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The Impact of Recommender Type on Tourist Price Sensitivity to Travel Plans

Abstract

Artificial intelligence (AI) has increasingly replaced humans in providing travel recommendations to tourists. Previous research has predominantly focused on investigating tourists' willingness to adopt AI. Given the perceived differences in recommendation capabilities between AI and human service providers, tourists may react differently to the prices of AI- and human-recommended travel plans. This study, therefore, examines how tourist price sensitivity to travel plans is influenced by each recommender. The study hypotheses were tested through four experiments. The results show that tourists have lower price sensitivity to travel plans recommended by AI (vs. human). This effect is mediated by tourists' illusion of understanding, wherein they perceive themselves to be more capable of understanding humans than AI. Furthermore, tourists' sense of uniqueness of travel needs moderates the effect of recommender type on price sensitivity, whereby the effect diminishes with an increase in tourists' sense of uniqueness. This study contributes to the reconsideration of tourist responses to AI recommendations from a price sensitivity perspective. By further exploring the shaping mechanism of tourists' different price sensitivities to AI and human recommendations, we also contribute to the understanding of tourists' comprehension processes regarding AI.

Keywords: artificial intelligence, travel plan, illusion of understanding, sense of uniqueness

Introduction

Tourism and hospitality service providers are progressively embracing artificial intelligence (AI) to improve service quality and engage consumers more effectively (Liu et al., 2022; Yin et al., 2023). With the rapid development of big data, cloud computing, and machine learning, the sources of travel information for tourists have evolved from traditional travel agencies to AI recommenders (Garvey et al., 2023; Shi et al., 2021; Tussyadiah, 2020). AI-powered recommendation systems such as Google Trips and IO Travel Planning can provide travel plans and cost estimates for tourists (Shi et al., 2021). Customers may demonstrate varying responses to different service agent types (AI vs. human) depending on the type of product (Wien & Peluso, 2021). Nevertheless, the limited research on AI recommendations for travel plans has predominantly focused on understanding customer adoption intentions (Lv et al., 2022; Shi et al., 2021), leading to a research gap in investigating whether there are distinctions in tourists' reactions to AI- and human-recommended travel plans.

Setting the price of tourism products is a vital managerial responsibility (Pellinen, 2003), influenced by various factors including tourists' sensitivity to price (Stangl et al., 2020). Particularly, amid the post-COVID-19 pandemic era, economic downturns have made individuals more cautious about financial planning, leading to changes in the price sensitivity of tourism products and services (Ivanova et al., 2021). However, prior studies on AI recommendations have primarily concentrated on the factors influencing customer intention to adopt recommendations, such as performance efficacy, anthropomorphism, technology quality, and personalization (Chi et al., 2022; Shi et al., 2021; Yoon & Lee, 2021). There is uncertainty regarding tourists' price sensitivity to AI-recommended travel plans. Given that

AI is a technology created by humans, individuals have distinct perceptions of AI and human recommenders (Garvey et al., 2023; Yeomans et al., 2019). Tourists may view AI recommenders as devoid of self-interest motives, resulting in AI recommending travel plans that do not primarily benefit themselves, in contrast to human recommenders (Garvey et al., 2023; Kim & Duhachek, 2020). In addition, AI recommenders may be considered more objective and consistent because they generate recommendations by collecting and analyzing information by adhering to standardized procedures (Peng et al., 2023; Xie et al., 2022). Thus, tourists might exercise less caution and display lower sensitivity to price when considering travel plans recommended by AI as opposed to humans. However, little is known about whether a difference in tourist price sensitivity to human- and AI-recommended travel plans exists and, if so, why. This question motivated the current research, given the importance of tourist price sensitivity in shaping corporate operational and marketing decisions regarding AI recommendations.

To address these gaps, this study employed theory of mind to examine tourists' price sensitivity to travel plans recommended by humans vs. AI. Theory of mind suggests that individuals can attribute mental states to themselves and others, including beliefs, perceptions, thoughts, emotions, desires, goals, and intentions (Premack & Woodruff, 1978). Accordingly, tourists may form attitudes toward the recommended travel plans by inferring the thoughts and intentions of the recommender. Given the difference between AI technology and humans, tourists typically perceive that they understand the psychological processes of human recommenders better than the "black box" functioning processes of AI recommenders, which may in turn lead to their different price sensitivity. Tourists' illusions that they possess a

better understanding of humans than of AI aligns with the concept of the illusion of understanding (Cadario et al., 2021), a phenomenon in which individuals overestimate their understanding of how others make judgments and decisions (Bonezzi et al., 2022; Rozenblit & Keil, 2002). This illusion occurs because people rely on their subjective understanding (i.e., what they believe they know) rather than their objective understanding (i.e., what they actually know) when making decisions (Cadario et al., 2021). This study proposes that the illusion of understanding mediates the relationship between recommender type and tourist price sensitivity. In addition, individuals often assume that AI technology operates in a standardized manner, treating each customer inflexibly (Longoni et al., 2019), whereas human recommenders may be perceived as more capable of meeting tourists' unique travel needs than AI recommenders (Kim et al., 2022). Because tourists with a higher sense of uniqueness may prioritize meeting their unique needs over the price of the travel plan, we further propose that for tourists with a high sense of uniqueness, the difference in price sensitivity to travel plans recommended by AI and human recommenders is mitigated. The conceptual model is illustrated in Figure 1.

[Figure 1]

Our research aimed to investigate the potential differences in tourists' price sensitivity toward travel plans recommended by AI compared with those recommended by humans. To achieve this objective, we conducted four experiments with 1,858 valid respondents. Specifically, Study 1 examined the impact of recommender type on tourist price sensitivity to the recommended travel plans. Study 1 had 150 valid respondents and involved two conditions featuring either an AI or human recommender. In Study 2 (valid sample of 613)

and Study 3 (valid sample of 564), we tested the mediating effect of the illusion of understanding. Study 2 showed that human (vs. AI) recommendations led to respondents' greater subjective understanding, which is their illusion of understanding. We employed a 2 (recommender type: human vs. AI) $\times$ 2 (explanation: with vs. without) between-subjects experimental design in Study 2, which involved four conditions. Study 3 further tested the mediating role of respondents' illusion of understanding between recommender type (human vs. AI) and price sensitivity to the recommended travel plans. In Study 3, we also eliminated the alternative interpretation that the observed effect is attributable to respondents' objective understanding. Finally, Study 4 (valid sample of 531) examined the moderating effect of sense of uniqueness of travel needs. Study 3 and Study 4 replicated the same experimental conditions as Study 1.

Our research makes three contributions. First, previous AI-related tourism marketing research has primarily concentrated on tourists' willingness to adopt AI (Lin et al., 2020; Shi et al., 2021). Considering the changes in tourists' financial capacity due to the COVID-19 pandemic (Colmekcioglu et al., 2022), this study presents a new perspective by examining how travel plan recommenders (AI vs. humans) influence tourist price sensitivity. Second, previous studies have shown the adverse impacts of the illusion of understanding, including a decline in consumer readiness to embrace AI (Bonezzi et al., 2022; Cadario et al., 2021). Contrary to these findings, this study reveals a different trend: Tourists' price sensitivity diminishes when receiving travel plan recommendations from AI rather than from humans, through the mediating role of illusion of understanding. This sheds new light on tourists' subjective cognition and attitude formation processes when they encounter AI

recommendations. Finally, our work expands AI and tourism literature by uncovering a boundary condition—tourists’ sense of uniqueness of travel needs—that influences the impact of recommender type on tourist price sensitivity. The study findings also provide important practical contributions. For instance, the study identified the moderating impact of the sense of uniqueness of travel needs on the relationship between recommender type and price sensitivity. Accordingly, companies are first encouraged to segment tourists with varying levels of unique travel needs through measures such as big data analysis and market surveys. Subsequently, distinct recommendation agents (AI vs. humans) can be tailored to different market segments to achieve the desired price sensitivity.

Literature Review and Hypothesis Development

First, we review the literature on travel plan recommendations and price sensitivity. Subsequently, we provide reasoning for the relationship between variables, specifically, developing a hypothesis on the association between recommender type and price sensitivity, followed by hypotheses on the mediating effect of the illusion of understanding and the moderating effect of tourists' sense of uniqueness of travel needs.

