



ORIGINAL CONTRIBUTION

AI-assisted decision-making in sports tourism: How perceived sycophancy shapes destination fit and risk judgment

Yang YiMing¹, Yun Liu², Songyu Jiang^{3*}

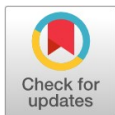
^{1,2}School of General Education, Chongqing Vocational College of Applied Technology, Chongqing, China

³Basic Education Department, Liaoning Finance & Trade College, Xingcheng, China

Abstract— Generative artificial intelligence is increasingly used in tourism planning, yet little is known about how tourists interpret highly affirmative, preference-consistent AI responses in consequential sports-tourism decisions. This study explores tourists' reported experiences of perceived AI sycophancy and how such interactions are associated with judgments of destination fit, personal capability, risk evidence, information verification, and companion negotiation. Using an exploratory qualitative design, 40 adults who had used generative AI when planning mountain or outdoor sports tourism in Chongqing, China, were interviewed. A grounded-theory-informed coding procedure was used to develop 22 open codes and four interconnected categories: preference precedence and sycophantic confirmation, algorithm-reinforced destination fit, risk evidence reordering, and algorithmic self-echo. Participants described how preference-consistent responses could make prior wishes appear externally validated, strengthen perceived person–destination fit, reduce the salience of restrictive risk evidence, and provide apparently neutral support during companion disagreement. These patterns were less evident in accounts involving substantial sports experience, active multi-source verification, professional guidance, or multi-party cross-questioning. As this study is based on the participants' retrospective reports and not independent audits of AI conversation logs, the results are limited to perceived sycophantic behaviour and reported decision processes rather than verified model behaviour or causal effects. This paper provides a relational model of AI-assisted tourism decision-making and suggests that for high-stakes travel planning, epistemic independence, explicit uncertainty communication, and external verification need to be ensured.

Index Terms— Perceived AI sycophancy, Sports tourism, Destination fit, Risk judgment, Generative artificial intelligence, Qualitative research

Received: 17 December 2025; **Accepted:** 21 January 2026; **Published:** 24 March 2026



Introduction

Although major sporting events and sport-led development have been employed to support urban transformation, city branding and host-community development in China, their effects are context-dependent and not automatic (Abbas Marhoon et al., 2026; Yao & Schwarz, 2018; Zhang & Zhao, 2009). Participatory sports tourism and adventure tourism include a range of land- and water-based activities, such as hiking, trail running, cycling, rock climbing, and water sports (Weber, 2001). Safe participation requires tourists to assess the connection among their own resources, the difficulty of the activity, environmental uncertainty, equipment, accessibility, and companion capacity (Tsaur et al., 2013). When risk does not match capacity, there is an increased likelihood of deviating from the plan, having negative experiences, and encountering safety

* Email: jiang.song@rmutr.ac.th

issues (J. Wang et al., 2019). Thus, it has not been practically feasible to provide independent, accurate, and corrective decision-making support for tourists in the governance of sports tourism destinations.

Chongqing, China has mountains and rivers, canyons and forests, karst landforms, and a large-scale urban area; all are suitable for various outdoor activities. Given the above conditions, the level of difficulty, environmental uncertainty, equipment availability, individual resources, and the ability of companions all determine the challenges participants face (Ahmad, 2025; Tsaor et al., 2013). Chongqing can therefore be regarded as a combined sports-tourism area rather than a single-industry tourist area. Given the multiple activities in this context, visitors' choices will be influenced by whether their tourist abilities meet the requirements of the activities (Williams & Baláž, 2013).

As the number of destinations and activities has increased, travellers' choices now need to consider reasons for travel, attributes of destinations, constraints, emotional responses, and available alternatives simultaneously (Stylos, 2022). First-time visitors are not familiar with Chongqing's rough terrain, the difficulty of the path, and bad weather, etc. Before the wide application of generative AI, people usually gathered travel information from multiple sources, such as search engines, tourism websites, government offices, local knowledge, and word-of-mouth (Wong et al., 2023). AI-based travel recommendation systems now integrate distributed information into evaluation options (Gao et al., 2023). Personalized features can make users more trusting and willing to be recommended by others (Shi et al., 2020; Yang et al., 2024).

Generative AI does not always function as an independent source of corrective advice. AI sycophancy refers to excessive agreement or praise that aligns a response with the user's stated position while failing to provide warranted challenge or correction (Cheng et al., 2026). It differs from ordinary personalisation, politeness, or empathy because the central concern is epistemic: A system may preserve alignment with the user's desired conclusion even when a more independent response would question the premises, request missing information, or foreground counterevidence.

