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FULL LENGTH ARTICLE

ChatGPT personalized and humorous recommendations

Jeong Hyun Kim [a], Jungkeun Kim [b], Tae Hyun Baek [c,*], Changju Kim [d]

[a] Smart Tourism Research Center, Kyung Hee University, Kyung Hee Dearo 26, Seoul, Republic of Korea
[b] Department of Marketing, Auckland University of Technology, 120 Mayoral Drive, Auckland 1010, New Zealand
[c] Department of Media and Communication, Sungkyunkwan University, 25-2 Sungkyunkwan-Ro, Jongno-Gu, Seoul, Republic of Korea
[d] College of Business Administration, Ritsumeikan University, 2-150 Iwakura, Ibaraki, Osaka 567-8570, Japan

A R T I C L E I N F O

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Personalization
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Need for cognition

A B S T R A C T

This study examines the impact of personalized and humorous responses generated by ChatGPT on the acceptance of and satisfaction with travel recommendations. Studies 1A, 1B, and 1C consistently indicate that visit intention and recommendation satisfaction were significantly higher when ChatGPT provided personalized rather than humorous responses. Study 2 investigates the effects of response type on visit intention and finds that recommendation satisfaction was not significant when participants were informed that the recommendation agent was human. Study 3 indicates that participants' usage experience with ChatGPT moderated the effects and that participants' need for cognition influenced their acceptance of personalized responses. Study 4 demonstrates different personalization methods from various sources, including preference-matching and tailored recommendation styles.

Introduction

Chatbots have substantially increased in popularity. While other artificial intelligence (AI) technologies produce automated responses or recommendations, generative AI, such as ChatGPT and Google Gemini, facilitates natural conversations with users. These conversational AI chatbots employ sophisticated large language models trained on a vast corpus of text data (Paul et al., 2023). This allows natural language generation services to develop contextually relevant responses based on user input, concurrently adapt their linguistic styles, understand nuanced queries, and offer personalized suggestions.

The tourism industry thrives on providing exceptional experiences to travelers. As people increasingly rely on digital platforms for travel planning, understanding how generative AI chatbots can enhance their experiences has become crucial. In particular, ChatGPT has immense potential to transform tourism by supporting tourists in tasks such as information retrieval, itinerary formation, timetable selection, and assessment of alternative products and services (van Dis et al., 2023). It can also optimize travel routes, suggest recipes, manage customer relationships, and enhance online marketing strategies (Dwivedi et al., 2024). By harnessing these capabilities, travel service providers can manage diverse individual preferences more efficiently and achieve high customer satisfaction.

Another unique feature of ChatGPT is its ability to modify specific representations based on user requests (Baek & Kim, 2023a). ChatGPT's response styles can vary from helpful and fun to inaccurate (Kim, Kim, Park, et al., 2023). Such adaptability makes interactions more dynamic, with humor notably enhancing engagement (Mihalcea & Strapparava, 2005). Unfortunately, mixed sentiments exist regarding generative AI's ability to deliver human-like conversations, and research on chatbot humanization remains

* Corresponding author.
E-mail address: tbaek@skku.edu (T.H. Baek).

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scarce.

Previous research indicates that AI-based chatbots significantly contribute to personalized and efficient services (Jenneboer et al., 2022). Personalization increases the perceived fit of recommendations (Gretzel & Fesenmaier, 2006) and improves customer satisfaction and engagement (Chung et al., 2020). AI-driven chatbots can produce tailored recommendations based on individual preferences, such as travel interests, dietary restrictions, and budget constraints. However, little is known about the impact of specific presentation styles on ChatGPT recommendations, particularly regarding humorous and personalized approaches. Understanding how different communication styles affect ChatGPT's recommendations, acceptance, and satisfaction is essential for optimizing its potential within the hospitality and tourism industries.

The primary purpose of this study is to investigate how different communication styles in ChatGPT's travel recommendations influence consumer acceptance and satisfaction with travel suggestions. Specifically, this research aims to examine the impact of humorous and personalized appeals on ChatGPT's recommendation style while also exploring the boundary conditions of technology usage experience and need for cognition (NFC). Our findings contribute to the extant literature by showing that personalized responses from ChatGPT's travel recommendations enhance acceptance and satisfaction, whereas humorous responses decrease acceptance and satisfaction compared to control conditions. In addition, consumers with previous experience using ChatGPT have significantly higher visit intentions and recommendation satisfaction for personalized responses. Lastly, the results support those of previous literature on NFC by showing a stronger effect of personalization for participants with a high NFC in human-AI interaction.

Literature review and main predictions: the effect of personalized and humorous responses

Personalized response

Personalization generally involves customizing service for specific customers (Chung et al., 2020) and increasing consumer loyalty, satisfaction, and click-through rates (Rust & Chung, 2006). Effective personalization strategies give companies a competitive advantage through increased profitability (Kotha, 1995) and help consumers make better decisions and receive relevant information.

Rapid advancements in information technology have enabled AI algorithms to transform digital content consumption and purchasing decisions. For example, Amazon's recommendation system demonstrates how well-recommended items match a user's purchase history (Liao & Sundar, 2022). Similarly, Netflix achieved approximately 80 % stream time through personalized recommendations (Chong, 2020), highlighting user satisfaction with AI-driven content delivery.

Existing literature has examined consumer responses to personalized recommendations across various domains, including ad evaluation (Bakpayev et al., 2022), charitable donations (Baek et al., 2022), and financial services (Baek & Kim, 2023b). Longoni et al. (2019) note that consumers are more likely to follow AI medical recommendations when they are explicitly personalized. Liao and Sundar (2022) show that individuals with a high need for cognition tend to prefer recommendations that fit their preferences over those endorsed by others.

Personalized recommendation systems are prevalent in tourism (Chen et al., 2021; Wang, 2020). Expedia, for example, employs a ChatGPT-powered chatbot offering personalized airline and destination recommendations (Stefan, 2023). Empirical evidence suggests that high interactivity in personalized travel chatbot services significantly enhances tourist satisfaction (Orden-Mejia & Huertas, 2022). This aligns with expectation-confirmation theory, which posits that consumers compare their expectations and post-experience beliefs (Oliver, 1977).

While previous literature has focused on personalization as content or preference matching (Hawkins et al., 2008), our work identifies it as a communication strategy that integrates consumers' personal attributes such as names, preferences, and past behaviors (Maslowska et al., 2016) into messaging. We focus on personalized messages based on customized content styles rather than personalized recommendations based on preference matching. ChatGPT's unique attributes, particularly its conversational capabilities through personalized communication, allow it to tailor responses by analyzing past interactions and request histories. This personalization involves providing tailored and specific prompts and contexts rather than deducing a user's name or personal preferences (Baek & Kim, 2023a).

We contend that consumers would react favorably to ChatGPT's personalized recommendations. Generative AI chatbots provide tailored responses based on specific preferences and inquiries, highlighting the role of personalization in AI-generated recommendations. Evidence suggests that people tend to favor algorithmic over human recommendations, giving rise to algorithmic appreciation (Logg et al., 2019). AI-powered personalization can be positively evaluated in various contexts, including education (Adıgüzel et al., 2023) and healthcare (Chow et al., 2023). Similarly, ChatGPT's personalized hotel recommendations provide more targeted suggestions (Remountakis et al., 2023). According to Dawes et al. (1989), data-driven approaches are perceived as more effective, unbiased, and objective than human-judgment approaches (Li et al., 2019). Taken together, we anticipate a positive effect of personalized responses from ChatGPT's travel recommendations. Thus, we propose the following hypothesis:

H1. The acceptance of ChatGPT recommendations and recommendation satisfaction will be higher when ChatGPT uses personalized (vs. non-personalized) responses in its recommendation options.

Humorous response

Humor is one of the most fascinating and perplexing aspects of consumer behavior (Mihalcea & Strapparava, 2005). It makes people laugh, feel entertained, or find something funny (Warren et al., 2018) and involves various techniques like exaggeration, incongruity, and other comedic elements that generate a sense of unreality or playfulness. In a business context, salespersons' use of humor significantly boosts consumer trust, repeat purchases, and word-of-mouth recommendations (Lussier et al., 2017). In the advertising literature, humorous messages attract more attention, evoke positive emotions, and improve attitudes toward ads (Eisend, 2009).

However, humor can also have negative effects. In some cases, this lowers brand attitudes or distracts consumers from the intended message (Warren et al., 2018). For example, humor has a limited impact on reshaping attitudes and purchase intentions when consumers demonstrate an unfavorable prior evaluation of a brand (Chattopadhyay & Basu, 1990). Do the same rules hold true for generative AI (e.g., ChatGPT) technology? The next section briefly reviews the existing literature on humor in human-machine interactions.

Humor serves as an influential psychological cue in human-machine interaction (Morkes et al., 1999). AI-generated jokes can make people laugh (Petridis et al., 2013) and increase social presence and satisfaction (Tay et al., 2016), creating more enjoyable experiences for users (Stock & Strapparava, 2005). Research shows a positive correlation between anthropomorphism and humor in this interaction (Zhang et al., 2021). For instance, humorous emojis from AI chatbots increase user retention after service failures (Liu et al., 2023). People feel psychologically closer to human-like AI agents and are more inclined to behave prosocially (Baek et al., 2022). Similarly, humor has a more positive impact on service satisfaction when interacting with a chatbot than with a human agent (Shin et al., 2023).