Travel Plan Recommendations

Travel plan recommendations can affect tourists' travel decisions and outcomes (Klenosky & Gitelson, 1998). Early studies focused on tourists' cognition of and responses to recommendations provided by traditional travel agencies. Many factors can influence tourists' decisions to adopt a recommendation, including recommendation-related factors such as the recommended destination (Kendall & Booms, 1989; Klenosky & Gitelson, 1998), recommendation methods and strategies (Laskey et al., 1994; Murphy, 2001), and the quality and value of the recommendation (He & Song; 2009), and recommender-related factors such as the travel agent's decision-making process (Buckley & Mossaz, 2016) and the role of social surrogates in tourism decisions (Stone, 2016). With the development of information technology, the sources of travel plan recommendations have shifted from offline to online (Kotiloglu et al., 2017). Studies have investigated the influence of online reviews on travel plan recommendations (Chatterjee & Mandal; 2020; Filieri et al., 2015) and the optimization of travel recommendation systems (Huang et al., 2021; Kotiloglu et al., 2017; Yeh & Cheng, 2015).

Recently, AI technology has been integrated into travel plan recommendations (Shi et al., 2021). AI pertains to the emulation of human intelligence, allowing computer systems to autonomously learn from experience and carry out assignments to enhance efficiency (Li et al., 2019; Shi et al., 2021). Previous studies have identified the determinants of tourists' willingness to adopt AI recommendations based on technology adoption theories. For example, social influence enhances tourists' willingness to use AI devices by improving performance expectancy and diminishing effort expectancy (Chi et al., 2022). Performance efficacy and perceived anthropomorphism were found to increase tourists' readiness to adopt AI-powered recommendation systems by enhancing their cognitive and emotional trust, respectively (Shi et al., 2021). Furthermore, research has examined additional factors such as perceived personalization and information quality of AI-based tourism recommendation systems (Yang et al., 2024), along with inaccurate information (Kim et al., 2023) and reducing options provided by ChatGPT (Shin et al., 2023), on tourists' acceptance of recommendations. These studies focused on tourists' evaluations of AI recommendation systems. Nevertheless, the attitudinal responses of individuals to suggestions provided by AI are influenced by their subjective understanding and cognition (Cadario et al., 2021; Yeomans et al., 2019). It remains unknown whether tourists exhibit distinct attitudinal responses to travel plans recommended by AI as opposed to humans, given that their subjective understanding of AI and humans may vary.

Tourists' attitudes toward prices play a pivotal role in determining their adoption intentions (Choi & Mattila, 2018; Chung & Petrick, 2013; Hou & Zhang, 2021). In addition, the global economic downturn fueled by COVID-19 and regional wars and conflicts has

resulted in a surge in living costs (Santos et al., 2021). This has caused growing price sensitivity in tourism products and services (Huang et al., 2024). Given that price sensitivity is underexplored, particularly within the domain of technology adoption (Natarajan et al., 2017), it is imperative to investigate tourists' price sensitivity within the context of AI recommendations for travel planning.

Type of Travel Plan Recommenders and Tourist Price Sensitivity

Price sensitivity indicates how individuals perceive and react to the price and/or changes in the price of a product or service (Goldsmith & Newell, 1997). It depends not only on personal factors but also on the context in which consumers make purchasing decisions. For instance, individuals are found to be more price sensitive when shopping or booking hotels online than when offline (Chu et al., 2010; Chung et al., 2022), because online channels minimize the search cost for pricing information (Lynch Jr & Ariely, 2000) and allow them to compare prices with less effort (Granados et al., 2012). Additionally, tourists rely more on their feelings to make judgments in crowded environments, making them less sensitive to prices (Hou & Zhang, 2021). This occurs because when tourists depend on feelings (as opposed to cognitive processes) for judgment, they tend to be less sensitive to the magnitude of numerical information (Chang & Hung, 2018; Hsee & Rottenstreich, 2004). These studies illustrate the influence of consumption situations and travel environments on customer price sensitivity. However, an emerging trend—the AI recommendation of travel plans—remains unexplored.

Because AI recommenders, as a type of technology, are perceived differently from

human recommenders (Dietvorst et al., 2015), tourists may generate different price sensitivities to the travel plans provided by these two types of recommenders. Theory of mind has been employed to comprehend customer trust, adoption of brands and companies (Craig et al., 2012; Minton et al., 2021; Pizzi et al., 2023), and processing of product recommendations (Faraji-Rad et al., 2015). Theory of mind suggests that individuals have the capability to attribute mental states to themselves and others, including beliefs, perceptions, thoughts, emotions, desires, goals, and intentions (Premack & Woodruff, 1978). This capability helps customers evaluate recommendations and determine whether they are in their best interests (Wien & Peluso, 2021). However, individuals tend to maintain divergent beliefs regarding the minds (i.e., mental state) of humans and AI agents (Wiese et al., 2017). Unlike humans, AI is commonly considered as lacking consciousness (Wien & Peluso, 2021) and self-awareness, which drive subsequent actions (Garvey et al., 2023; Russell & Norvig, 2010). Thus, customers are less likely to infer AI intention from their decisions and actions (Garvey et al., 2023; Malle et al., 2001). For instance, in a scenario in which the AI system of an autonomous vehicle, rather than a human driver, directs the vehicle into a wall to safeguard a child, individuals would withhold praise for the AI system because of the perception that it lacks the intention to prioritize human well-being (Awad et al., 2018). Accordingly, when delivering travel plan recommendations, AI may be perceived by tourists as devoid of self-awareness and the motivation to prioritize its own benefits (Bratman, 1987; Garvey et al., 2023), in contrast to humans who might be more susceptible to being driven by personal motives in price decisions (Peng et al., 2023). Although companies utilize and control AI recommenders, individuals typically do not perceive them as commercial entities with profit-

making and persuasive intentions (Kim & Duhachek, 2020). Additionally, in comparison to their human counterparts, AI recommenders are believed to be more adept at providing recommendations based on facts, logic, and rationality, as they make decisions based on information collected and analyzed through consistent algorithms and programs (Xie et al., 2022). Consequently, tourists generally perceive AI recommenders as capable of minimizing human subjectivity in the recommendation process (Newman et al., 2020), making them appear more consistent and neutral compared to human recommenders (Lee, 2018; Ötting & Maier, 2018). This perception, in turn, reduces tourists' focus on the price information of AI recommendations compared to human recommendations, indicating a lower sensitivity to price.

H1: Tourist price sensitivity to travel plans is lower when they are recommended by AI (vs. human).

The Mediating Role of Illusion of Understanding

The illusion of understanding refers to individuals developing an understanding that leans toward subjective understanding (what they believe they know) rather than objective understanding (what they actually know) when making decisions (Cadario et al., 2021; Rozenblit & Keil, 2002). It elucidates the differences in people's responses to decision-making between humans and AI (Cadario et al., 2021). Specifically, individuals often harbor the illusion that they understand human recommendations better than AI recommendations because the latter is like a "black box" (Bonezzi et al., 2022; Campolo et al., 2017). However surprisingly, the decision-making process of humans is also a "black box" (Bonezzi et al.,

2022). For example, patients have no way of knowing how doctors arrive at a diagnosis (Cadario et al., 2021), recruiters may not be able to explain their criteria for evaluating candidates (Klehe et al., 2008), and judges cannot tell exactly how they assess the defendants' risk of crime (Bonezzi et al., 2022). These decisions, although made by fellow humans, remain a "black box." However, people tend to believe that the decision-making process of human is easier to comprehend than that of AI (Bonezzi et al., 2022; Castelvechi, 2016). Such an illusion of understanding may also prevail among tourists, who typically assert a higher subjective understanding of human recommendations than AI recommendations. Theory of mind further supports this notion.

According to theory of mind, individuals evaluate recommendations and their associated benefits by understanding the mental state of the recommender, operating under the assumption that the recommender possesses a mind (i.e., mental state) (Wiese et al., 2017; Wien & Peluso, 2021). As customers may be more hesitant to regard AI (vs. human) recommenders as having a mind (Gray & Wegner, 2012), it is challenging to comprehend how AI recommendations are generated (Aksoy et al., 2006; Yeomans et al., 2019). Accordingly, tourists may have the illusion that they comprehend human recommenders better than AI recommenders, although this perception is not necessarily true (Bonezzi et al., 2022; Cadario et al., 2021).