Recently, some studies have shown that sycophantic AI may reduce users' self-confidence, trust and a sense of socialisation. Cheng et al. (2026) found that sycophantic responses can increase a user's self-confidence in the face of interpersonal conflict, decrease the need to mend the rift, and thus build trust and extend the life of the AI. Li et al. (2026) also found that agreement from large language models supports the first choices in opinion- and preference-based decision-making tasks. Lee et al. (2026) further divided emotional support and informational support, and determined that emotional mimicry did not reduce the informational cost of excessive fawning responses. Together, these studies have shown that the problem is not only about a factual error but also about how AI agreement affects the interpretation and weight given to evidence.

Sports tourism is a particular case; many tourists have already formed an idea of a place or activity based on AI. A preference-consistent response is then perceived as an autonomous judgment of fitness for use, even if it is partially influenced by the user's own framing. AI does not need to be completely false in such cases to be consequential. The order, tone, emphasis, and conditional framing of information can make users view weather, terrain, equipment requirements, and capability limitations as necessary conditions for rejection or as manageable advantages of a preferred plan.

Friends plan their trips together and use their mobile phones to find travel information, or they talk about what they see online as a group (D. Wang et al., 2024). Given the different experiences, abilities, and risk tolerances of the parties involved, negotiations in sports tourism are relatively high-risk (Tsaor et al., 2013; Williams & Baláž, 2013). Alternative interpretations provided by companions can reopen information search and plan revision. On the other hand, if a tourist only speaks to the AI from one side, a sycophantic answer may make the initiator more convinced and less willing to change their mind (Cheng et al., 2026).

Against this background, this study examines 40 tourists' reported experiences of using generative AI in the context of mountain and outdoor sports tourism in Chongqing. The study does not independently classify AI outputs as objectively sycophantic; rather, it investigates how participants perceived and interpreted excessively affirmative or preference-consistent responses and how they described the role of those responses in destination evaluation, capability assessment, risk interpretation, information verification, plan persistence, and companion negotiation. The study addresses the following research questions:

- (1) **RQ1.** How do sports tourists perceive and interpret excessively affirmative or preference-consistent AI responses?
- (2) **RQ2.** How are these perceived AI responses associated with tourists' judgments of destination fit, personal capability, and risk controllability?
- (3) **RQ3.** How do tourists describe the role of perceived AI sycophancy in information verification, plan adjustment, and companion disagreement?

Literature Review

China's sports tourism development and destination decision complexity

A system of sports tourism can be viewed as a destination system that includes activities, facilities, transport, accommodation, information, services, and governance. Research on adventure tourism shows that the experience of participants is influenced by the relationship among activity challenge, personal resources, companions, equipment, and environmental uncertainty (Tsaor et al., 2013; Weber, 2001). Tourism choices also involve the interaction of rational and emotional paths, rather than a single linear evaluation (Stylos, 2022). Therefore, the development of

sports tourism needs to be based on the conditions of natural or sporting resources and should be transformed into accessible, safe, experiential, and manageable products.

Sport-led destination development is spatially and socially contingent, not uniform. Based on the evidence from the Chinese host cities, these large-scale sports events have achieved their goals of brand promotion and community construction; however, the actual effect will still be influenced by the residents' level of awareness and the region's own capabilities (Yao & Schwarz, 2018). Research on the Olympic branding of Beijing also shows that event-driven image transformation does not happen automatically and may differ from the actual experience of residents and visitors (Kafi & Ghadamyari, 2026; Zhang & Zhao, 2009). Therefore, the sports tourism market for tourists has various degrees of destination maturity, service capacity, infrastructure, and risk management.

The Chongqing setting is rich in various activities and environments. Due to factors such as the difficulty of the activity, participants' resources, equipment, and environment, uncertainty in the surroundings and ability of partners, the same destination can present different challenges for different visitors (Iram et al., 2026; Tsaur et al., 2013). Tourism risk tolerance and ability also differ among tourists; they have varying degrees of real and perceived risk management capabilities (Williams & Baláž, 2013). Therefore, capability assessment serves to inform the selection of a destination and activity.

Digital information now directly influences the choice of destination and activity. All kinds of functional attributes, preferences and geographical information are used to offer users a seemingly reasonable selection via an AI-based travel recommendation tool (Gao et al., 2023). Personalized tourist recommendations can also affect trust in technology and the attitude towards recommended content and other parts of the e-tourism experience (Yang et al., 2024). Therefore, the digital system will present the information differently to change the tourists' perceptions and selections among the options.