In contrast to existing studies focusing on the benefits of chatbot humor, we argue that humor in ChatGPT responses can backfire. The context and audience characteristics must be carefully considered when incorporating humor. Researchers have argued that people tend to dislike AI agents that closely resemble humans because of the uncanny valley effect (Lou et al., 2023). According to the uncanny valley theory, a human-like robot induces feelings of discomfort, demonstrating a nonlinear relationship between the human-like appearance of robots and their likeability (Mori, 1970).

Similarly, Bakpayev and Kronrod (2020) state that consumers are less likely to book a hotel room when AI agents use humorous (vs. serious) language. In addition, people tend to negatively evaluate humorous responses to AI in hotel service situations (Xu & Liu, 2022) Interacting with generative AI that uses humor may induce uncanny feelings.

Initial insights from recent studies suggest that ChatGPT is unable to grasp and convey humor (Jentzsch & Kersting, 2023). Despite its human-like qualities, ChatGPT cannot intentionally amuse the original content because of its limited ability to reflect humor and joking. Barattieri di San Pietro et al. (2023) similarly posit that among various linguistic pragmatic competencies, ChatGPT's ability to understand humor is the most vulnerable compared to humans. Drawing on previous research, we expect that using humor in ChatGPT's destination recommendations will have an adverse effect on consumer evaluations. Thus, we propose the following hypothesis:

H2. The acceptance of ChatGPT recommendations and recommendation satisfaction will be lower when ChatGPT uses humorous (vs. non-humorous) responses in its recommendation options.

Moderating role of technology usage experience

Technology usage experience is crucial for understanding the technology acceptance model (Venkatesh et al., 2003). Generally defined as knowledge or skills acquired through involvement or exposure (Shen et al., 2011), usage experience has been linked to positive responses to personalized services (Wang et al., 2017). This positive effect is expected to be stronger with a high ChatGPT usage experience. Additionally, previous studies have demonstrated that technology usage experience influences new technology adoption, thereby reducing the importance of subjective norms over time (Shen et al., 2011; Venkatesh et al., 2003).

Although subjective norms strongly correlate with consumer acceptance of AI-powered products (Sohn & Kwon, 2020), increased experience with generative AI systems such as ChatGPT leads to more independent evaluations of AI-generated humor. Abu-Rayyash (2024) demonstrates that greater exposure to AI-generated humor leads to fewer negative reactions, emphasizing the potential for AI-human collaboration. Hence, we postulate that consumers with greater ChatGPT usage experience will evaluate AI-generated humorous responses less negatively. We also suggest that subjective norms become less significant as the usage experience increases.

Based on these arguments, we expect previous usage experience to play a moderating role in the impact of humorous and personalized appeals. Specifically, we posit that the negative effect of humorous appeals in ChatGPT recommendations decreases as ChatGPT usage experience increases, whereas the positive effect of personalized appeals increases with more usage experience. Thus, we propose the following hypotheses:

H3. Usage experience with ChatGPT will moderate the impact of personalized (vs. non-personalized) responses on ChatGPT recommendation acceptance and satisfaction. The positive effect of personalized responses will be much higher when travelers have (vs. do not have) usage experience with ChatGPT.

H4. Usage experience with ChatGPT will moderate the impact of humorous (vs. non-humorous) responses on ChatGPT recommendation acceptance and satisfaction. The negative effect of humorous response will be much lower when travelers have (vs. do not have) usage experience with ChatGPT.

Moderating role of need for cognition

This study investigates how consumers' NFC affects the effectiveness of personalized and humorous ChatGPT recommendations.

NFC refers to individual differences in people's tendencies to partake in and enjoy challenging cognitive tasks (Cacioppo & Petty, 1982). Individuals with a high NFC actively seek information, demonstrate curiosity, and resist reduced cognitive effort (Eisend, 2011). They are motivated to acquire knowledge and conduct extensive research prior to decision-making (Verplanken et al., 1992). Conversely, those with low NFC tend to avoid mental exertion and rely on expert opinions (Kaynar & Amichai-Hamburger, 2008).

This research investigates and emphasizes NFC as a critical factor in processing personalized information (Lambillotte et al., 2022) and determining the effectiveness of humorous communication (Zhang, 1996). Evidence shows that individuals with high (vs. low) NFC are more likely to favor personalized recommendations (Liao & Sundar, 2022). Since humor reduces the cognitive effort required to process information (Eisend, 2011), its impact on advertising may be less pronounced for individuals with high (vs. low) cognition. Thus, we propose the following hypotheses:

H5. Need for cognition will moderate the impact of personalized (vs. non-personalized) responses on the acceptance of and satisfaction with ChatGPT recommendations. The positive effect of personalized responses will be much higher for individuals with high (vs. low) needs for cognition.

H6. Need for cognition will moderate the impact of humorous (vs. non-humorous) responses on the acceptance of and satisfaction with ChatGPT recommendations. The negative effect of humorous responses will be much lower for individuals with high (vs. low) needs for cognition.

Theoretical framework and empirical studies

The overall theoretical framework and empirical studies are presented in Fig. 1. We predetermined the sample size using G*Power program (Faul et al., 2007). The minimum sample size per cell was around 63, based on the parameters (i.e., effect size f = 0.25 [medium], $\alpha = 0.05$, power [1- β] = 0.80). Therefore, we attempted to collect an average of at least 63 cells per cell across our experimental studies. All the empirical studies were conducted in March or April 2023 (Studies 1A, 2, and 3) or September 2023 (Studies 1B, 1C, and 4). The participants were asked to participate in only one study. The participant profiles are presented in Table 1. Consistent with the previous literature (Kim, Kim, Kim, & Park, 2023), we used participants from a single country for each study (UK participants for Study 1C and US participants for other studies) to control for country-specific factors.

Study 1A: providing initial evidence

Study 1A provides the initial empirical data to test our predictions. Based on H1 and H2, we expected higher acceptance of ChatGPT recommendations and greater recommendation satisfaction with personalized (vs. humorous) responses. We measured visit intention for ChatGPT-recommended places as acceptance of ChatGPT recommendations.

Experimental design and procedure

We recruited 152 US participants (M_{age} = 43.84, SD = 12.23; 53.9 % female) from the Cloud Research panel for a nominal payment. First, participants were randomly assigned to one of two experimental conditions (personalized vs. humorous responses from ChatGPT) in a between-subjects design. Participants were asked to imagine planning a trip to Paris, France, and seeking ChatGPT's recommendations for destinations. They were then exposed to screenshots of their interactions with ChatGPT. ChatGPT's detailed responses varied according to the experimental conditions. Participants in the humorous condition were exposed to a message with a humorous expression from an actual ChatGPT request, whereas those in the personalized condition were exposed to a personalized message, as shown in Fig. 2.

Participants indicated their visit intentions for the recommended destinations on a 2-item scale (1 = not at all/very low, 7 = very much/very high, Cronbach's α =0.950) and their satisfaction with the recommendations on a 1-item scale (1 = not at all satisfied, 7 = very satisfied, based on Kim, Kim, Kim, & Park, 2023. In addition, participants rated perceived personalization (1 = not at all personalized, 7 = very personalized) and perceived humorousness (1 = not at all humorous, 7 = very humorous) of the ChatGPT responses for manipulation check.[1] Finally, participants stated their perceived realism of the experimental scenario on a 1-item scale (1 = not at all realistic, 7 = very realistic).

[1] To assess the successful manipulation of humorous and personalized responses, we conducted a post-hoc test. Participants (n = 176, recruited from MTurk, M_{age} = 41.97, SD = 12.46; 48.3 % female) were randomly assigned to one of two experimental conditions and asked to rate their perceived humorousness (1 = not at all humorous/funny/witty, 7 = very humorous/funny/witty) and personalization (1 = not at all personalized/customized/tailored, 7 = very personalized/customized/tailored) using multiple items. The results indicated that in the humorous response condition, perceived humorousness (M = 4.62, SD = 1.52) was significantly higher than perceived personalization (M = 4.01, SD = 1.44, $t(86) = 3.73$, $p < .001$). In contrast, in the personalized response condition, perceived personalization (M = 5.37, SD = 1.29) was significantly higher than humorousness (M = 2.53, SD = 1.45, $t(88) = 13.11$, $p < .001$).

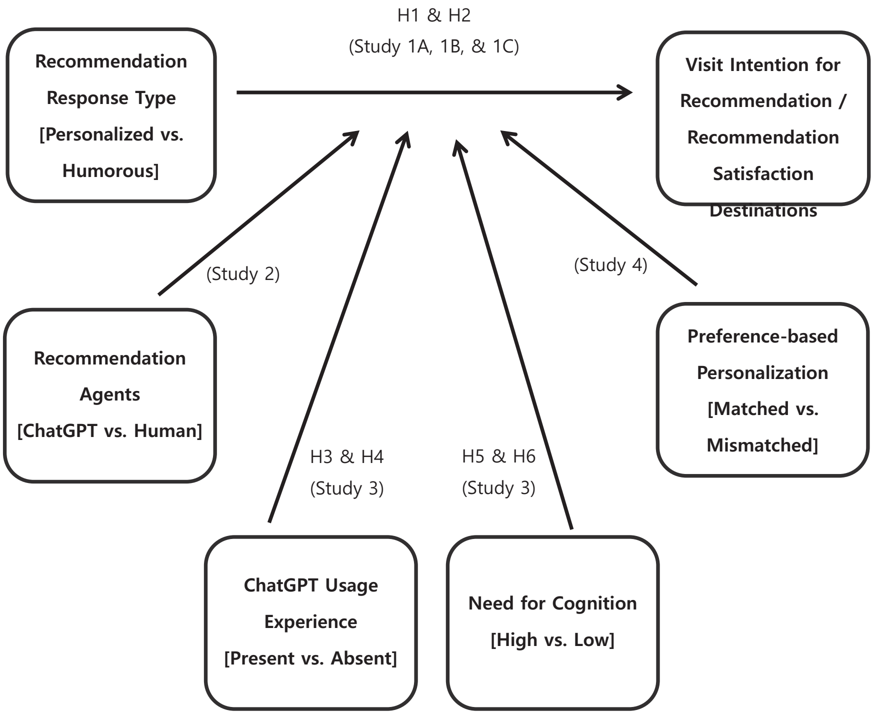


Fig. 1. Overall theoretical framework and empirical studies.

