPT prevented decision-makers from generating recommendation options freely and easily, ChatGPT allows decision-makers to generate various recommendations based on optimizing specific situations or individual characteristics or preferences (e.g., Minton et al., 2022). Therefore, we expect that the reliance on recommendations during decision-making will be much greater with interactions with ChatGPT (vs. traditional online and offline recommendation agents) in the future.

9.2. Managerial and practical implications

This research has several important managerial and practical implications. First, the findings of this study can be used to inform the design of recommendation systems, particularly those that involve providing a large number of options. By incorporating the insights gained from this study, designers can create more customized and user-friendly recommendation systems that better meet the needs and preferences of users. Expedia, for example, showcased a plugin version of ChatGPT into their mobile application so that users could begin a conversation and receive personalized recommendations (Expedia, 2023). Considering the wide range of choices that travellers must make, ranging from hotels, destinations, transportation modes, attractions, and restaurants, our findings provide valuable insight for travel industry to help customers create a better trip.

Second, the results of this paper highlight the importance of enhancing information accuracy and personalization in product recommendations. Also, by leveraging the advantages of ChatGPT, businesses can signal that the recommendation agents care for customers' needs and provide personalized recommendations, promote customer trust and engagement.

Finally, with the advanced technologies, the ChatGPT system can be integrated with traditional online shopping stores. For instance, Amazon is contemplating the addition of a ChatGPT search function within their online store (Day, 2023). Consequently, customers may utilize ChatGPT while shopping online, enabling them to explore a wider range of options with the assistance of ChatGPT. This has the potential to bring about significant changes in search behaviors within the online setting, as well as influencing the ultimate decision outcomes.

9.3. Limitations and future directions

One limitation of this research is the use of hypothetical scenarios to investigate participants' responses to recommendation options from ChatGPT. While hypothetical scenarios can provide valuable insights and have been widely used, they may not fully capture the real-world dynamics and complexities of actual interactions with recommendation systems. Future research could consider incorporating real-world data or conducting field studies to further validate the findings in more ecologically valid settings. Another limitation is the limited geographic representation of participants in the studies. Future research could include participants from a broader range of countries to investigate potential cross-cultural differences in response to ChatGPT recommendations and enhance external validity. In addition, this research may not have fully explored the interaction functions of ChatGPT or the mechanisms underlying its recommendation generation process. Future research could conduct qualitative or mixed-methods studies to gain deeper insights into how ChatGPT generates recommendations, how users interact with the system, and how users perceive and evaluate the recommendations. This could provide a more comprehensive understanding of the underlying mechanisms and processes of ChatGPT's recommendation generation, which can further inform the design and improvement of recommendation systems.

Future studies should also investigate the long-term effects of ChatGPT recommendations on user preferences, decision-making behaviors, and satisfaction. In addition, future research needs to examine consumers' responses from different GPT (Generative Pre-trained Transformer) models, combined with an interface including voice-based or robot-embedded presentations (Borau et al., 2021; Hermann, 2022; Jan et al., 2023) as well as the metaverse environment (Zhou, 2023). Finally, future research needs to understand the psychological aspects and influencing factors of accepting ChatGPT recommendations (e.g., Kim et al., 2021). Future research should further explore the moderating role of individual differences, such as consumer expertise (Chinchanachokchai et al., 2021), gender stereotypes (Ahn et al., 2022; Kim et al., 2018), and decision style (Kim et al., 2019) in the acceptance of ChatGPT. Examining these factors can provide valuable insights into how various personal characteristics and tendencies influence individuals' willingness to adopt and engage with ChatGPT.

In conclusion, while this research provides valuable insights into the responses of participants to recommendation options from ChatGPT, future research can build upon these findings to further advance the understanding and application of AI-generated recommendations in real-world contexts.

Declaration of competing interest

The authors declare that there is no conflict of interest. No funding was received to assist with the preparation of this manuscript.

Data availability

Data will be made available on request.

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