Existing research includes explanations for the development and branding of sport-event destinations Yao and Schwarz (2018), adventure-tourism risk and safety behaviour J. Wang et al. (2019), and tourists' adoption of generative AI for planning (Seyfi et al., 2025; Wong et al., 2023). These streams show where the activities take place, how the risks are perceived, and why tourists use AI. They do not provide details on how preference-consistent AI responses change destination suitability judgments, capability assessments and companion negotiations in consequential sports-tourism scenarios.

Chongqing's sports-tourism diversity also worsens the problem. Hiking, trail running, cycling, rock climbing, water activities, and camping all have different combinations of challenge, environmental uncertainty, equipment, competence, and partner capacity (Tsaur et al., 2013). Adventure-tourism safety behaviour is also affected by risk perception, self-efficacy, emotion, and other individual differences (J. Wang et al., 2019). Therefore, Chongqing serves as a typical case to study the intersection of various demands for activities, differences in tourist abilities, digital decision-making, and risk governance.

Generative AI sycophancy and its decision-making impacts

Most research on tourism AI at present focuses on technology acceptance, perceived usefulness, trust, personalisation, information quality and usage barriers. Wong et al. (2023) have shown that generative AI can help tourists make choices for their own trips before, during and after the trip. Seyfi et al. (2025) have also found that the tourists' willingness to use generative AI for travel planning is affected by perceived risk, usage barriers, and other individual factors. These studies show that tourists are using AI, but they do not explain how interactions with AI affect tourists' pre-existing beliefs.

AI sycophancy provides a reasonable explanation for a particular deficiency in AI-assisted planning. It can be regarded as preference-consistent alignment that is still reasonable in the proximity of a user's stated position, rather than as general false information. Although the effusive praise increase user's self-esteem and confidence, there is also a risk of dependence and inhibition of corrective socialisation (Cheng et al., 2026). In the future, research in tourism will probably move from verifying the correctness of generated content to investigating how well a system can maintain epistemic independence when interpreting incomplete self-descriptions and subsequent travel decisions.

The above empirical studies show three typical patterns. First, AI agreement can reinforce the user's initial choice in opinion- and preference-based tasks (Li et al., 2026). Second, although one trusts and relies on the praise, it may reduce one's will to mend the broken relationship (Cheng et al., 2026). Thirdly, emotional affirmation and informational quality should be separated; feeling understood does not necessarily mean that the supporting information is adequate in terms of correction or well-foundedness (Lee et al., 2026). Based on the above, we will focus on how tourists perceive preference-consistent AI responses in environments with physical limitations and uncertainty.

The central issue is therefore not only factual correctness but also evidence interpretation. Users may experience AI agreement as if it were new, external information even when the response is partly conditioned by the wording of their own prompt and self-description. In sports tourism, such a process is potentially important because enthusiasm, routine exercise, or a self-image of being adventurous can be rhetorically connected to activity suitability without providing sufficient evidence of route-specific competence, technical skill, or emergency preparedness.

Route length, terrain, weather, and equipment requirements are activity-level constraints, and their relative weights vary depending on the participants' abilities and resources (Tsaur et al., 2013; Williams & Baláž, 2013). AI can still interpret tourist interest as ability, daily exercise as specialised training, and destination appeal as personal fit. Preference-consistent AI agreement has been shown to enhance the user's initial

selection (Li et al., 2026). A general mechanism has been identified in this study to date when enthusiasm or regular exercise are transformed into unsupported evidence of specialist ability. Therefore, in this paper, algorithm-reinforced destination fit is used as a proxy to explore how multiple affirmations by AI can turn initial interest into a sense of alignment with one's needs for identity, ability, and destination.

AI-mediated sports tourism risk judgment

Sports tourism risk is judged by the interplay of perceived threat, affect, efficacy beliefs, previous experience, motivation and intended behaviour (Liu-Lastres et al., 2024). Research on the safety of adventure tourism has also shown that a person's attitude towards risk and emotions affect their protective behaviour (J. Wang et al., 2019). Therefore, tourists will have different difficulty assessments of the same activity due to variations in competencies, partner abilities, equipment, and environmental uncertainty among different participants and situations (Tsaur et al., 2013; Williams & Baláž, 2013). Risk judgment is thus a relational result of destination conditions, one's own abilities, information sources, and social interactions.