This illusion of understanding indicates that tourists have a lower subjective understanding of AI (vs. human) recommenders, leading them to be less attentive to the intentions of AI recommenders and disconnecting them from commercial entities and their profit-driven motives (Kim & Duhachek, 2020). Tourists may also understand that AI

recommendations rely on algorithms or programs (Huang & Rust, 2018; Lee, 2018). However, they lack comprehension of the specific principles and logic underlying these algorithms (Yeomans et al., 2019), and tend to perceive AI recommendations as consistent and objective (Choi et al., 2023). Therefore, they place less emphasis on the price of travel plans recommended by AI (i.e., lower price sensitivity). In contrast, a greater subjective understanding of human (vs. AI) recommenders makes tourists instinctively assume the intentions and thoughts of a human recommender (Wien & Peluso, 2021), and use this to assess the rationality and feasibility of the recommended travel plans (Choi et al., 2023; Garvey et al., 2023). In turn, this results in a more cautious approach to evaluating human-recommended travel plans (Peng et al., 2023) and an increased focus on the relevant information, including the price (i.e., higher price sensitivity).

H2: Illusion of understanding mediates the relationship between recommender type (AI vs. human) and tourist price sensitivity to travel plans.

The Moderating Role of Sense of Uniqueness of Travel Needs

People's perceived differences between the minds of human and AI recommenders also relate to the perception that AI recommenders may overlook an individual's unique characteristics (Longoni et al., 2019; Yalcin et al., 2022). Next, this study investigates whether the effect of recommender type on tourists' price sensitivity to travel plans is influenced by individual differences, such as their sense of uniqueness of travel needs. Sense of uniqueness refers to the "private sense of experiencing the self that can only be acknowledged by the individuals themselves" (Şimşek & Yalınçetin, 2010, p. 576), which may influence price perceptions

(Bastos, 2019; Wu et al., 2012). Individuals' unique needs are often met by making purchases that reflect their unique identities (Carter & Gilovich, 2010; Snyder & Fromkin, 1980). Thus, consumption and experiences that better acknowledge uniqueness tend to elicit more well-disposed consumer reactions to price increases (Bastos, 2019; Dwivedi et al., 2018). Accordingly, we expect the sense of uniqueness of travel needs to moderate the impact of recommender type on tourists' price sensitivity to travel plans.

H1 proposes that tourists exhibit lower price sensitivity to travel plans recommended by AI than those recommended by humans. Such trends persist among tourists with a low sense of uniqueness. This is attributed to these tourists prioritizing the utilitarian performance of products and services over the satisfaction of their unique needs (Burns & Warren, 1995; Karagöz & Uysal, 2022). They are reluctant to pay premiums for unique products or services (D'Angelo et al., 2019; Tian & McKenzie, 2001). Their indifference toward the uniqueness of products leads them to regard AI recommenders, which base decisions on consistent algorithms and procedures, as more objective and fairer than human recommenders (Newman et al., 2020; Xie et al., 2022), while ignoring the potential loss of uniqueness resulting from such algorithmic decisions (Longoni et al., 2019). Correspondingly, they give less consideration to the potential unique value of human-recommended travel plans, resulting in lower price sensitivity to AI-recommended travel plans than to those recommended by humans.

However, this difference in price sensitivity may decrease for tourists with a high sense of uniqueness. Such tourists are prone to perceive their preferences and needs as idiosyncratic traits (Longoni et al., 2019), prioritizing the pursuit of uniqueness through consumption

experiences over the consideration of prices (Bastos, 2019). For instance, individuals with a high sense of uniqueness favor first-class flights and other luxury products that accentuate their distinctiveness (Hwang & Hyun, 2017; Xu & Mehta, 2022). As human decisions are perceived as more flexible and tailored to specific conditions (Kim et al., 2022; Longoni et al., 2019), human recommenders are often perceived to surpass AI recommenders in considering tourists' unique travel needs and preferences. In contrast, AI-generated recommendations are based on pre-coded categories of individual characteristics that are commonly shared, while overlooking unique characteristics specific to an individual (Newman et al., 2020; Yalcin et al., 2022). Additionally, AI recommenders operating on algorithms are often seen as cognitively inflexible and lacking the ability to adapt to unexpected conditions (Longoni et al., 2019). Thus, people tend to believe that AI approaches each case in a standardized and routine manner (Longoni et al., 2019; Yu et al., 2024). Hence, tourists' heightened price sensitivity to travel plans recommended by human (vs. AI) recommenders may be overcome if they have a high sense of uniqueness. In other words, the difference in price sensitivity to travel plans recommended by human and AI recommenders is mitigated for tourists with a high sense of uniqueness.

H3: Sense of uniqueness of travel needs moderates the effect of recommender type (AI vs. human) on tourist price sensitivity to travel plans. Specifically, tourists with a low sense of uniqueness exhibit lower price sensitivity to travel plans recommended by AI (vs. human). The difference in price sensitivity to human- and AI-recommended travel plans diminishes for tourists with a high sense of uniqueness.

Study 1: The Effect of Recommender Type on Tourist Price Sensitivity

Method

A single-factor (recommender type: human vs. AI) between-subjects design was employed in Study 1. We recruited 153 respondents from China through the marketing research platform, Credamo, which has over three million registered users and specializes in recruiting respondents from various backgrounds and regions across China (Lei, 2024; Wang et al., 2024). Each respondent received an incentive of two CNY (Chinese Yuan). They were randomly allocated to one of two experimental conditions and instructed to imagine themselves planning a four-day trip for the following week and search for information on the travel plan. They were then presented with recommendations for a four-day travel plan to Shanghai.

We manipulated the recommender type (human vs. AI) following Longoni and Cian (2022) and Wien and Peluso (2021) (see Appendix A). In the human recommender condition, the recommendation source was represented by a generic person icon accompanied by a generic human name. The respondents were clearly told that a person recommended the travel plan. In contrast, in the AI-recommender condition, the source of the recommendation was represented by a typical robotic head. The respondents were explicitly informed that it was an AI recommender who provided the recommendations. Note that the contents of the recommended travel plan under the two conditions were identical, except for the display of the icon and the names of the recommenders. Subsequently, respondents answered the survey questions.

First, respondents were prompted to respond to the question “Who do you think

recommended this travel plan to you?” with the two options of a human and AI agent, as a manipulation check question. Then, they reported their price sensitivity ($\alpha = 0.798$) on a six-item Likert scale (1 = strongly disagree, 7 = strongly agree), adapted from Goldsmith et al. (2005) and Wakefield and Inman (2003) (see Appendix E). Finally, they answered questions for the measurements of destination familiarity, expertise ($\alpha = 0.786$), and demographic information, which were used as the control variables. Destination familiarity was measured by a single-item Likert scale: 1 = not familiar at all; 7 = very familiar (Wien & Peluso, 2021). Expertise was assessed utilizing a three-item Likert scale (1 = strongly disagree; 7 = strongly agree) which was adapted from previous research (Alba & Hutchinson, 1987; Elettigerra et al., 2021; see Appendix E). Gender was represented by a dummy variable with two categories: female and male. Education level was captured by three dummy variables: high school or below, professional/vocational college degree, university degree, and postgraduate degree or above. Monthly income level was represented by three dummy variables: below 5,000 CNY, 5,000–9,999 CNY, 10,000–15,000 CNY, and above 15,000 CNY.

Results

Manipulation check. Study 1 involved 153 respondents in total, and 98.04% correctly recognized the recommender type under their experimental conditions. We performed a logistic regression with the recommender type (0 = human travel agent, 1 = AI travel agent) as the dependent variable and the experimental condition (0 = human agent condition, 1 = AI agent condition) as the independent variable. Results show that the effect of experiment condition on recommender type is significant ($\beta = 7.940$, $z = 6.426$, $p < 0.001$), suggesting

successful manipulation of recommender type. In the subsequent analysis, three participants were excluded because of incorrect answers to the manipulation check question. This resulted in a valid sample of 150 respondents (58.70% female, $M_{\text{age}} = 28.850$, $SD_{\text{age}} = 7.583$).

Hypothesis test. A one-way ANCOVA shows that compared to the human recommender condition ($M_{\text{human}} = 5.788$, $SD_{\text{human}} = 0.448$), the price sensitivity of respondents in the AI recommender condition ($M_{\text{AI}} = 4.986$, $SD_{\text{AI}} = 1.048$) is significantly lower ($F(1, 139) = 26.909$, $p < 0.001$, partial $\eta^2 = 0.162$).

The finding of Study 1 supports H1 in that tourists have lower price sensitivity to travel plans recommended by AI (vs. humans). The results are similar when control variables are not included in the analysis. Our results are consistent with prior studies that argued that individuals respond differently to AI and humans (Castelo et al., 2019; Wien & Peluso, 2021).