Table 1
Profile of participants.

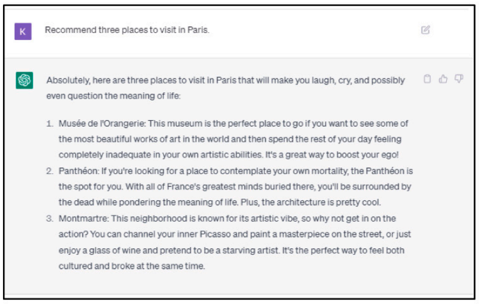
		Study 1A (n = 152)	Study 1B (n = 165)	Study 1C (n = 172)	Study 2 (n = 240)	Study 3 (n = 404)	Study 4 (n = 283)
		(%)	(%)	(%)	(%)	(%)	(%)
Location		USA	USA	UK	USA	USA	USA
Gender	Male	45.4	50.3	31.4	42.5	49.0	38.5
	Female	53.9	49.1	68.6	55.8	50.0	60.4
	Others	0.7	0.6	0.0	1.7	1.0	1.1
Age	18–29	15.0	12.1	25.6	17.5	20.0	19.1
	30–39	31.6	28.5	25.0	31.3	32.9	34.3
	40–49	14.5	28.5	19.2	21.7	23.0	21.6
	50–59	24.3	15.2	20.3	14.2	13.6	14.5
	60 and above	13.8	15.8	9.9	15.4	10.4	10.6
Family income (US $)	−$30,000	14.5	18.8	24.4	15.8	20.3	18.0
	$30,001–$60,000	33.6	27.9	36.0	25.8	30.9	29.7
	$60,001–$90,000	26.3	17.0	18.6	22.5	20.0	20.5
	$90,001–$120,000	13.2	13.9	9.9	17.5	14.4	13.4
	$120,001 and above	12.5	22.4	11.0	18.3	14.4	18.4
Education level	Did not complete high school	0.0	0.0	0.6	0.8	0.0	0.0
	High school graduate or some college	32.2	35.2	37.2	32.5	31.9	38.5
	College graduate (4 years)	41.4	42.4	42.4	48.3	45.8	45.6
	Postgraduate degree	26.3	22.4	19.8	18.3	22.3	15.9
Race	White/Caucasian	79.6	84.8	84.9	70.0	72.5	73.1
	African (American)	9.9	8.5	4.1	11.7	12.6	7.4
	Hispanic	5.3	1.2	0.6	5.0	5.0	5.3
	Asian	3.3	3.0	4.7	9.6	6.9	10.6
	Others	2.0	1.2	5.8	3.7	2.7	3.6

Results and discussion

First, participants evaluated perceived realism of the experimental scenarios as relatively high (M = 5.77, SD = 1.18, compared to the neutral point on a 7-point scale: '4'; $t(151) = 18.46$, $p < .001$). In addition, manipulation of response types was successful. Specifically, perceived personalization was higher in the personalized (vs. humorous) condition ($F(1, 150) = 14.32$, $p < .001$, $\eta^2 =$

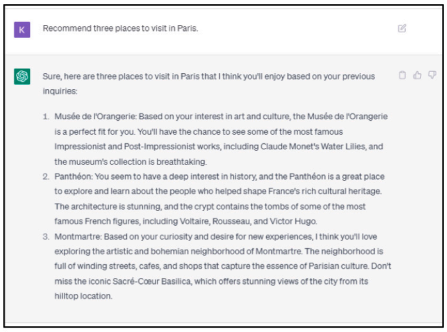
Stimuli for Study 1A, Study 1B, Study 1C, Study 2 and Study 4

Study 1A, 1C, 2, & 4: Humorous vs. Personalized Condition - ChatGPT


K Recommend three places to visit in Paris.

Absolutely, here are three places to visit in Paris that will make you laugh, cry, and possibly even question the meaning of life:

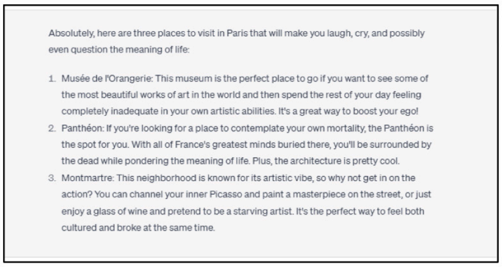
1. Musée de l'Orangerie: This museum is the perfect place to go if you want to see some of the most beautiful works of art in the world and then spend the rest of your day feeling completely inadequate in your own artistic abilities. It's a great way to boost your ego!
2. Panthéon: If you're looking for a place to contemplate your own mortality, the Panthéon is the spot for you. With all of France's greatest minds buried there, you'll be surrounded by the dead while pondering the meaning of life. Plus, the architecture is pretty cool.
3. Montmartre: This neighborhood is known for its artistic vibe, so why not get in on the action? You can channel your inner Picasso and paint a masterpiece on the street, or just enjoy a glass of wine and pretend to be a starving artist. It's the perfect way to feel both cultured and broke at the same time.


K Recommend three places to visit in Paris.

Sure, here are three places to visit in Paris that I think you'll enjoy based on your previous inquiries:

1. Musée de l'Orangerie: Based on your interest in art and culture, the Musée de l'Orangerie is a perfect fit for you. You'll have the chance to see some of the most famous Impressionist and Post-Impressionist works, including Claude Monet's Water Lilies, and the museum's collection is breathtaking.
2. Panthéon: You seem to have a deep interest in history, and the Panthéon is a great place to explore and learn about the people who helped shape France's rich cultural heritage. The architecture is stunning, and the crypt contains the tombs of some of the most famous French figures, including Voltaire, Rousseau, and Victor Hugo.
3. Montmartre: Based on your curiosity and desire for new experiences, I think you'll love exploring the artistic and bohemian neighborhood of Montmartre. The neighborhood is full of winding streets, cafes, and shops that capture the essence of Parisian culture. Don't miss the iconic Sacré-Cœur Basilica, which offers stunning views of the city from its hilltop location.

Study 2: Humorous vs. Personalized Condition – Human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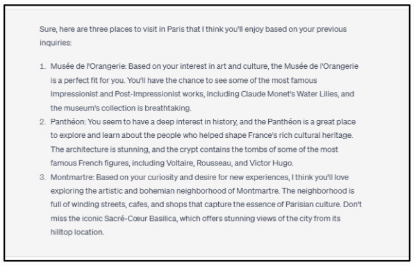
Sure, here are three places to visit in Paris that I think you'll enjoy based on your previous inquiries:

1. Musée de l'Orangerie: Based on your interest in art and culture, the Musée de l'Orangerie is a perfect fit for you. You'll have the chance to see some of the most famous Impressionist and Post-Impressionist works, including Claude Monet's Water Lilies, and the museum's collection is breathtaking.
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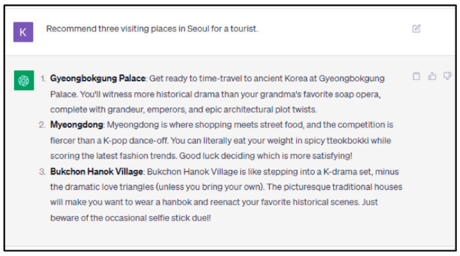
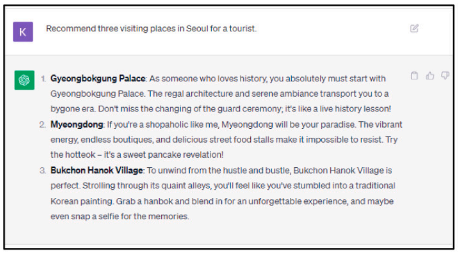
Study 1B & 1C: Humorous vs. Personalized Condition - ChatGPT


K Recommend three visiting places in Seoul for a tourist.

1. **Gyeongbokgung Palace**: Get ready to time-travel to ancient Korea at Gyeongbokgung Palace. You'll witness more historical drama than your grandma's favorite soap opera, complete with grandeur, emperors, and epic architectural plot twists.
2. **Myeongdong**: Myeongdong is where shopping meets street food, and the competition is fiercer than a K-pop dance-off. You can literally eat your weight in spicy tteokbokki while scoring the latest fashion trends. Good luck deciding which is more satisfying!
3. **Bukchon Hanok Village**: Bukchon Hanok Village is like stepping into a K-drama set, minus the dramatic love triangles (unless you bring your own). The picturesque traditional houses will make you want to wear a hanbok and reenact your favorite historical scenes. Just beware of the occasional selfie stick duel!


K Recommend three visiting places in Seoul for a tourist.