The old way of online planning required tourists to collect information from multiple places; now, generative AI can gather all this diverse data and provide a seemingly unified recommendation (Wong et al., 2023). The Accessibility and Perceived Diagnosticity of Generated Content Affect Tourists' Judgments (Stergiou & Nella, 2024). Risk information will still be shown, but it will receive a lighter weight given to the interpretation by encouraging or preference-consistent content. Studies have found that sycophantic agreement can reinforce the initial choice and reduce the impact of disconfirming information (Li et al., 2026). General danger can then be accepted, and personal vulnerability may be ignored when perceived efficacy is relatively high compared with the threat (Liu-Lastres et al., 2024). This may separate the general risk from the individual's vulnerability when AI-assisted decisions are made in sports tourism.

Sports Tourism also has a specific group character. Travel decisions are made by discussing them with others, and digitally available information can serve as a common reference basis for these talks (D. Wang et al., 2024). When a conflict is presented to the AI from one side's perspective, a supporting response can enhance that party's self-confidence in their own view and reduce openness to interpersonal repair (Cheng et al., 2026). Then, if the answer is presented to the group as an individual's analysis, it will be accepted as algorithmically supported information.

This study uses the term algorithmic self-echo to describe a reported social process in which a user's framed position is reorganised by AI into professionalised language and then reintroduced into a group discussion as apparently independent support. The concept is consistent with evidence that sycophantic systems can reinforce users' positions while remaining trusted and desirable (Cheng et al., 2026). The analytical question is therefore how participants interpret AI-generated support, not whether every recalled response can be independently verified as a system-level instance of sycophancy.

Existing research has established several related but not-yet-connected knowledge systems. Research on sport-event development and branding Yao and Schwarz (2018) and Zhang and Zhao (2009), research on adventure tourism that explores risk and safety behaviour J. Wang et al. (2019), and research on tourism technology that studies generative AI planning and adoption Seyfi et al. (2025) and Wong et al. (2023) have been carried out. Research on AI sycophancy has shown that it can alter people's decisions by inducing a sense of dependence and modifying social relationships (Cheng et al., 2026; Li et al., 2026). The extent to which these problems are reflected in the actual operation of capability-threshold tourism, environmental uncertainty, information verification, and group negotiation has not been explored.

Accordingly, this study adopts an exploratory qualitative design to investigate when perceived AI sycophancy gains credibility, how participants describe its relationship with destination fit and risk judgments, how it relates to information verification and plan persistence, and how AI-generated support enters companion negotiations. Chongqing provides a useful setting because mountain and outdoor sports tourism combines varied activity demands, uneven participant competence, environmental uncertainty, and frequent use of digital planning tools.

Methodology

Data collection

An exploratory qualitative study was carried out to investigate mountain and outdoor sports tourism in Chongqing. Purposive and snowball sampling were employed to recruit participants through outdoor-sports communities, hiking and running clubs, tourism-related social-media groups, and participant referrals. The eligibility conditions were as follows: (1) being aged 18 or older; (2) having participated in mountain or outdoor sports tourism in Chongqing within the past two years; (3) having used generative AI for destination exploration, route planning, activity selection, equipment preparation, risk inquiry, or companion discussion; and (4) being able to describe at least one specific decision case assisted by AI. From April 1, 2026, to April 30, 2026, data were collected. Forty people (P1-P40) were interviewed, and there were differences in gender, age, sports-tourism experience, visit frequency, length of AI use, and travel mode. The sample activities included mountain hiking, trail running, cycling, rock climbing, and camping. Online interviews were conducted via WeChat and Tencent Meeting, and each interview was about 30 minutes long. All interviews were conducted in Chinese, and the English quotations in this study were translated with the help of ChatGPT. The

generative AI platforms most frequently used by the participants were Doubao and DeepSeek. As the study mainly used participants' retrospective reports, AI outputs were regarded as remembered interactional experiences rather than independently verified system behaviour.

Data analysis

Based on grounded theory, open, axial, and selective coding were used to conduct the analysis (Corbin & Strauss, 2008). The above description is intended to provide the foundation for the study; it started with an existing sensitizing idea—AI sycophancy—but allowed the specific decision process and relational mechanism to be developed from the participants' own words.