Study 2: The Effect of Recommender Type on Tourist Illusion of Understanding

Method

We recruited 647 Chinese respondents from Credamo, each of whom received an incentive of two CNY for their participation. A 2 (recommender type: human vs. AI) $\times 2$ (explanation: with vs. without) between-subjects design was employed. Respondents were randomly allocated to one of four conditions. The tourism scenario was a ten-day travel plan for Yunnan. The manipulation of the recommender type was the same as in Study 1 by changing the display of the icon and the name of the recommenders (see Appendix B).

To manipulate explanation, we followed the approach of Bonezzi et al. (2022) (see Appendix B). The illusion of understanding can be revealed by prompting individuals to

provide detailed explanations of how something works (Rozenblit & Keil, 2002). Specifically, under the explanation conditions, respondents were initially requested to explain the recommendation process upon reading the scenario. They were requested to include a detailed description of the recommendation process, such as the factors to be considered by the recommender and the recommendation generation process. Subsequently, participants were asked to report their subjective understanding. Under these conditions, the explanation procedure exposed individuals to an illusion of understanding; that is, they became aware that they might not actually understand the recommendation process, thus inhibiting their subjective understanding, which was subsequently measured (Rozenblit & Keil, 2002).

In contrast, in the conditions without explanation, respondents were asked to report their subjective understanding immediately after reading the material. They were then asked to explain the recommendation process to ensure consistency and avoid differential dropout (Bonezzi et al., 2022). Under these conditions, respondents' subjective understanding was not influenced by the explanation procedure because it occurred after their subjective understanding was measured. Thus, a greater reduction in the subjective understanding rating in the with-explanation conditions than in the without-explanation conditions indicated a more pronounced illusion of understanding. We assessed subjective understanding ($\alpha = 0.878$) using a four-item Likert scale (1 = do not understand at all, 7 = completely understand) adapted from Bonezzi et al. (2022) and Cadario et al. (2021) (see Appendix E).

Finally, respondents were asked to recall who recommended the travel plan to them (human or AI agent) as the manipulation check and answer questions about the measurements of destination familiarity, expertise ($\alpha = 0.769$), and demographic information, which were

the same as those in Study 1.

Results

Manipulation check. The results show that 94.74% of the respondents correctly indicated the recommender type under the experimental conditions. The effect of experiment condition on recommender type is significant ($\beta = 5.815$, $z = 16.257$, $p < 0.001$), indicating successful manipulation of recommender type. In the subsequent analysis, 34 participants were excluded because of incorrect answers to the manipulation check question. This resulted in a valid sample of 613 respondents (61.70% female, $M_{\text{age}} = 28.100$, $SD_{\text{age}} = 9.090$).

Subjective understanding. A two-way ANCOVA reveals a significant effect of recommender type ($F(1, 600) = 30.702$, $p < 0.001$, partial $\eta^2 = 0.049$), a significant effect of explanation ($F(1, 600) = 21.008$, $p < 0.001$, partial $\eta^2 = 0.034$), and a significant interaction effect between the two variables ($F(1, 600) = 11.252$, $p = 0.001$, partial $\eta^2 = 0.018$) on respondents' subjective understanding. In conditions without explanation, respondents show a greater subjective understanding of human recommendations ($M_{\text{human}} = 4.492$, $SD_{\text{human}} = 1.057$) than of AI recommendations ($M_{\text{AI}} = 3.696$, $SD_{\text{AI}} = 1.024$; $F(1, 600) = 39.266$, $p < 0.001$). In conditions with explanation, the difference in the respondents' subjective understanding of human ($M_{\text{human}} = 3.761$, $SD_{\text{human}} = 1.248$) and AI recommendations ($M_{\text{AI}} = 3.572$, $SD_{\text{AI}} = 1.183$; $F(1, 600) = 2.496$, $p = 0.115$) is not significant. This is because the explanation procedure in the with-explanation conditions reduced respondents' subjective understanding of human recommendations, but not of AI recommendations. Specifically, when the recommender is a human, the respondents' subjective understanding is significantly

lower in the with-explanation condition ($M_{\text{human}} = 3.761$, $SD_{\text{human}} = 1.248$) than in the without-explanation condition ($M_{\text{human}} = 4.492$, $SD_{\text{human}} = 1.057$; $F(1, 600) = 32.023$, $p < 0.001$). However, when the recommender is AI, the difference in the respondents' subjective understanding in the with-explanation ($M_{\text{AI}} = 3.572$, $SD_{\text{AI}} = 1.183$) and the without-explanation condition ($M_{\text{AI}} = 3.696$, $SD_{\text{AI}} = 1.024$; $F(1, 600) = 0.739$, $p = 0.390$) is not significant. These results are shown in Figure 2. Excluding the control variables from the analysis yields similar results.

[Figure 2]

The findings of Study 2 indicate that respondents demonstrate a more pronounced illusion of understanding of human recommendations than of AI recommendations. Specifically, in the without-explanation conditions, respondents have a greater subjective understanding of human (vs. AI) recommendations, while in the with-explanation conditions, the difference in subjective understanding of human and AI recommendations vanishes because prompting respondents to explain the recommendation process results in a greater reduction in their subjective understanding of human recommendations compared to AI recommendations. These findings suggest that individuals' illusion of understanding in the decision-making processes of certain professionals such as doctors, judges, and recruiters (Bonezzi et al., 2022; Cadario et al., 2021), also applies to travel agents.

Study 3: The Mediating Effect of Illusion of Understanding

Method

We recruited 597 Chinese respondents from Credamo. They were rewarded 2.5 CNY. We

employed a single-factor (recommender type: human vs. AI) between-subjects design.

Respondents were randomly allocated to one of two conditions. The procedures were similar to those used in Study 1. The tourism scenario was a six-day travel plan to Bali (Appendix C).

After reading the experiment material, respondents were asked to report their price sensitivity ($\alpha = 0.811$), and subjective ($\alpha = 0.874$) and objective understanding in turn. Subjective understanding refers to the individuals' subjective perception of their understanding of the recommendation process, whereas objective understanding refers to their actual understanding. The purpose of measuring objective understanding was to eliminate the alternative explanation that tourists' different price sensitivities to travel plans recommended by humans and AI recommenders might be attributed to their objective understanding. Objective understanding was measured using three multiple-choice questions adapted from Cadario et al. (2021) (see Appendix E). Objective understanding scores were calculated by summing the number of correct answers, ranging from 0 to 3. Price sensitivity and subjective understanding were measured using the same scales employed in Study 1 and Study 2.

Finally, we asked the respondents to recall who recommended the travel plan to them (human or AI agent) as the manipulation check and to complete measurements for the control variables, including familiarity with the destination, expertise ($\alpha = 0.712$), and demographic information. The measurements remained the same with those used in Study 1.

Results

Manipulation check. Results show that 94.47% of respondents correctly indicated their

experimental conditions. The effect of experiment condition on recommender type is significant ($\beta = 5.886$, $z = 14.714$, $p < 0.001$), suggesting successful manipulation of recommender type. In the following analysis, 33 participants were excluded due to their incorrect answers to the manipulation check question, leaving a valid sample of 564 responses (65.40% female, $M_{\text{age}} = 28.150$, $SD_{\text{age}} = 8.816$).

Hypothesis test. First, we performed a one-way ANCOVA. Results indicate that respondents in the AI recommender condition have significantly lower price sensitivity ($M_{\text{AI}} = 5.309$, $SD_{\text{AI}} = 0.812$) than the human recommender condition ($M_{\text{Human}} = 5.757$, $SD_{\text{Human}} = 0.774$; $F(1, 553) = 47.327$, $p < 0.001$, partial $\eta^2 = 0.079$), supporting H1.

In further MANCOVA, subjective and objective understanding were employed as the dependent variables. The results show that respondents have greater subjective understanding of human recommendations ($M_{\text{human}} = 4.850$, $SD_{\text{human}} = 1.104$) than that of AI recommendations ($M_{\text{AI}} = 3.885$, $SD_{\text{AI}} = 1.165$; $F(1, 553) = 86.980$, $p < 0.001$, partial $\eta^2 = 0.136$). However, the difference in respondents' objective understanding of human recommendation ($M_{\text{human}} = 1.290$, $SD_{\text{human}} = 0.785$) and that of AI recommendation ($M_{\text{AI}} = 1.390$, $SD_{\text{AI}} = 0.746$; $F(1, 553) = 1.334$, $p = 0.249$, partial $\eta^2 = 0.002$) is not significant.