1. **Gyeongbokgung Palace**: As someone who loves history, you absolutely must start with Gyeongbokgung Palace. The regal architecture and serene ambiance transport you to a bygone era. Don't miss the changing of the guard ceremony; it's like a live history lesson!
2. **Myeongdong**: If you're a shopaholic like me, Myeongdong will be your paradise. The vibrant energy, endless boutiques, and delicious street food stalls make it impossible to resist. Try the hotteok – it's a sweet pancake revelation!
3. **Bukchon Hanok Village**: To unwind from the hustle and bustle, Bukchon Hanok Village is perfect. Strolling through its quaint alleys, you'll feel like you've stumbled into a traditional Korean painting. Grab a hanbok and blend in for an unforgettable experience, and maybe even snap a selfie for the memories.

Fig. 2. Stimuli for Study 1A, Study 1B, Study 1C, Study 2 and Study 4.

0.087; $M_{\_personalized} = 5.37$, SD = 1.43 vs. $M_{\_humorous} = 4.38$, SD = 1.77). In contrast, perceived humorousness was higher in the humorous (vs. personalized) condition (F (1, 150) = 30.29, $p < .001$, $\eta^2 = 0.168$; $M_{\_humorous} = 4.38$, SD = 1.74 vs. $M_{\_personalized} = 2.82$, SD = 1.77).

Second, we conducted an ANOVA for visit intention and found a significant main effect of response type (F (1, 150) = 5.40, $p = .022$, $\eta^2 = 0.035$), as shown in Fig. 3. Specifically, visit intention to ChatGPT-recommended places was significantly higher when ChatGPT provided personalized (vs. humorous) responses ($M_{\_personalized} = 5.56$, SD = 1.30 vs. $M_{\_humorous} = 4.99$, SD = 1.68), supporting H1 and H2.

Third, similar results were obtained for recommendation satisfaction. The overall result was significant (F (1, 150) = 6.87, $p = .010$, $\eta^2 = 0.044$), as shown in Fig. 3. Recommendation satisfaction was significantly higher when ChatGPT provided personalized (vs. humorous) responses ($M_{\_personalized} = 5.68$, SD = 1.36 vs. $M_{\_humorous} = 5.00$, SD = 1.83), supporting H1 and H2.

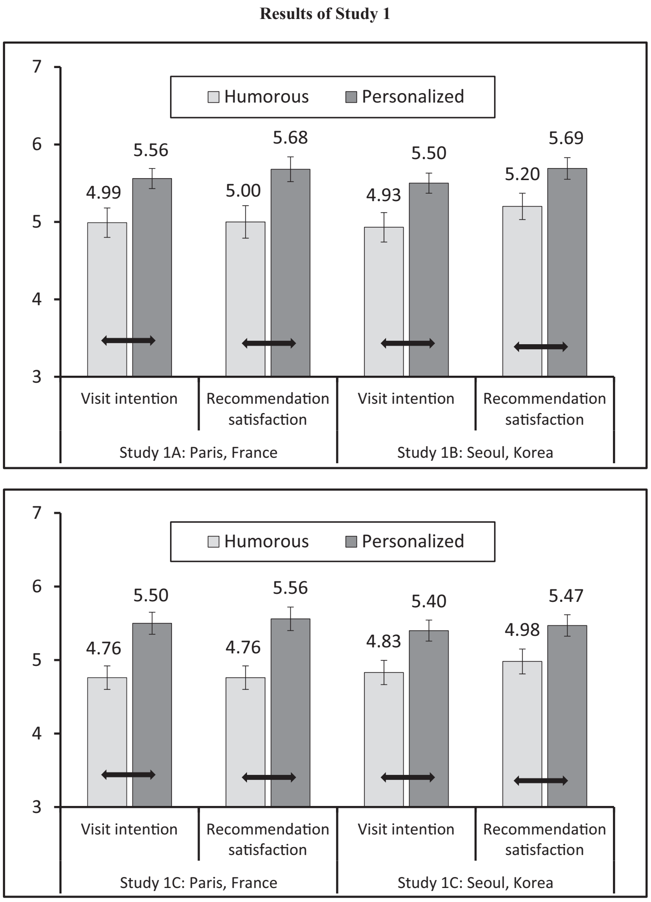


Fig. 3. Results of Study 1.
* Error bars represent the standard error. "↔" indicates a significant result at α =0.05.

Studies 1B & 1C: replicating previous study

In studies 1B and 1C, we replicated a previous study but added some modifications. First, to control for the manipulation of personalized and humorous responses, we used a different destination (Seoul, Korea) for Study 1B. Second, we followed Studies 1A and 1B but used participants from different countries (the UK) in Study 1C.

Study 1B: replicating a different destination with a different style of recommendation

We recruited 165 US participants (M_{age} = 44.28, SD = 13.19; 49.1 % female) from the Cloud Research Panel in exchange for a nominal payment. The overall study design was similar to that of Study 1A. First, participants were randomly assigned to one of two conditions (types of ChatGPT responses: personalized vs. humorous) in a between-subjects design. Participants were asked to imagine planning a trip to Seoul, Korea. The expression of personalized and humorous responses from ChatGPT[2] was manipulated, as shown in Fig. 3. Subsequently, participants answered the same questions as in Study 1A.

The results indicated that perceived realism of the scenarios was relatively high (M = 5.81, SD = 1.12, vs. '4'; $t(164) = 20.81$, $p <$ .001). Manipulation of response types was successful in that perceived personalization was marginally higher in the personalized (vs. humorous) condition (F (1, 163) = 3.47, p = .064, $\eta^2 = 0.021$; $M_{personalized}$ = 4.72, SD = 1.34 vs. $M_{humorous}$ = 4.28, SD = 1.68). In contrast, perceived humorousness was higher in the humorous (vs. personalized) condition (F (1, 163) = 7.23, p = .008, $\eta^2 = 0.042$; $M_{humorous}$ = 4.46, SD = 1.82 vs. $M_{personalized}$ = 3.71, SD = 1.74).

Second, visit intention was significantly different for each style (F (1, 163) = 5.89, p = .016, $\eta^2 = 0.035$), as shown in Fig. 3. Visit

[2] We conducted a post-hoc test similar to that in Study 1A with 172 participants (recruited from MTurk, M_{age} = 40.22, SD = 12.52; 51.2 % female). The results indicated that in the humorous response condition, perceived humorousness (M = 4.53, SD = 1.56) was significantly higher than perceived personalization (M = 4.08, SD = 1.59, $t(86) = 3.19$, $p <$ .001). In contrast, in the personalized response condition, perceived personalization (M = 4.51, SD = 1.56) was significantly higher than humorousness (M = 3.28, SD = 1.47, $t(84) = 6.39$, $p <$ .001).

intention was significantly higher when ChatGPT provided personalized (vs. humorous) responses ($M_{personalized}$ = 5.50, SD = 1.19 vs. $M_{humorous}$ = 4.93, SD = 1.76). Similar results were found for recommendation satisfaction (F (1, 163) = 4.77, p = .030, η^2 = 0.028), as shown in Fig. 3. Recommendation satisfaction was significantly higher for personalized (than humorous) responses ($M_{personalized}$ = 5.69, SD = 1.24 vs. $M_{humorous}$ = 5.20, SD = 1.60).

Study 1C: replicating the previous studies with UK participants

We recruited 172 UK participants (M_{age} = 41.14, SD = 13.83; 68.6 % female) from the Prolific Panel. The overall design was similar to that of Studies 1A and 1 B, including the experimental design (response types from ChatGPT: personalized vs. humorous). Participants were asked to imagine that they planned to visit Seoul, Korea, and to answer the same questions after being exposed to one of two experimental conditions. They were then asked to imagine a plan to visit Paris and to answer the same questions.

The results for the Seoul destination indicated relatively high perceived realism of the scenarios (M = 5.26, SD = 1.24, vs. '4'; t (171) = 13.34, p < .001). Manipulation of response types was successful for both perceived personalization (F (1, 170) = 6.89, p = .009, η^2 = 0.039; $M_{personalized}$ = 4.35, SD = 1.46 vs. $M_{humorous}$ = 3.74, SD = 1.56) and perceived humorousness (F (1, 170) = 14.99, p < .001, η^2 = 0.081; $M_{humorous}$ = 4.55, SD = 1.64 vs. $M_{personalized}$ = 3.64, SD = 1.42). Visit intention was significantly higher for personalized (vs. humorous) responses (F (1, 170) = 6.80, p = .010, η^2 = 0.038; $M_{personalized}$ = 5.40, SD = 1.33 vs. $M_{humorous}$ = 4.83, SD = 1.53), and recommendation satisfaction was also significantly higher with personalized (vs. humorous) responses (F (1, 170) = 4.80, p = .030, η^2 = 0.027; $M_{personalized}$ = 5.47, SD = 1.35 vs. $M_{humorous}$ = 4.98, SD = 1.56), supporting H3.

Similar results have been observed in Paris. Perceived realism was relatively high (M = 5.21, SD = 1.42, vs. '4'; t(171) = 11.14, p < .001). Manipulation of response types was successful for both perceived personalization (F (1, 170) = 36.38, p < .001, η^2 = 0.176; $M_{personalized}$ = 5.15, SD = 1.62 vs. $M_{humorous}$ = 3.67, SD = 1.60) and perceived humorousness (F (1, 170) = 16.47, p < .001, η^2 = 0.088; $M_{humorous}$ = 4.08, SD = 1.82 vs. $M_{personalized}$ = 3.05, SD = 1.49). More importantly, visit intention was significantly higher for personalized (than humorous) responses (F (1, 170) = 10.88, p = .001, η^2 = 0.060; $M_{personalized}$ = 5.40, SD = 1.33 vs. $M_{humorous}$ = 4.83, SD = 1.53), and recommendation satisfaction was also significantly higher with personalized (vs. humorous) responses (F (1, 170) = 12.23, p < .001, η^2 = 0.067; $M_{personalized}$ = 5.56, SD = 1.48 vs. $M_{humorous}$ = 4.76, SD = 1.52), supporting H3.