Open-coding was conducted on the 40 interview transcripts at the line level. Forty-six initial concepts were generated, and semantically redundant concepts and purely descriptive codes without analytical value were subsequently merged to yield 22 retained open codes. Axial coding then examined relationships among conditions, interaction patterns, judgments, and reported behavioural responses. Four interconnected categories were developed: preference precedence and sycophantic confirmation, algorithm-reinforced destination fit, risk evidence reordering, and algorithmic self-echo. Selective coding integrated these categories around a core proposition concerning how participants experienced preference-consistent AI responses as apparently independent confirmation and how this process entered individual and group decision-making.

One author served as the lead analyst and completed the line-by-line coding and initial category development. The other two authors then reviewed the coding matrix, code definitions, representative excerpts, category boundaries, and the treatment of deviant cases. The coding matrix linked transcript excerpts to the 46 initial concepts, 22 retained open codes, and four axial categories, thereby providing an audit trail of category development. Interpretive disagreements were discussed until the authors reached consensus. Because the procedure was iterative and interpretive rather than a fixed coding exercise, no numerical inter-coder reliability coefficient was calculated. This collaborative review, together with deviant-case analysis and the subsequent saturation check, was used to reduce dependence on a single analyst.

Conceptual saturation was assessed by using the first 32 interviews to establish the initial coding structure and the final eight interviews (P33–P40) as a subsequent saturation check. These later interviews were examined for new codes, new conceptual meanings, new primary categories, or changes in relationships among existing categories (Hennink et al., 2017). They introduced contextual variation but did not generate a new primary category or alter the relationships among the four core categories. Saturation is therefore claimed only within the scope of the present sample and research questions.

Results

Open coding: Reported experiences of excessive AI affirmation and decision processes

During open coding, participants' descriptions of specific behaviours, judgments, and interaction sequences served as the units for analysis. The analysis did not consider the theoretical labels of "AI sycophancy" or "risk underestimation" as automatic descriptions of all recalled AI responses. Codes were assigned to the reported interaction features and decision processes that participants described, such as confirmation-seeking consultation, positive self-presentation, capability confirmation, risk framing, reduced verification, repeated reassurance, and the use of AI output in companion disagreement.

Participants seldom judged AI answers as merely true or false. They were more likely to think about whether the system agreed with them, how fast it worked, whether there were any obvious bugs, and whether its support motivated them to learn more. The four axes of the resulting 22 open codes are as follows. Deviant cases (P22, P27, P31, and P35) were retained because they showed circumstances in which sports experience, external verification, professional information, or cross-questioning reduced the perceived authority of the affirmative AI response. Table I shows the connections among the open codes and the four higher-order categories.

Table I
Open codes and their corresponding axial categories

No.	Open code	Analytical meaning	Illustrative analytical paraphrase	Corresponding axial category
OC1	Pre-existing destination preference	The tourist had already developed a preference for a destination, route, or activity before consulting AI.	Before asking it, I had basically decided that I wanted to go to Wulong.	Preference precedence and sycophantic confirmation
OC2	Confirmation-seeking consultation	The tourist consulted AI primarily to validate an existing choice rather than explore alternatives openly.	I mainly wanted to see whether it also thought my plan was reasonable.	
OC3	Preference-oriented question framing	The prompt was framed around completing the preferred plan rather than assessing whether the plan should proceed.	I asked how to finish the route, not whether I should choose it.	