We adopted the PROCESS approach to test for the mediation effect (Model 4; Hayes, 2018). In this model, the recommender type (AI = 0, human = 1) was the independent variable, and subjective and objective understanding were the two mediating variables. Price sensitivity was the dependent variable. The respondents' gender, education level, monthly income level, destination familiarity, and expertise were included as covariates. The results support a direct effect of recommender type on price sensitivity ($b = 0.326$, $SE = 0.070$, 95%

CI [0.189, 0.463]) and an indirect effect on price sensitivity via subjective understanding ($b = 0.130$, $SE = 0.038$, 95% CI [0.062, 0.211]) as the confidence interval excludes 0. However, there is no indirect effect via objective understanding as the confidence interval includes 0 ($b = -0.001$, $SE = 0.004$, 95% CI [-0.009, 0.008]). The results of the mediation analysis are shown in Figure 3. These findings suggest that the difference in tourists' price sensitivity to travel plans recommended by humans and AI is mediated by subjective rather than objective understanding.

[Figure 3]

These results support H2: The illusion of understanding (i.e., a greater subjective understanding of humans than AI recommendations) mediates the relationship between recommender type and tourist price sensitivity to travel plans, and further rules out an alternative explanation of the role of objective understanding. These results are similar when control variables are not included in the analysis.

Study 4: The Moderating Effect of Sense of Uniqueness

Method

We recruited 564 Chinese respondents from Credamo. Each respondent received four CNY for participation in the study. We employed a single-factor (recommender type: human vs. AI) between-subjects design. All respondents were randomly allocated to one of two conditions. The manipulation of the recommender type resembled the one used in Study 1. The tourism scenario was a ten-day travel plan for Switzerland (Appendix D).

Upon reading the material, respondents were instructed to report their sense of

uniqueness of travel needs ($\alpha = 0.869$), subjective understanding ($\alpha = 0.914$), and price sensitivity ($\alpha = 0.820$). The sense of uniqueness was assessed using a three-item Likert scale (1 = strongly disagree, 7 = strongly agree) adapted from Longoni et al. (2019) (see Appendix E). Finally, respondents were asked to recall who recommended the travel plan to them (human or AI agent) as the manipulation check and to complete questions about demographic information, and the measurements of familiarity with the destination and expertise ($\alpha = 0.745$), which were the same as those used in Study 1.

Results

Manipulation check. Results show that 94.15% of the respondents correctly indicated the recommender type under their experimental conditions. The effect of experiment condition on recommender type is significant ($\beta = 5.564$, $z = 15.445$, $p < 0.001$), indicating successful manipulation of recommender type. In the subsequent analysis, 33 participants were excluded because of incorrect answers to the manipulation question, resulting in a valid sample of 531 responses (65.50% female, $M_{\text{age}} = 28.530$, $SD_{\text{age}} = 8.834$).

Hypothesis test. We performed a one-way ANCOVA. The results show that compared to the human recommender condition ($M_{\text{human}} = 5.679$, $SD_{\text{human}} = 0.741$), respondents in the AI recommender condition have lower price sensitivity to the recommended travel plan ($M_{\text{AI}} = 5.374$, $SD_{\text{AI}} = 0.813$; $F(1, 520) = 21.040$, $p < 0.001$, partial $\eta^2 = 0.039$). Thus, H1 is supported again.

A regression analysis was performed to test the moderating effect of sense of uniqueness. Price sensitivity was the dependent variable; recommender type (0 = AI, 1 = human) and

sense of uniqueness (mean-centered; $M = 4.480$, $SD = 1.364$) were the independent variables; gender, education level, monthly income level, destination familiarity, and expertise were the covariates. The analysis employed a bootstrapping method (PROCESS Model 5 in SPSS 25; Hayes, 2018). First, the results show a significant effect of recommender type ($b = 0.184$, $SE = 0.067$, $p = 0.006$, 95% CI [0.052, 0.315]), a significant effect of sense of uniqueness ($b = -0.050$, $SE = 0.025$, $p = 0.046$, 95% CI [-0.100, -0.001]), and a significant interaction effect between the two variables ($b = -0.155$, $SE = 0.048$, $p = 0.001$, 95% CI [-0.248, -0.061]).

Second, we examined the interaction further using the Johnson-Neyman approach since the moderator sense of uniqueness is a continuous measure (Longoni et al., 2019; Spiller et al., 2013). The results unveil a significantly positive effect of recommender type on price sensitivity when the sense of uniqueness score (mean-centered) is below 0.316 ($b_{J-N} = 0.135$, $SE = 0.069$, $p = 0.050$), indicating that respondents exhibit greater price sensitivity to the human-recommended travel plans than the AI-recommended travel plans when their sense of uniqueness score (mean-centered) is below 0.316, as shown in Figure 4. The positive effect of recommender type on price sensitivity loses significance when the sense of uniqueness score (mean-centered) exceeds 0.316. Furthermore, the indirect effect of recommender type on price sensitivity via subjective understanding is supported again ($b = 0.116$, $SE = 0.030$, 95% CI [0.060, 0.177]).

[Figure 4]

The findings of Study 4 again support H1 and show that respondents are more price sensitive to travel plans recommended by humans (vs. AI). Furthermore, respondents with a low sense of uniqueness show high price sensitivity to the travel plans recommended by

humans (vs. AI). However, for those with a high sense of uniqueness, the difference in price sensitivity to travel plans recommended by humans and AI diminishes. Thus, the results support H3—the sense of uniqueness of travel needs moderates the relationship between recommender type and price sensitivity. These results are similar when control variables are not included in the analysis. Our findings further demonstrate the impact of sense of uniqueness on individuals' responses to AI (Longoni et al., 2019).

General Discussion

This study explores tourists' differentiated cognitions toward travel plans recommended by humans and AI. Specifically, through four experiments, we obtain consistent evidence on the impact of recommender type (human vs. AI) on tourists' price sensitivity to recommended travel plans and further reveal the mediating effect of the illusion of understanding and the moderating effect of the sense of uniqueness of travel needs.

Study 1 show that tourists have higher price sensitivity to travel plans recommended by humans (vs. AI). Study 2 show that when faced with travel plans recommended by humans (vs. AI), tourists have a greater subjective understanding in the condition without explanation. However, tourists' subjective understanding of both human and AI recommendations is relatively low after they are asked to provide an explanation of the human/AI recommendation process. These results confirm that tourists have the illusion that they can better understand human recommenders than AI recommenders. Study 3 further reveals that higher price sensitivity to human-recommended travel plans is caused by tourists' greater subjective understanding of human recommendations (vs. AI recommendations), that is, their illusion of understanding. Study 4 finds that tourists' sense of uniqueness of travel needs moderates the relationship between recommender type and price sensitivity to recommended travel plans. Specifically, tourists with a low sense of uniqueness show higher price sensitivity to travel plans recommended by humans (vs. AI). However, this effect diminishes for tourists with a high sense of uniqueness.

Theoretical Implications

As AI has emerged as a replacement for human employees in providing product/service recommendations to customers in various sectors, prior research has investigated individuals' different cognitions, preferences, and choices between AI and human recommendations (Garvey et al., 2023; Wien & Peluso, 2021). Studies focusing on algorithm aversion argue that people are less willing to take the recommendations from AI (vs. humans), especially for products with emotional and experiential value (Longoni & Cian, 2022; Xu & Mehta, 2022). Unlike these studies, our research takes a novel perspective of tourists' price perceptions and provides evidence of the positive role of AI recommenders in overcoming tourist price sensitivity to travel plans. The COVID-19 pandemic has profoundly impacted individuals' financial capacity, and one of the results is reflected in changes in tourists' price sensitivity to tourism products and services (Colmekcioglu et al., 2022; Ivanova et al., 2021). Although customer price sensitivity is crucial for companies to make pricing and marketing decisions (Jeong et al., 2019), little is known about how different types of travel service recommenders shape price sensitivity, especially in the context of the increasing prevalence of AI technology. Prior studies have demonstrated the impact of context cues such as online channels and crowding on customers' price perceptions (Chu et al., 2010; Hou & Zhang, 2021). Our research follows this body of literature and takes the first step in examining how tourists' price perception is affected by a new contextual cue, that is, whether a travel plan is recommended by humans or AI. Hence, our study enriches the AI and pricing literature in the tourism marketing field.

In addition, this study extends theory of mind to AI recommendations. Previous research has explored individuals' reactions to AI recommendations primarily based on technology

adoption theories (Chi et al., 2022; Shi et al., 2021). We offer a novel perspective of “minds”—specifically, individuals’ distinctive perceptions of the minds of AI and human, to understand how and why tourists exhibit different attitudinal responses to recommendations by AI and human recommenders. Furthermore, this study highlights the role of the illusion of understanding on individuals’ travel decision-making. Previous studies have shown that, owing to the lack of understanding of algorithms and the illusion of understanding human decision-making, people distrust and resist algorithms (Bonezzi et al., 2022; Cadario et al., 2021). However, our research shows a positive effect of tourists’ illusion of understanding on lowering their price sensitivity to AI-recommended (vs. human-recommended) travel plans. These findings extend the research on the illusion of understanding and cognitive processes regarding AI/human recommendations.