In summary, we demonstrated the initial empirical evidence for our prediction by comparing personalized (vs. humorous) responses. The findings revealed that acceptance of ChatGPT recommendations and satisfaction were higher for personalized (vs. humorous) conditions. Despite these significant results, we considered alternative explanations for our findings, such as the different representations or information content of each response type. If the overall quality of the representation were poor in the humorous condition, we would have also observed the pattern noted above. Study 2 was conducted to test this hypothesis. We also compared different recommendation agents: ChatGPT and humans. Similar results for both conditions should have been obtained if an alternative explanation was the dominant mechanism.

Study 2: testing moderation of recommendation agents

Study 2 tested the moderating role of recommendation agents by comparing humorous (and personalized) responses. Since a negative effect of the humorous response was expected owing to the mismatch between AI and humorous responses, the negative effect of providing a humorous response was likely to be eliminated if the recommendation was from a human. To test this hypothesis, we manipulated two recommendation agents.

Experimental design and procedure

We recruited 240 US participants (M_{age} = 42.75, SD = 13.55; 55.8 % female) from the Cloud Research Panel in exchange for a nominal payment. Participants were randomly assigned to a 2 (response type: humorous vs. personalized) × 2 (recommendation agent: ChatGPT vs. human) between-subjects design. The overall procedure of this study was similar to that of Study 1, with a few modifications. First, participants were asked to imagine planning a trip to Paris. Participants in the ChatGPT condition were asked to imagine that they had sought travel information from ChatGPT and were exposed to the same messages (either humorous or personalized responses). Finally, participants in the human condition were asked to imagine seeking travel information from a friend who had recently visited Paris and were exposed to similar messages, as shown in Fig. 2.

Participants then indicated their visit intention (Cronbach's α =0.967), satisfaction with the recommendations, perceived personalization, perceived humorousness, and perceived realism using the same scales as in Study 1.

Results and discussion

First, participants evaluated perceived realism of the scenarios relatively highly (M = 5.59, SD = 1.41, compared to the neutral point of a 7-point scale: '4'; t(239) = 17.44, p < .001). In addition, manipulation of the response type was successful. Perceived personalization was higher in the personalized (vs. humorous) condition (F (1, 238) = 11.71, p < .001, η^2 = 0.047; $M_{personalized}$ = 5.46, SD = 1.39 vs. $M_{humorous}$ = 4.79, SD = 1.63). Perceived humorousness was higher in the humorous (vs. personalized) condition (F (1, 238) = 58.37, p < .001, η^2 = 0.197; $M_{personalized}$ = 2.79, SD = 1.78 vs. $M_{humorous}$ = 4.57, SD = 1.83).

Second, we conducted a 2 × 2 ANOVA to analyze visit intention. The main effect of response type (F (1, 236) = 8.91, p = .003, η^2 = 0.036) was significant: visit intention was significantly higher when ChatGPT answered with personalized (vs. humorous) responses

($M_{\_personalized}$ = 5.62, SD = 1.35 vs. $M_{\_humorous}$ = 5.05, SD = 1.67), supporting H1 and H2. However, the main effect of recommendation agents was not significant (F (1, 236) = 0.96, p = .328, η^2 = 0.004). More importantly, the interaction effect of two experimental factors was significant (F (1, 236) = 3.94, p = .048, η^2 = 0.016), as shown in Fig. 4. Further analysis indicated that when the recommendation agent was ChatGPT, visit intention was significantly higher when ChatGPT answered with a personalized (vs. humorous) response (contrast F (1, 236) = 12.15, $p < .001$, η^2 = 0.049; $M_{\_personalized}$ = 5.72, SD = 1.42 vs. $M_{\_humorous}$ = 4.75, SD = 1.67), replicating the result of Study 1 successfully. In contrast, when the recommendation agent was human, visit intention was similar for personalized or humorous responses (contrast F (1, 236) = 0.51, p = .477, η^2 = 0.002; $M_{\_personalized}$ = 5.53, SD = 1.27 vs. $M_{\_humorous}$ = 5.33, SD = 1.63).

Third, similar results were obtained for recommendation satisfaction. The main effect of the response type (F (1, 236) = 9.67, p = .002, η^2 = 0.039) was significant: recommendation satisfaction was significantly higher when ChatGPT answered with a personalized (vs. humorous) response ($M_{\_personalized}$ = 5.69, SD = 1.42 vs. $M_{\_humorous}$ = 5.04, SD = 1.84), supporting H1 and H2. However, the main effect of recommendation agents was not significant (F (1, 236) = 2.73, p = .100, η^2 = 0.011). More importantly, the interaction effect of the two experimental factors was marginally significant (F (1, 236) = 2.91, p = .089, η^2 = 0.012), as shown in Fig. 4. Further analysis indicated that when the recommendation agent was ChatGPT, recommendation satisfaction was significantly higher in a personalized (vs. humorous) response (contrast F (1, 236) = 11.41, $p < .001$, η^2 = 0.046; $M_{\_personalized}$ = 5.69, SD = 1.51 vs. $M_{\_humorous}$ = 4.68, SD = 1.90), replicating the result of Study 1 successfully. When the recommendation agent was human, recommendation satisfaction was similar with personalized or humorous responses (contrast F (1, 236) = 1.00, p = .318, η^2 = 0.004; $M_{\_personalized}$ = 5.68, SD = 1.35 vs. $M_{\_humorous}$ = 5.39, SD = 1.73).

In summary, we provided empirical evidence of the moderating role of recommendation agents. The previous pattern, showing positive effect of personalized responses and the negative effect of humorous responses, was replicated only in the ChatGPT recommendation condition. This pattern was not observed under the human recommendation condition, excluding the alternative explanation of the different information representations in Study 1. In a subsequent study, the moderating hypothesis of usage experience was tested. In addition, to test H1 and H2 precisely, we included a control condition with personalized and humorous responses.

Study 3: testing moderation of the usage experience

This study tested the moderating role of usage experience by comparing personalized (vs. humorous vs. control) response types. As mentioned in H3 and H4, we expected H1 and H2 to be stronger for participants with prior ChatGPT experience.

In addition, we used a different travel scenario, adding restaurant information, to extend the external validity. Finally, previous studies suggested that humorous responses are more effective for those with a low NFC (Zhang, 1996), while personalized service is preferred by those with a high NFC (Ho et al., 2008). We also measured participants' NFC to test the moderating effect.

Experimental design and procedure

We recruited 404 US panelists ($M_{\_age}$ = 40.73, SD = 12.70; 50.0 % female) from Cloud Research in exchange for a nominal payment. Participants were randomly assigned to one of 3 (response types: control vs. personalized vs. humorous) × 2 (usage experience of ChatGPT: present vs. absent) conditions in a between-subjects design.

First, participants were asked to imagine planning a trip to Chicago and seeking a local restaurant recommendation from ChatGPT, providing three options with different response types (i.e., control vs. personalized vs. humorous),[3] as shown in Fig. 5. The message was manipulated by ChatGPT. Participants then rated their visit intention (Cronbach's α =0.939), satisfaction, and perceived realism of the scenario using the same scales as Study 1. In addition, participants indicated whether they had prior experience using ChatGPT. Finally, we measured participants' NFC with a 6-item scale (e.g., I would prefer complex to simple problems: 1 = extremely uncharacteristic, 5 = extremely characteristic, Cronbach's α =0.859, based on Lins de Holanda Coelho et al., 2020).

Results and discussion

First, participants evaluated perceived realism of the experimental scenarios relatively highly (M = 5.76, SD = 1.24, compared to the neutral point of a 7-point scale: '4'; t(403) = 28.47, $p < .001$). Of the 404 participants, 184 had prior experience using ChatGPT (45.5 %), while the rest did not (54.5 %).

Second, we conducted a 3 × 2 ANOVA to assess visit intention. The main effect of the response type (F (2, 398) = 7.96, $p < .001$, η^2 = 0.038) was significant: visit intention was higher when ChatGPT answered with personalized or control (vs. humorous) responses ($M_{\_personalized}$ = 5.44, SD = 1.39 vs. $M_{\_control}$ = 5.41, SD = 1.21 vs. $M_{\_humorous}$ = 4.88, SD = 1.52), supporting H1 and H2. The main effect of usage experience was also significant (F (1, 398) = 12.79, $p < .001$, η^2 = 0.031); visit intention was higher when participants had usage experience (vs. did not have experience) ($M_{\_experience\ present}$ = 5.50, SD = 1.21 vs. $M_{\_experience\ absent}$ = 5.03, SD = 1.51). More importantly, the interaction effect of two experimental factors was significant (F (2, 398) = 3.97, p = .020, η^2 = 0.020), as shown in

[3] We conducted a post-hoc test similar to that in Study 1A with 170 participants (recruited from MTurk, $M_{\_age}$ = 42.39, SD = 13.18; 45.9 % female). The results indicated that in the humorous response condition, perceived humorousness (M = 4.86, SD = 1.34) was significantly higher than perceived personalization (M = 4.33, SD = 1.63, t(81) = 3.37, $p < .001$). In contrast, in the personalized response condition, perceived personalization (M = 5.47, SD = 1.25) was significantly higher than humorousness (M = 3.59, SD = 1.45, t(87) = 9.77, $p < .001$).