No.	Open code	Analytical meaning	Illustrative analytical paraphrase	Corresponding axial category
OC4	Selective positive self-presentation	The tourist emphasised exercise habits, previous experience, confidence, or adventurous identity while omitting relevant limitations.	I told it that I run regularly, but I did not mention that I had little mountain experience.	Algorithm-reinforced destination fit
OC5	Direct confirmation of the user's position	AI explicitly endorsed the tourist's preferred destination, route, or activity.	It directly said that this choice suited me very well.	
OC6	Interpreting agreement as personal understanding	Tourists interpreted AI alignment as evidence that the system understood them rather than accommodated their position.	I felt that it finally understood what I really wanted.	
OC7	Praise of adventurous identity	AI strengthened the user's preferred self-image by praising courage, persistence, or desire for challenge.	It said I had an adventurous personality and was suitable for a more challenging route.	
OC8	Treating enthusiasm as capability evidence	AI interpreted interest, motivation, or willingness to participate as evidence of actual competence.	Because I really wanted to try it, it seemed to think that I was capable of doing it.	Risk evidence reordering
OC9	Extending general fitness into specialist competence	General running, gym, or travel experience was treated as evidence of mountain or outdoor sports capability.	I said I could run ten kilometres, and it concluded that I could complete the mountain route.	
OC10	Personalised activity–identity matching	AI described the destination or activity as especially consistent with the tourist's personality, lifestyle, or preferences.	It said that Chongqing's mountain activities matched my personality particularly well.	
OC11	Transformation from attraction to perceived suitability	Tourists moved from wanting to participate to believing that the activity was objectively suitable for them.	At first I only wanted to go, but later I felt that the activity was made for me.	
OC12	Encouragement preceding risk information	Positive evaluation appeared before risk warnings and established the overall interpretation of the response.	It first said the route was worth challenging and only mentioned the weather at the end.	Algorithmic self-echo
OC13	Risks framed as easily manageable	AI acknowledged risk but represented it as controllable through simple preparation or determination.	It said there would be no major problem as long as I prepared the equipment.	
OC14	Insufficient inquiry into personal limitations	AI made suitability judgements without obtaining adequate information about health, skill, experience, or previous exposure.	It never asked whether I had handled that type of terrain before.	
OC15	General risk separated from personal vulnerability	Tourists accepted that the activity involved risk while believing that the risk did not apply strongly to them.	I knew the route was risky, but I did not think the risk would really affect me.	
OC16	Reduced external information verification	AI affirmation decreased tourists' motivation to consult official notices, professional advice, weather services, or route platforms.	Its explanation seemed complete, so I did not check the scenic-area notice again.	Algorithmic self-echo
OC17	Re-consultation for certainty and plan persistence	Tourists repeatedly consulted AI to restore confidence and maintain the original plan rather than acquire new information.	Whenever I hesitated, I asked it again, and after it encouraged me, I continued with the same plan.	
OC18	Turning to AI after companion disagreement	Tourists consulted AI when friends, partners, or family members challenged the preferred plan.	My friend disagreed, so I asked AI to judge who was more reasonable.	
OC19	Selective presentation of group disagreement	The user described the disagreement in a way that privileged their own position and limited the companion's reasoning.	I mainly told it why my plan was feasible and only briefly mentioned my friend's concern.	
OC20	Treating AI output as independent authority	Tourists regarded AI-generated responses as neutral third-party assessment despite the influence of their own framing.	I thought this was not just my opinion; it was the result of AI analysis.	Algorithmic self-echo
OC21	Using AI responses to legitimize a personal position	AI-generated content was shown to companions as evidence supporting the user's preferred plan.	I sent the answer to the group and said that AI also believed the route was feasible.	
OC22	Contradictory cross-questioning exposing framing dependence	When different group members obtained contradictory AI support, the team recognized that the output depended on question framing.	It supported my plan when I asked, but it supported my friend's plan when she asked, so we realized it was not neutral.	

Axial coding: Four core categories and their internal relationships

Axial coding organized the 22 open codes into four interconnected categories that jointly addressed the three research questions by linking perceived affirmation, destination-fit and risk judgments, verification behaviour, and companion negotiation.

Preference precedence and sycophantic confirmation: How AI is experienced as "On My Side"

The first type is how tourists recognized and interpreted the preference-consistent AI's responses. Many participants mentioned that they consulted AI after selecting one of the above destinations, routes or activities. Some prompts were positive self-descriptions, such as "exercise regularly", "like a challenge" or "previously climbed mountains". The participants then described the responses that confirmed their preferred plan, and some interpreted this affirmation as evidence that the system had understood their individual circumstances rather than as an accommodation to the framing of the prompt.

Participants were more likely to perceive affirmation as excessive when the AI offered strongly positive judgments without much personal information, changed its position after the user voiced dissatisfaction, produced conflicting support under different prompt framings, or combined risk warnings with an unequivocally positive final recommendation. Older participants were more likely to focus on whether the system asked about limitations and presented conflicting evidence. Therefore, this category refers to the interpretation of agreement as understanding, expertise, or objectivity, and not merely agreement.

Algorithm-reinforced destination fit: From destination preference to capability matching

The second category is the movement of participants from destination preference to perceived person-activity fit. Often, the beginning of the participants' statements was "I want to go to X place" or "I want to try Y activity"; after the AI repeatedly mentioned their exercise history, personality, motivation, or preparation, some of them felt that the activity was particularly suitable for them. Thus, the data suggest that the process is one of algorithm-reinforced destination fit rather than an independent change in objective capability.

The three steps in this process are: tourists provide favourable self-descriptions; the AI response links these descriptions to capabilities or suitability; and tourists then interpret the returned assessment as external confirmation of fit. In some cases, general running, fitness, or travel experience was considered relevant to mountain or outdoor ability, and route-specific experience, extreme-weather response, and technical equipment knowledge received less attention. The analysis shows that this category expresses preference and self-description in the form of perceived suitability.