This study furthers the research on price sensitivity by revealing the moderating effect of sense of uniqueness, which is regarded as an important personal trait that can only be recognized and perceived by individuals themselves (Şimşek & Yalınçetin, 2010; Karagöz & Uysal, 2022). This has been found to be an important factor influencing individuals’ attitudes toward prices (Bastos, 2019). Our research specifies this finding in travel recommendation contexts and further indicates that tourists’ sense of uniqueness of travel needs moderates the relationship between recommender type and price sensitivity to the recommended travel plans. For tourists with a low sense of uniqueness, price sensitivity to travel plans recommended by AI (vs. humans) is lower. However, the difference in price sensitivity to travel plans recommended by the two types of agents diminishes for tourists with a high sense of uniqueness because they prioritize acquiring distinctiveness over price-related

information. Given that human recommenders, compared to AI, are believed to be more capable of considering tourists' unique needs, the higher price sensitivity to travel plans recommended by humans is expected to be mitigated. This finding aligns with earlier studies arguing that AI is perceived as less flexible than humans and tends to overlook uniqueness (Canas, et al. 2003; Longoni & Cian, 2022; Yalcin et al. 2022). Thus, our study enriches existing literature on price sensitivity and uniqueness.

Managerial Implications

The current research provides several managerial implications. First, the findings show that tourists have lower price sensitivity to travel plans recommended by AI (vs. humans).

Therefore, tourism companies could encourage the use of AI recommendation systems to cope with tourists' heightened price sensitivity during a global economic downturn. The introduction of AI can decrease labor costs and provide tourists with consistent and instant service. Specifically, companies can enhance the promotion of AI recommendation services by incorporating slogans such as "AI recommenders, enabling you to experience standardized travel recommendation services" in advertisements or promotional materials. In addition, the fact that tourists display less sensitivity to the price of AI-recommended products provides the scope of skimming pricing or reducing discounts to increase corporate revenue when adopting an AI recommendation system.

Second, this study suggests that tourists subjectively feel that they understand human recommenders better than AI recommenders, making them exhibit higher price sensitivity to travel plans recommended by humans (vs. AI). However, this subjective understanding may

not necessarily be accurate. Tourists may be overconfident about how humans provide recommendations, resulting in an illusion of understanding. Currently, human recommenders remain the primary source of travel recommendation services, and they may outperform their AI counterparts in certain ways (Caber et al., 2013; Sigala, 2018). For example, human recommenders have better capability of showing empathy and can adapt to tourists' specific emotional states (Liu-Thompkins et al., 2022). Therefore, addressing the illusion of understanding of human recommenders is crucial for tourism companies that rely heavily on human employees. Tourism companies can enhance the transparency of human recommendations by establishing standardized criteria and workflows. This approach enables tourists to gain a clearer and more comprehensive understanding of the factors and processes involved in recommendation service. Thus, tourists' illusion of understanding human recommenders may be inhibited, which, in turn, contributes to lower price sensitivity to human-recommended travel plans.

Third, our study suggests that tourists' sense of uniqueness of travel needs moderates the relationship between the recommender type and tourists' price sensitivity to travel plans. Specifically, tourists with a low sense of uniqueness show lower price sensitivity to travel plans recommended by AI (vs. humans), whereas such an effect diminishes for tourists with a high sense of uniqueness. Thus, it is advisable to segment tourists according to their sense of uniqueness of travel needs. For example, tourism companies could segment tourists with varying degrees of unique travel needs using emerging technologies, such as big data analytics and cloud computing. Companies should foster strong relationships with tourists and gather information about their travel needs through market surveys and in-depth

interviews. Once the market is segmented, tourism companies may use AI rather than human employees to provide recommendations for tourists with a low sense of uniqueness. In contrast, for tourists with a high sense of uniqueness, human (vs. AI) recommendations are a better strategy because they are believed to be more considerate of tourists' unique travel needs. Furthermore, using customized and personalized cues (e.g., "tailored to your unique travel needs") when offering services may better address the distinctive needs of this market segment.

Limitations and Future Research

While the present research has important implications for the application of AI technology in the tourism sector, we acknowledge the limitations of this work and offer directions for future research. First, "human" in our research refers to employees of travel agencies. However, people seek recommendations not only from service providers, but also from friends, family, and social media. Therefore, investigating whether the study results are consistent with those of other types of human recommenders is a promising research direction. Second, future research could investigate the influence of recommender type on other attitude elements, such as satisfaction with the recommended travel plans. Third, further studies are needed to explore whether tourists' price sensitivity to AI-recommended travel plans is influenced by prior use of AI. Previous research has examined price discrimination driven by big data (Wang et al., 2022). Because big-data technology is closely related to algorithms and AI, future research could investigate whether the experience of big data-enabled price discrimination increases tourists' price sensitivity to travel plans recommended by AI. Fourth,

with the advancement of AI, its capacity may exceed that of humans, leading to the evolution of people's understanding and cognition of AI. Hence, future studies could validate our results by tracking the evolution of tourists' attitudes toward the latest advancements in AI. Lastly, field studies could be employed to provide more in-depth knowledge for tourists' cognition and perception of AI recommendations.

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Figure 1. The conceptual model

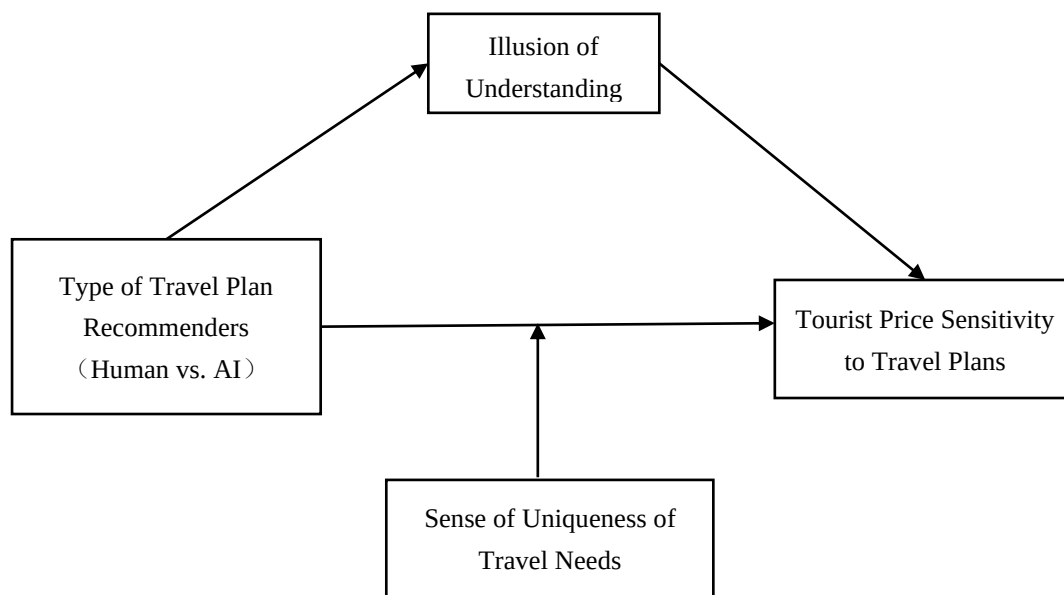


Figure 2. Subjective understanding as a function of recommender type and explanation