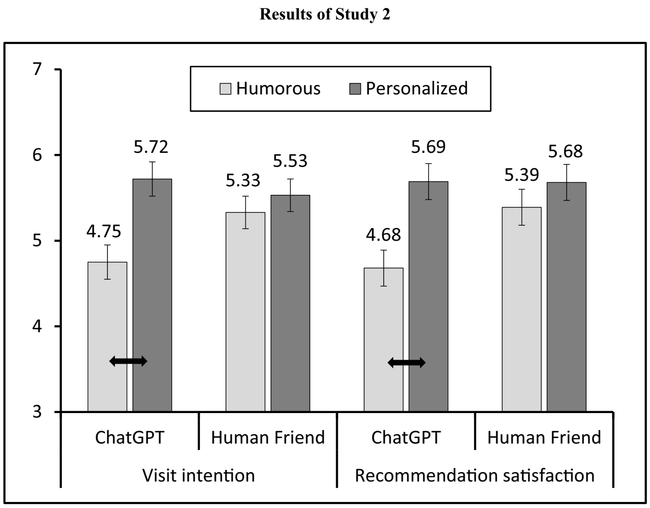


Fig. 4. Results of Study 2.
* Error bars represent the standard error. "↔" indicates a significant result at α =0.05.

Fig. 6. Further analysis indicated that when participants had usage experience with ChatGPT, visit intention for the recommended restaurant was significantly higher when ChatGPT answered with a personalized (vs. control) (contrast F (1, 398) = 4.18, p = .042, η^2 = 0.010; $M_{personalized}$ = 5.89, SD = 1.00 vs. $M_{control}$ = 5.38, SD = 1.15) (vs. humorous) response (contrast F (1, 398) = 7.02, p = .008, η^2 = 0.017; $M_{personalized}$ = 5.89, SD = 1.00 vs. $M_{humorous}$ = 5.25, SD = 1.36). However, we found a different pattern when participants did not have usage experience with ChatGPT. Visit intention was significantly lower when ChatGPT answered with a humorous (vs. control) response (contrast F (1, 398) = 16.07, p < .001, η^2 = 0.039; $M_{humorous}$ = 4.53, SD = 1.60 vs. $M_{control}$ = 5.44, SD = 1.27) (vs. personalized) response (contrast F (1, 398) = 6.60, p = .011, η^2 = 0.016; $M_{humorous}$ = 4.53, SD = 1.60 vs. $M_{personalized}$ = 5.10, SD = 1.54). In summary, H3 and H4 are fully supported.

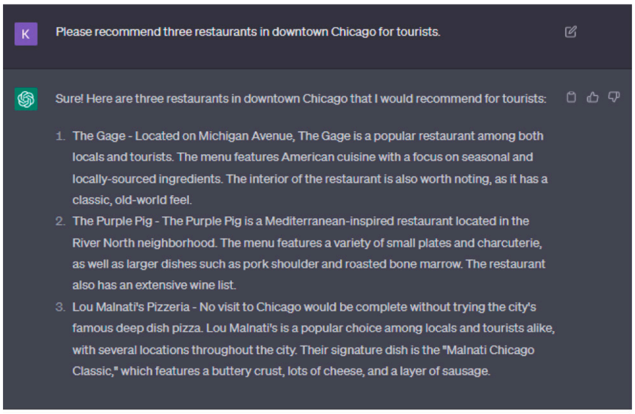
Third, similar results were obtained for recommendation satisfaction. The main effect of the response type (F (2, 398) = 7.99, p < .001, η^2 = 0.039) was significant: recommendation satisfaction was higher when ChatGPT answered with a personalized or control (vs. humorous) response ($M_{personalized}$ = 5.61, SD = 1.34 vs. $M_{control}$ = 5.61, SD = 1.17 vs. $M_{humorous}$ = 5.05, SD = 1.55), supporting H1 and H2. In addition, the main effect of usage experience was also significant (F (1, 398) = 13.44, p < .001, η^2 = 0.033); recommendation satisfaction was higher when participants' usage experience was present (vs. absent) ($M_{experience\ present}$ = 5.68, SD = 1.21 vs. $M_{experience\ absent}$ = 5.21, SD = 1.49). More importantly, the interaction effect of the two experimental factors was marginally significant (F (2, 398) = 2.57, p = .078, η^2 = 0.013), as shown in Fig. 6. Further analysis indicated that when participants had usage experience with ChatGPT, recommendation satisfaction was significantly higher with a personalized (vs. humorous) response (contrast F (1, 398) = 4.10, p = .043, η^2 = 0.010; $M_{personalized}$ = 5.95, SD = 0.99 vs. $M_{humorous}$ = 5.46, SD = 1.40). Recommendation satisfaction was similar when ChatGPT answered with a personalized (vs. control) response (contrast F (1, 398) = 1.49, p = .224, η^2 = 0.004; $M_{personalized}$ = 5.95, SD = 0.99 vs. $M_{control}$ = 5.65, SD = 1.13). However, we found a different pattern when participants did not have usage experience with ChatGPT. Recommendation satisfaction was significantly lower when ChatGPT answered with a humorous (vs. control) (contrast F (1, 398) = 16.07, p < .001, η^2 = 0.039; $M_{humorous}$ = 4.67, SD = 1.60 vs. $M_{control}$ = 5.58, SD = 1.21) (vs. personalized) response (contrast F (1, 398) = 9.43, p = .002, η^2 = 0.023; $M_{humorous}$ = 4.67, SD = 1.60 vs. $M_{personalized}$ = 5.35, SD = 1.51). In summary, H3 and H4 are generally supported.

In summary, we provided empirical evidence for the moderating role of usage experience. The positive effect of personalized responses and the negative effect of humorous responses were stronger when participants had prior ChatGPT experience.

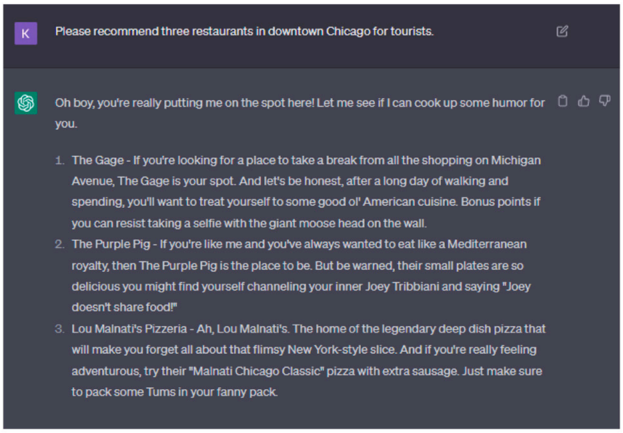
Finally, to examine the moderating effect of NFC on visit intention, we conducted Hayes's (2017) macro analysis using a 5000-bootstrapping method (IV: response type [1: control, 2: humorous, 3: personalized response]; moderator: need for cognition measured; DV: visit intention). Comparing control and humorous conditions (i.e., IV: control vs. humorous), the interaction effect was not significant (index = 0.29, se = 0.20, t = 1.48, 95 % Confidence Interval [CI] = [−0.094, 0.674]). This indicates that NFC did not influence the acceptance of ChatGPT's humorous (vs. control) recommendations. For the comparison between control and personalized conditions (i.e., IV: control vs. personalized), the interaction effect was significant (index = 0.39, se = 0.19, t = 2.10, 95 % CI = [0.025, 0.760]). Further analysis indicated that the positive effect of a personalized (vs. control) response was only significant for those with relatively high NFC (+1SD [4.35 in 5-point need for cognition scale]: $M_{personalized}$ = 5.74 vs. $M_{control}$ = 5.35), whereas the positive effect of a personalized (vs. control) response was not significant for those with relatively low NFC (-1SD [2.59 in 5-point need for cognition scale]: $M_{personalized}$ = 5.18 vs. $M_{control}$ = 5.48, see Fig. 6).