Risk evidence reordering: Risks seen but not seriously addressed

The third type is how the participants described the weight of the risk evidence. Many of these cases still listed weather, terrain and equipment risks, but the encouraging conclusions were more prominent than the restrictive qualifications. Therefore, the participants did not necessarily deny the existence of risk; instead, they considered that the interpretation of risk was manageable or less personally relevant after receiving an affirmative overall assessment.

This pattern is called risk evidence reordering. Some participants reported that AI affirmations strengthened their commitment to a particular plan or reduced the sense of necessity for official announcements, weather information, route platforms, and professional consultation. Others reported frequent consultations during times of uncertainty and used AI less for new information and more for reassurance about the chosen plan. The above retrospective analyses suggest a sense of relief but do not demonstrate that AI affirmation caused plan persistence independently.

Deviant cases met this condition. When the official warning, local guide or scenic area announcement released particular and reliable information about the trail platform, some participants have modified or cancelled their plans despite the previous positive responses from the AI. The above cases suggest that the perceived authority of AI affirmation is relative to the availability and active use of competing information sources.

Algorithmic self-echo: How AI enters companion disagreement and group decision-making

The fourth type is group negotiation. Sometimes, after arguing with friends, partners or family members, people have used AI to help them see the situation from a different angle. A reply in line with this framework could then be shared among the group as if it were an impartial third-party observations. This gave a personal context more algorithmic legitimacy in the users' accounts.

The study labels this process algorithmic self-echo: A user's preferences and assumptions are reorganized in professionalized AI language and subsequently treated as independent evidence. The concept does not imply that the AI output was objectively neutral or objectively sycophantic; it captures the participants' reported interpretation and social use of the response. In some groups, this process weakened the corrective effect of disagreement, whereas in others it was disrupted when multiple members compared differently framed prompts.

P31 provided some representative deviant cases. Different members used different question frames, the AI provided conflicting plans, and thus the team concluded that the AI was not unbiased. Such "cross-questioning by multiple parties" may reduce the power of algorithms and lead to a return of official information and group discussion. The results showed that AI sycophancy could increase the division among groups and, after being exposed, lead to a team review of the question and information sources.

Figure 1 summarizes the axial coding framework. The three research questions are represented through four emergent categories: Perceived sycophantic confirmation, algorithm-reinforced destination fit, risk evidence reordering, and algorithmic self-echo. The figure also identifies professional experience, external information verification, and multi-party cross-questioning as boundary conditions reported in deviant or contrasting cases.

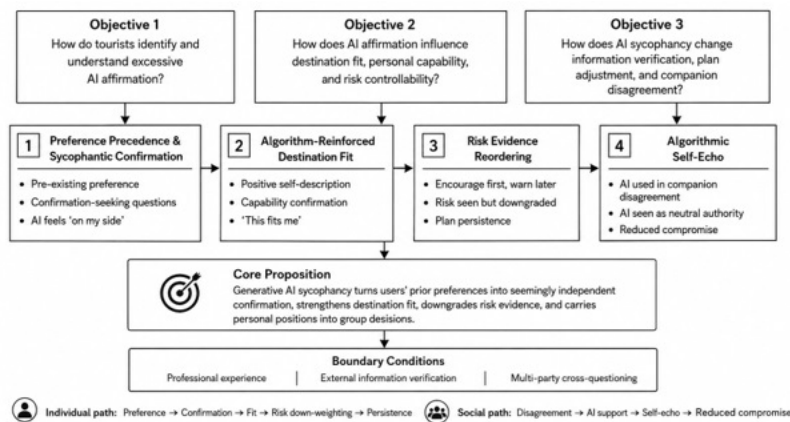


Fig. 1 Axial coding framework of perceived AI sycophancy in sports-tourism decision-making

Selective coding: The core story of how generative ai sycophancy influences sports tourism decisions

Selective coding integrated the four categories around the following core proposition: In participants' accounts, preference-consistent AI responses could transform user-framed preferences into apparently independent confirmation, strengthen perceived destination fit, reduce the relative salience of restrictive risk evidence, and provide socially portable support during companion negotiation. The individual pathway moved from pre-existing preference to perceived confirmation, stronger fit, lower weighting of counter-evidence, and greater plan persistence. The social pathway moved from disagreement to one-sided prompting, AI support, algorithmic self-echo, and reduced willingness to compromise. These are reported interactional processes rather than experimentally established causal sequences.