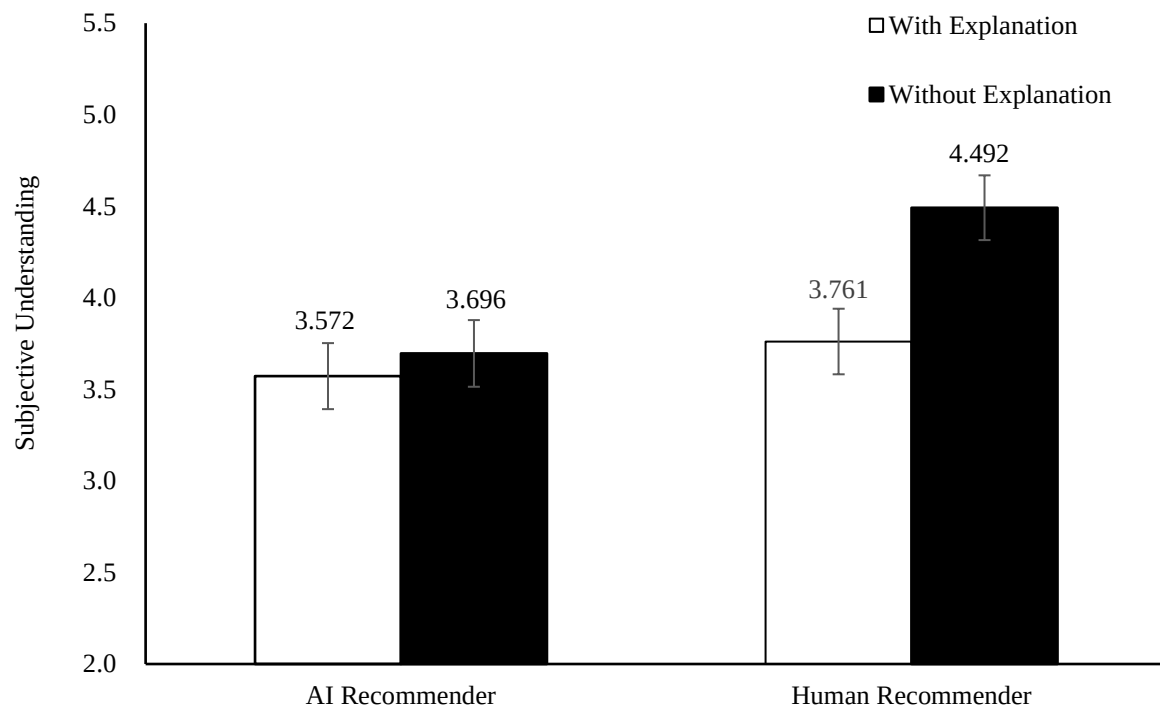


Figure 3. The mediating effect of illusion of understanding

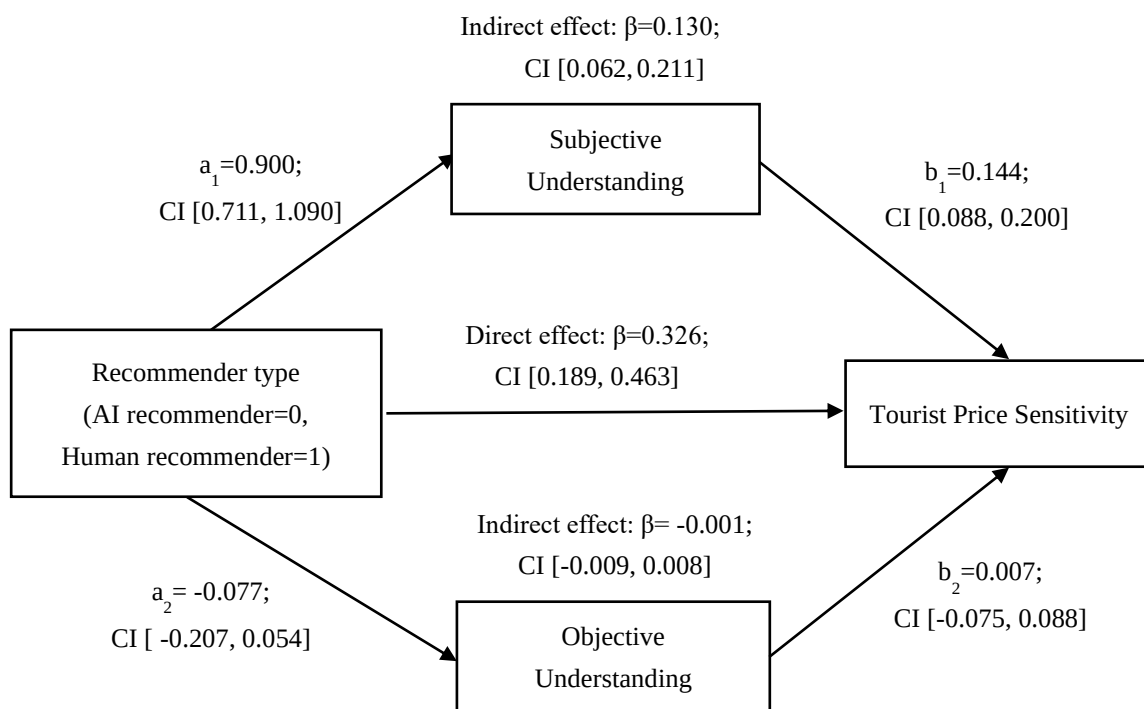
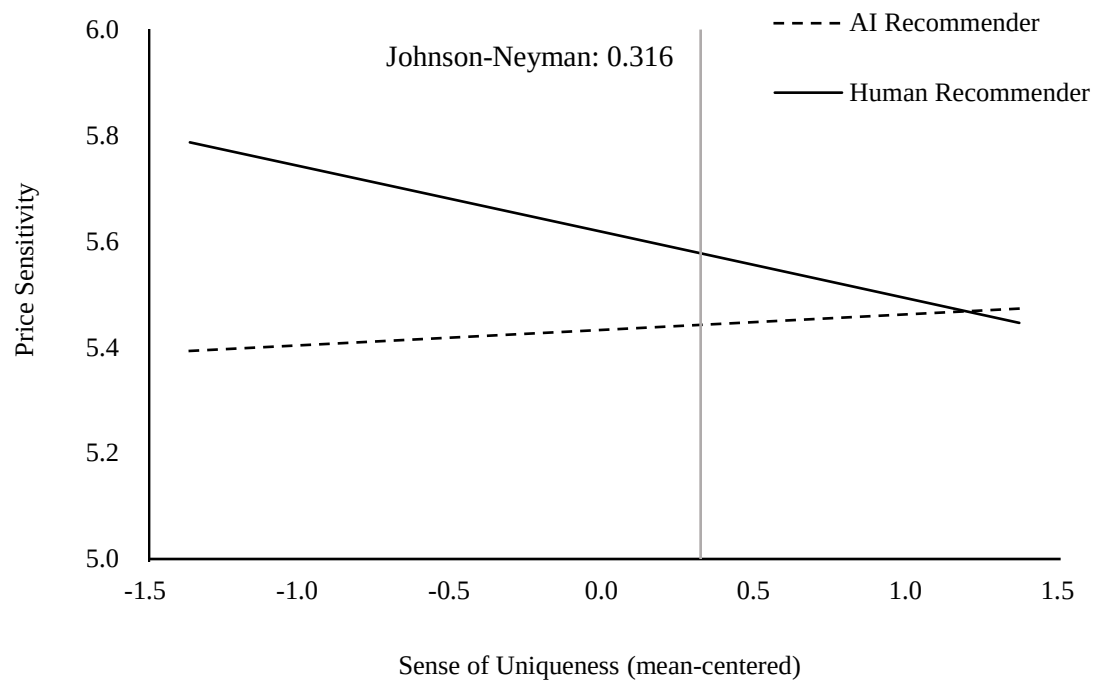


Figure 4. The moderating effect of sense of uniqueness



Note: Sense of Uniqueness: Mean=4.480. Respondents have higher price sensitivity to travel plans recommended by human than by AI when their sense of uniqueness scores (mean-centered) is lower than 0.316.

Appendix A. Experiment materials of Study 1

Imagine you are planning to take a four-day trip in the following week. To make better decisions, you search for travel plan information online. As you search, you find a relevant recommendation provided by a human (an AI) travel agent as shown below:



Hello, I recommend you to travel to Shanghai!

Travel agent——Xiao Mei

Shanghai not only retains an ancient atmosphere, but also embodies the charm of a metropolis. A trip to Shanghai allows you to fully experience the fusion of Eastern and Western cultures from the Bund, Oriental Pearl Tower, Chenghuang Temple, Yu Garden and many other attractions.

If you like Shanghai and want to know more about it, you can contact Xiaomei. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You'll have great fun in this Magic City for 4 days and 3 nights for only 2000 CNY per person!



Hello, I recommend you to travel to Shanghai!

AI agent——CX1

Shanghai not only retains an ancient atmosphere, but also embodies the charm of a metropolis. A trip to Shanghai allows you to fully experience the fusion of Eastern and Western cultures from the Bund, Oriental Pearl Tower, Chenghuang Temple, Yu Garden and many other attractions.

If you like Shanghai and want to know more about it, you can contact AI agent CX1. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You'll have great fun in this Magic City for 4 days and 3 nights for only 2000 CNY per person!