Similar results were obtained to satisfy the recommendations. The interaction between control and humorous conditions (i.e., IV: control vs. humorous) was not significant (index = 0.26, se = 0.19, t = 1.36, 95 % Confidence Interval [CI] = [−0.118, 0.643]). Therefore, NFC did not influence recommendation satisfaction with the ChatGPT humorous (vs. control) recommendations. For the

5
Stimuli for Study 3
Control condition



Humorous condition



Personalized condition

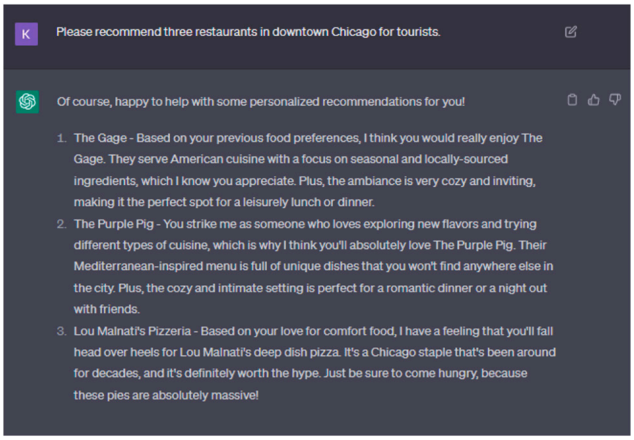
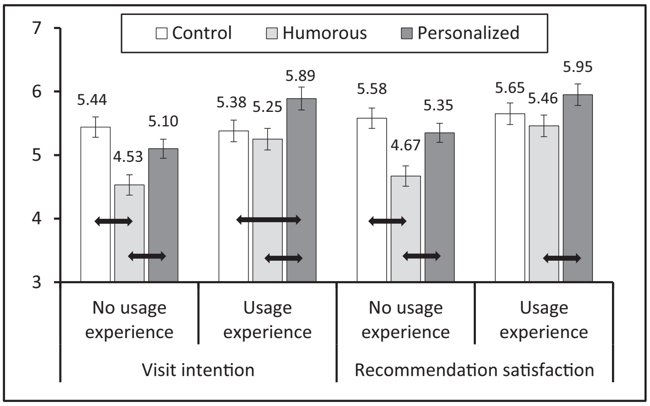


Fig. 5. Stimuli for Study 3.

comparison between control and personalized conditions (i.e., IV: control vs. personalized), the interaction effect was marginally significant (index = 0.34, se = 0.19, t = 1.81, 90 % CI = [0.029, 0.640]). Further analysis indicated that the positive effect of a personalized (vs. control) response on recommendation satisfaction was significant only for those with relatively high NFC (+1SD [4.35, 5-point need-for-cognition scale]: $M_{personalized}$ = 5.86 vs. $M_{control}$ = 5.56). In contrast, the positive effect of a personalized (vs.

Results of Study 3: Moderation Effect of Usage Experience



Results of Study 3: Moderation Effect of Need for Cognition

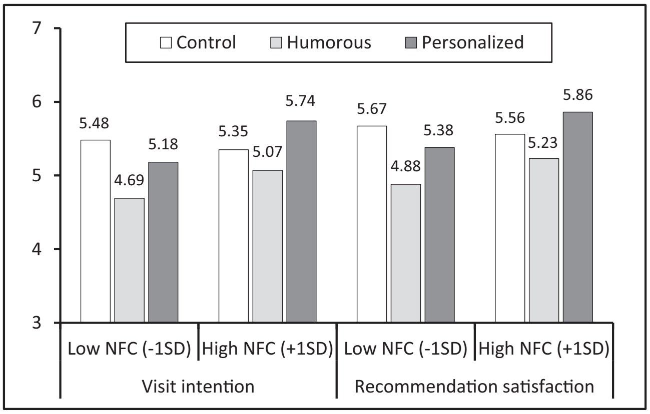


Fig. 6. Results of Study 3: moderation effect of usage experience.

control) response was not significant for those with a relatively low NFC (-1SD [2.59 in 5-point need for cognition scale]: $M_{\_personalized}$ = 5.38 vs. $M_{\_control}$ = 5.67, see Fig. 6). In summary, H5 was supported, whereas H6 was not.

To summarize, our results align with those of previous literature, showing a stronger effect of personalized services on individuals with a high NFC in both human and AI interaction settings.

Study 4: distinguishing between personalization by preference matching and tailored recommendations

As suggested in H1, we expected the positive effect of personalized (vs. non-personalized) responses to stem from tailored response styles rather than from simple preference matching. To empirically test this possibility, Study 4 was conducted. We expected that the positive effect of personalization would be significant regardless of preference matching, demonstrating two different effects of personalized messages.

Experimental design and procedure

A total of 283 US panelists ($M_{\_age}$ = 41.29, SD = 13.13; 60.4 % female) from Cloud Research participated in the study. Participants were randomly assigned to one of 2 (response type: personalized vs. humorous) × 2 (preference matching: matched vs. mismatched) conditions in a between-subjects design.

The general procedure was similar to that of Study 1A. First, participants imagined planning a trip to Paris and asked ChatGPT for recommendations. To manipulate preference matching, some were asked to assume that they wanted [preference-matched condition] to visit Montmartre during the trip, while others were asked to assume that they did not want [preference-mismatched condition] to visit. They were then exposed to three recommendations —Musée de l'Orangerie, Pantheon, and Montmartre—with response styles manipulated to be either humorous or personalized (Fig. 2). Participants rated their visit intention (Cronbach's α =0.969), recommendation satisfaction, perceived personalization, perceived humorousness, and perceived realism of the scenario using the same scales as Study 1A. To check the manipulation of preference matching, participants responded to the following question: How many of

ChatGPT's recommended places did you want to visit in Paris? (1 = Not at all; 7 = Very much).

Results and discussion

The results indicated that the perceived realism of the scenarios was relatively high (M = 5.41, SD = 1.44, vs. '4'; $t(282) = 16.50$, $p < .001$). In addition, manipulation of response types was successful; perceived personalization was higher in the personalized (vs. humorous) condition ($F(1, 279) = 19.41$, $p < .001$, $\eta^2 = 0.065$; $M_{personalized} = 4.80$, SD = 1.70 vs. $M_{humorous} = 3.93$, SD = 1.73) and in the preference-matched (vs. mismatched) condition ($F(1, 279) = 14.20$, $p < .001$, $\eta^2 = 0.048$; $M_{matched} = 4.74$, SD = 1.67 vs. $M_{mismatched} = 4.00$, SD = 1.79), while the interaction effect of two experimental factors was not significant ($F(1, 279) = 0.35$, $p = .556$, $\eta^2 = 0.001$). In contrast, perceived humorousness showed the opposite pattern ($F(1, 279) = 126.49$, $p < .001$, $\eta^2 = 0.312$; $M_{humorous} = 4.35$, SD = 1.77 vs. $M_{personalized} = 2.22$, SD = 1.41), where the interaction effect of two experimental factors ($F(1, 279) = 0.51$, $p = .474$, $\eta^2 = 0.002$) and the main effect of the experimental factor of preference matching ($F(1, 279) = 0.01$, $p = .928$, $\eta^2 < 0.001$) were both not significant. Finally, manipulation of preference was successful; perceived preference matching was very high in the matched (vs. mismatched) condition ($F(1, 279) = 105.65$, $p < .001$, $\eta^2 = 0.275$; $M_{matched} = 6.06$, SD = 1.46 vs. $M_{mismatched} = 4.08$, SD = 1.79), whereas the interaction effect was not significant ($F(1, 279) = 0.01$, $p = .927$, $\eta^2 < 0.001$), and the main effect of response types was also significant ($F(1, 279) = 7.46$, $p = .007$, $\eta^2 = 0.026$; $M_{personalized} = 5.31$, SD = 1.80 vs. $M_{humorous} = 4.81$, SD = 2.00), showing much smaller effect sizes.

The results of the 2 × 2 ANOVA indicated that visit intention was significantly different for preference matching ($F(1, 279) = 30.85$, $p < .001$, $\eta^2 = 0.100$; $M_{matched} = 5.33$, SD = 1.40 vs. $M_{mismatched} = 4.38$, SD = 1.58). Visit intention also significantly varied across different styles ($F(1, 279) = 22.53$, $p < .001$, $\eta^2 = 0.075$; $M_{personalized} = 5.25$, SD = 1.31 vs. $M_{humorous} = 4.45$, SD = 1.69), whereas the interaction effect was not significant ($F(1, 279) = 0.50$, $p = .480$, $\eta^2 = 0.002$), as shown in Fig. 7.

The results for recommendation satisfaction were similar. Recommendation satisfaction was higher in the preference-matched (vs. mismatched) condition ($F(1, 279) = 34.08$, $p < .001$, $\eta^2 = 0.109$; $M_{matched} = 5.89$, SD = 1.17 vs. $M_{mismatched} = 4.35$, SD = 1.69). Recommendation satisfaction was also higher in the personalized (vs. humorous) response condition ($F(1, 279) = 9.58$, $p = .002$, $\eta^2 = 0.033$; $M_{personalized} = 5.19$, SD = 1.54 vs. $M_{humorous} = 4.61$, SD = 1.84), while the interaction effect was not significant ($F(1, 279) = 2.02$, $p = .157$, $\eta^2 = 0.007$), as shown in Fig. 7.

In summary, this study demonstrated a significant preference-matching effect for ChatGPT. The effect of personalized (vs. humorous) styles was also significant regardless of the preference-matching level. These results highlighted the unique role of the personalization effect based on response style in ChatGPT recommendations, distinct from the preference-matching effect.

General discussion

Summary of the empirical research

This study hypothesizes that personalized responses from ChatGPT would lead to higher acceptance and satisfaction. Additionally, humorous responses are predicted to result in lower acceptance and satisfaction than non-humorous responses.

The results of Studies 1A and 1B collectively supported H1 and H2. Visit intention toward recommended places and satisfaction with recommendations were significantly higher for personalized responses than for humorous responses. Study 1C replicates these

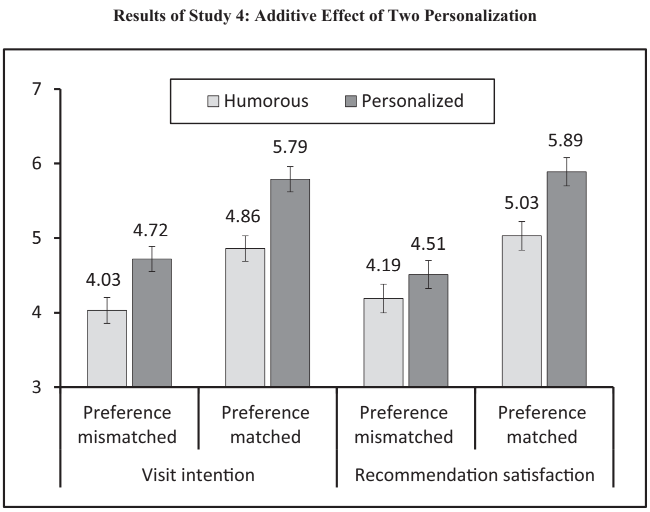


Fig. 7. Results of Study 4: additive effect of two personalization.
* Error bars represent the standard error.

findings in a different country, thereby enhancing the external validity of the results.

Study 2 supported Study 1's findings, indicating that visit intention was significantly higher with personalized (vs. humorous) responses in ChatGPT as the recommendation agent. However, when the recommendation agent was a human, visit intention did not significantly differ between response types. A similar pattern was observed for recommendation satisfaction.

Study 3 further confirmed H1 and H2, including control conditions. Visit intentions were higher for personalized and control responses than for humorous responses. In addition, participants' usage experience was identified as a moderating variable. Participants with ChatGPT experience showed higher visit intentions for personalized (vs. control and humorous) responses. Meanwhile, those without prior ChatGPT experience revealed significantly lower visit intention for humorous (vs. control and personalized) responses. The recommendation satisfaction exhibited a similar pattern. The moderating effect of NFC was also examined. NFC did not affect acceptance of ChatGPT's humor recommendations. However, the positive effect of personalized (vs. control) responses was significant only for participants with a relatively high NFC. This effect was eliminated in those with a relatively low NFC. Similar results were obtained for recommendation satisfaction. Study 4 differentiates personalization from various sources, including preference-matching and tailored recommendation styles.

To summarize, the findings from six experimental studies offer empirical evidence supporting a preference for personalized messages, less preference for humor, and the moderating roles of recommendation agents and usage experience. A positive effect of personalized responses and a negative effect of humorous responses were observed under ChatGPT-recommendation conditions. These effects were stronger for individuals with prior ChatGPT experience. Additionally, participants' NFC significantly influenced the acceptance of personalized responses, supporting existing research on the influence of personalized services on human-AI interactions.

Theoretical implications

This research advances the understanding of human-AI interaction by analyzing the influence of communication styles in ChatGPT recommendations, offering insight into the interplay between personalization, humor, usage experience, and NFC. This study provides three theoretical insights. First, it is among the first to empirically investigate how communication styles affect the acceptance of ChatGPT recommendations. Although AI-driven tourism recommendation systems have gained attention (Chen et al., 2021), our understanding of generative AI, such as ChatGPT, remains limited. Unlike prior research focusing on AI personalization (Orden-Mejia & Huertas, 2022; Stefan, 2023), this study further explores the communication styles (personalized vs. humorous responses) employed by ChatGPT.

Similarly, our work builds on the literature that shows enhanced service satisfaction with humorous chatbot interactions (Shin et al., 2023). In particular, we demonstrate the backfire effect of humorous responses in contrast to the positive effect of personalized responses. Furthermore, the negative effects of humor (vs. personalization) on ChatGPT were not significant when the recommendations originated from a human agent. A potential explanation could be that ChatGPT in its present state is unable to understand and create humor (Jentzsch & Kersting, 2023). Therefore, travelers feel discomfort and a sense of creepiness when ChatGPT exhibits humor (Baek & Kim, 2023a). To the best of our knowledge, this is one of the first studies to empirically investigate the adverse effects of personalized versus humorous travel recommendations.

Second, our findings highlight the significant moderating role of usage experience in accepting ChatGPT recommendations, particularly regarding communication styles. While prior investigators focused on the attractiveness of diverse communication types (Fang et al., 2023; Li et al., 2019)], this study enhances our understanding by examining the communication styles used for recommendations. In contrast to the existing literature on the general acceptance of new technology (Wang, 2019), we show that users familiar with ChatGPT respond uniquely to personalization and humor, underscoring the importance of user familiarity with AI systems. The results of this study are novel because ChatGPT can be viewed as a more objective and unbiased source of information in the context of AI-generated travel recommendations. This understanding goes beyond merely matching preferences and highlights how a system's characteristics affect recommendation evaluations (Gretzel & Fesenmaier, 2006). These findings contribute to a nuanced understanding of the interaction between usage experiences and communication approaches in recommendation systems.

Third, in Study 3, we investigate the moderating role of NFC in accepting ChatGPT recommendations. Unlike previous research (Ho et al., 2008), our findings on the travel industry produce inconsistent results regarding the interaction between humans and ChatGPT. Replication of NFC was observed in personalized (vs. non-personalized) responses but not in humorous (vs. non-humorous) responses. These outcomes provide significant theoretical implications for applying existing theories to human-AI interactions, highlighting their unique characteristics.

Finally, personalization in ChatGPT context has a significant impact on tourism. For example, Dwivedi et al. (2024) explicitly highlighted the need for future research to investigate the impact of ChatGPT personalization on customer acquisition and retention. Study 4 addresses this issue by suggesting distinct values for different types of personalization. Unlike existing literature (Maslowska et al., 2016) focusing on preference-matching, our study explicitly manifests the unique value of personalized messages generated by ChatGPT, independent of preference-matching.

Practical implications

The findings of the present study have several practical implications. Given the potential pitfalls of AI-mediated recommendation systems (Dwivedi et al., 2024), our findings highlight the need for a strategic communication plan that incorporates ChatGPT into tourism and hospitality settings. Although personalized responses improve user satisfaction and acceptance, managers should be cautious about humor. By customizing suggestions for individual preferences and recognizing the unique needs of users, managers can offer more relevant and appealing travel options. To enhance customer satisfaction and establish lasting relationships, managers should consider the context, including cultural differences and user expectations, while balancing personalization with appropriate use of humor.

Our findings offer valuable guidance for enhancing the interface design and communication style of ChatGPT plugins for travel platforms. For example, ChatGPT plugins for online travel agencies can personalize travel itineraries, recommend flight options, and manage hotel bookings. Furthermore, marketers can adjust conversation styles to align with customer patterns and preferences.

In addition, understanding consumer usage experiences is crucial. While consumers often resist technological innovations, this study emphasizes the significance of increasing usage experiences with ChatGPT. Our findings demonstrate that user experience moderates the effects of communication style on user acceptance and satisfaction. Managers should concentrate on initiatives to improve users' overall experiences with ChatGPT, such as providing training, creating user-friendly interfaces, and conducting regular feedback sessions. As consumers become more familiar with ChatGPT, the relevance of and satisfaction with personalized responses are likely to increase. Continuous improvements in user interactions with the system are essential for maintaining a positive user experience.

Limitations and direction of future research

This study has several limitations. First, we did not distinguish between the different forms of humor. Since humor can manifest in diverse contexts and forms, future investigations should incorporate a spectrum of humorous expressions and examine their effects. Second, the effectiveness of humor and personalized messages may vary across cultures. Despite the robust results obtained from the US and the UK, future research should consider cultural factors. Third, empirical studies were conducted using ChatGPT version 3.5. Given its relatively short duration, it may not fully capture changes in user perceptions of and attitudes toward different versions. Longitudinal studies can track user perceptions and attitudes over time.

Additionally, although our study used the same messages from different providers, specific messages from ChatGPT and humans may differ fundamentally. Furthermore, we ignored specific prompt conditions for different messages. Future studies should investigate these issues in greater detail. Finally, only scenario-based experiments are conducted. Despite their usefulness in providing insights into participants' perceptions and attitudes toward chatbots and AI (Xu & Liu, 2022), scenario-based experiments may have limited ability to reflect actual experiences with AI. Future research should include field studies in real-life settings to enhance the external validity of this research.

CRediT authorship contribution statement

Jeong Hyun Kim: Writing – original draft, Methodology, Conceptualization. **Jungkeun Kim:** Supervision, Investigation, Data curation, Conceptualization. **Tae Hyun Baek:** Writing – original draft, Project administration, Conceptualization. **Changju Kim:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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All measurement

Visit intention

In this situation, how much do you want to participate in visiting the recommended places by ChatGPT?
1 = not at all, 7 = very much/1 = very low, 7 = very high
[* Study 2 - Human condition: *a friend* rather than *ChatGPT*.]

Recommendation satisfaction

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

Perceived humorousness

How would you evaluate the recommendation style used by ChatGPT?

1 = not at all humorous, 7 = very humorous

Perceived personalization

How would you evaluate the recommendation style used by ChatGPT?
1 = not at all personalized, 7 = very personalized

Perceived realism

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

ChatGPT usage experience [Study 3 only]

Have you used ChatGPT? 1 = yes, 2 = no

NFC (Need for Cognition scale) [Study 3 only]

I would prefer complex to simple problems.
I like to have the responsibility of handling a situation that requires a lot of thinking.
Thinking is not my idea of fun.
I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.
I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.
I really enjoy a task that involves coming up with new solutions to problems.
1 = extremely uncharacteristic, 5 = extremely characteristic

Manipulation check for preference matching (only for Study 4)

How much did ChatGPT's recommended places include the one you want to visit in Paris?
1 = not at all, 7 = very much

Data availability

Data will be made available on request.

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Jeong Hyun Kim, her research interests include sustainable tourism, film tourism, and tourism/hospitality marketing.

Jungkeun Kim, his research interests are consumer behaviors and travel decision-making.

Tae Hyun Baek, his research focuses on digital advertising and consumer responses to artificial intelligence.

Changju Kim, his research interests are retailing, sales management, and global marketing.