Appendix B. Experiment materials of Study 2

Imagine you are planning to take a ten-day trip in the following week. To make better decisions, you search for travel plan information online. As you search, you find a relevant recommendation provided by a human (an AI) travel agent as shown below:



Hello, I recommend you to travel to Yunnan!

Travel agent——A-Ming

Yunnan is famous for its beautiful natural scenery and unique customs. It is called a "secret land" by many tourists. A trip to Yunnan allows you to fully appreciate the beauty of mountains, lakes, seas of flowers, snow-capped mountains, and terraced fields, and experience the charm of Yunnan from many scenic spots such as Meili Snow Mountain, Cangshan Mountain, Erhai Lake, Songzanlin Temple, and Lijiang Ancient Town.

If you like Yunnan and want to know more about it, you can contact A-Ming. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You'll have great fun in Yunnan for 10 days and 9 nights for only 5000 CNY per person!



Hello, I recommend you to travel to Yunnan!

AI agent——CX1

Yunnan is famous for its beautiful natural scenery and unique customs. It is called a "secret land" by many tourists. A trip to Yunnan allows you to fully appreciate the beauty of mountains, lakes, seas of flowers, snow-capped mountains, and terraced fields, and experience the charm of Yunnan from many scenic spots such as Meili Snow Mountain, Cangshan Mountain, Erhai Lake, Songzanlin Temple, and Lijiang Ancient Town.

If you like Yunnan and want to know more about it, you can contact AI agent CX1. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You'll have great fun in Yunnan for 10 days and 9 nights for only 5000 CNY per person!



Instruction for the explanation procedure

Now, we would like to know a bit more about your knowledge. We would like you to explain how you think a human/AI agent makes travel recommendations for you.

Using the space below, please describe all the details you know about how a human/AI agent makes travel recommendations. What are the steps that a human/AI agent takes when analyzing tourists' need to design travel plans? What is the order of these steps? What do you know about the factors that a human/AI agent considers, and the factors that a human/AI agent does not consider, when analyzing tourists' need to design travel plans?

Note: please do not search for information online and answer the questions to best of your knowledge. According to your knowledge, how does a human/AI agent make travel recommendations for you? [Text entry open-ended question with 30 characters minimum]

Appendix C. Experiment materials of Study 3

Imagine you are planning to take a six-day trip in the following week. To make better decisions, you search for travel plan information online. As you search, you find a relevant recommendation provided by a human (an AI) travel agent as shown below:



Hello, I recommend you to travel to Bali!

Travel agent——Xiao Mei

Famous for its typical seaside natural scenery and unique customs, Bali is known as ‘Island of Flowers’, ‘Island of Poems’ and ‘Island of Paradise’. A trip to Bali allows you to fully experience the magnificence of the coast and mountains from Tanah Lot Temple, Kuta Beach, Lovers Cliff, Holy Spring Temple, Besakih Temple, Mount Agung and many other attractions.

If you like Bali and want to know more about it, you can contact Xiaomei. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You’ll have great fun in Bali for 6 days and 5 nights for only 7000 CNY per person!



Hello, I recommend you to travel to Bali!

AI agent——CX1

Famous for its typical seaside natural scenery and unique customs, Bali is known as ‘Island of Flowers’, ‘Island of Poems’ and ‘Island of Paradise’. A trip to Bali allows you to fully experience the magnificence of the coast and mountains from Tanah Lot Temple, Kuta Beach, Lovers Cliff, Holy Spring Temple, Besakih Temple, Mount Agung and many other attractions.

If you like Bali and want to know more about it, you can contact AI agent CX1. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You’ll have great fun in Bali for 6 days and 5 nights for only 7000 CNY per person!



Appendix D. Experiment materials of Study 4

Imagine you are planning to take a ten-day trip in the following week. To make better decisions, you search for travel plan information online. As you search, you find a relevant recommendation provided by a human (an AI) travel agent as shown below:



Hello, I recommend you to travel to Switzerland!

Travel agent——A-Ming

The entire territory of Switzerland is dominated by plateaus and mountains, known as ‘the Garden of Europe’ and ‘the Roof of Europe’. Switzerland is rich in tourism resources and countless beauties. A trip to Switzerland allows you to experience the magnificence of lakes, snow-capped mountains, and small towns from many scenic spots such as the Jungfrauoch, the old city of Bern in the small town of Mürren, and Lake Lucerne.

If you like Switzerland and want to know more about it, you can contact A-Ming. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You’ll have great fun in Switzerland for 10 days and 9 nights for only 25000 CNY per person!



Hello, I recommend you to travel to Switzerland!

AI agent——CX1

The entire territory of Switzerland is dominated by plateaus and mountains, known as ‘the Garden of Europe’ and ‘the Roof of Europe’. Switzerland is rich in tourism resources and countless beauties. A trip to Switzerland allows you to experience the magnificence of lakes, snow-capped mountains, and small towns from many scenic spots such as the Jungfrauoch, the old city of Bern in the small town of Mürren, and Lake Lucerne.

If you like Switzerland and want to know more about it, you can contact AI agent CX1. I will recommend travel plans according to your schedule and preferences, including classic routes, niche routes, local customs, and special food. You’ll have great fun in Switzerland for 10 days and 9 nights for only 25000 CNY per person!



Appendix E. Measurements

Variable	Measurement
Price sensitivity (1 = strongly disagree, 7 = strongly agree) Adapted from Goldsmith et al. (2005) and Wakefield & Inman (2003)	In general, the price or cost of the travel recommended in the travel plan is important to me. Price is the main factor in my choice of travel plans. I am less willing to buy a travel service as planned if I think the price is high. I do mind spending a lot of money in travelling. I am willing to make extra efforts to compare prices of different travel plans. I am sensitive to differences in the prices of travel plans.
Subjective understanding (1 = do not understand at all, 7 = completely understand) Adapted from Bonezzi et al. (2022) and Cadario et al. (2021)	To what extent do you feel that you understand the information a travel agent (AI) considers when recommending travel plans? To what extent do you feel that you understand the process by which a travel agent (AI) recommends travel plans? To what extent do you feel that you understand how a travel agent (AI) recommend travel plans to tourists? To what extent do you feel that you understand the factors that a travel agent (AI) considers when recommending travel plans?
Objective understanding (One point for each question if answered correctly. By adding the number of correct answers, the score ranges from 0 to 3) Adapted from Cadario et al. (2021)	Q1. When recommending travel plans, a travel agent (AI) will generally... A. Consider multiple criteria at once/at the same time. [The correct answer for AI recommenders, following a more holistic process.] B. Consider various criteria, one criterion at a time and in a certain order. [The correct answer for human recommenders, following a decision tree.] C. Simulate potential travel patterns. [Incorrect answer for both AI and human recommenders, as both would not simulate additional data.] Q2. When recommending travel plans, a travel agent (AI) will generally estimate if the likelihood of customers adopting the travel plan... A. Falls along a range from 0% to 100% [The correct answer for AI recommenders, which compute the probability of customers adopting the travel plan.] B. Only falls into a low-likelihood category or a high-likelihood category. [The correct answer for human recommenders, whose decision trees' outcomes are generally binary.] C. Is absent or present. [Incorrect answer for both since it is unlikely that AI or human estimation would be 100%.] Q3. When recommending travel plans, a travel agent (AI) will generally... A. Consider a check list of features and tourists' previous travel experience.

	[The correct answer for human recommenders, following intuition and heuristic decision-making and considering factors that might not be easily quantifiable, such as experience and feelings.]
	B. Consider broad features and compare the similarity of the tourist's behavior to other tourists' behaviors.
	[The correct answer for AI recommenders, following collaborative filtering algorithm which identifies similarities between users or items.]
	C. Rely only on a single feature (such as price).
	[Incorrect answer for both, as both would consider more than one features.]
Sense of uniqueness (1 = strongly disagree, 7 = strongly agree)	I feel that some of my travel needs are completely unique to me. I think that my travel needs are completely different from others.
Adapted from Longoni et al. (2019)	I feel my travel needs unique.
Destination familiarity (1 = not familiar at all, 7 = very familiar)	Please indicate your familiarity with ... [Shanghai, Yunnan, Bali, and Switzerland for Study 1 to Study 4, respectively].
Adapted from Wien & Peluso (2021)	
Expertise (1 = strongly disagree, 7 = strongly agree)	I can easily understand everything that is related to travel planning. My knowledge on travel planning helps me understand information about the services offered.
Adapted from Alba & Hutchinson (1987) and Elettigerra et al. (2021)	I keep up to date on what is related to travel destinations and services.