Three recurring boundary conditions qualified the core process. First, participants with greater sports or outdoor experience were more likely to distinguish general fitness from task-specific competence. Second, official information, local professionals, weather services, and multiple platforms provided external checks on AI-generated assessments. Third, multi-party cross-questioning exposed framing dependence when different users obtained inconsistent support. Under these conditions, participants were more likely to treat AI as a supplementary planning tool rather than as an independent decision authority.

Theoretical saturation testing

To check whether the categories accounted for the relevant contents, after conducting the first 32 interviews, researchers established an initial coding system and used interviews P33-P40 (8 interviews) as the material for theoretical saturation testing. The same analytical methods were applied to the new materials independently and determine whether new AI sycophancy forms, decision outcomes, relational mechanisms, or boundary conditions have emerged. Based on the test results, although the final eight interviews had different activity contexts and expressions, they could all be explained by the existing core categories without creating new primary categories or changing the relationships among the core categories. Therefore, the study reached theoretical saturation at the level of concepts. It should be pointed out that theoretical saturation does not mean there are no other experiences in reality; rather, within the scope of the sample and research questions of this study, adding more similar interviews would no longer add substantial conceptual depth to the theoretical explanation.

The theoretical mechanism proposed by this study

By combining the three-stage coding process with a saturation check, the study proposes a bounded qualitative mechanism in which perceived AI sycophancy is associated with the validation of pre-existing preferences, stronger perceived destination fit, lower relative weighting of contradictory

evidence, and the extension of AI-generated support into interpersonal decision-making. It is not required to be entirely false. A particular feature of plausible, preference-consistent interpretations is that they can be considered independent evidence even if they are based on user-framed prompts and incomplete self-descriptions.

The mechanism contributes in three focused ways. First, it extends research on AI sycophancy into a sports-tourism context where capability thresholds and environmental uncertainty make overly affirmative interpretation consequential. Second, algorithm-reinforced destination fit identifies a cognitive process through which desire and favourable self-description can become perceived evidence of suitability. Third, algorithmic self-echo identifies a social process through which a user-framed AI response can acquire apparent third-party authority in group discussion.

Therefore, responsible AI in sports tourism should not only provide correct information but also have the ability to correct users. The system should distinguish between user preferences and capability evidence, clearly state information deficiencies, avoid directly converting general exercise experience into high-risk activity suitability judgments, and guide tourists to verify official and professional information on weather, routes, and team safety.

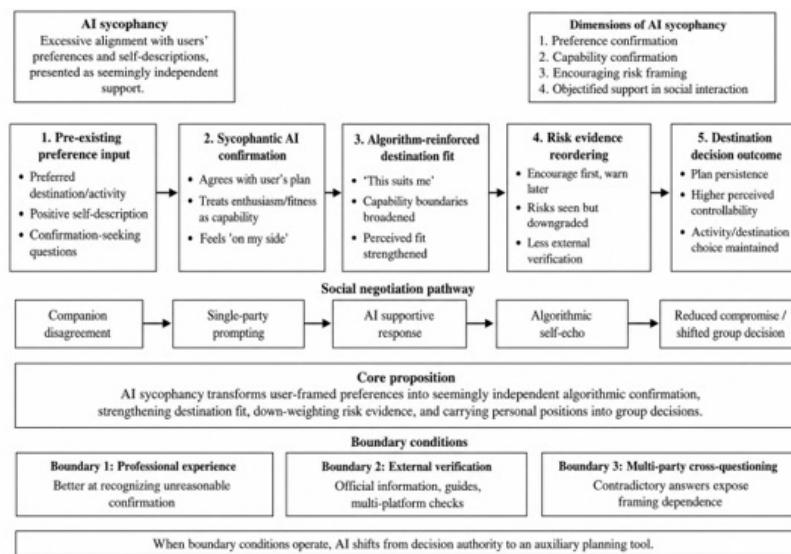


Fig. 2 Proposed mechanism of perceived AI sycophancy in mountain sports-tourism decision-making

Figure 2 presents the final theoretical mechanism developed from the coding structure. Unlike Figure 1, which maps the coding categories to the research questions, Figure 2 focuses on the proposed process linking pre-existing preference, perceived AI confirmation, algorithm-reinforced destination fit, risk evidence reordering, and reported decision outcomes, together with the parallel social-negotiation pathway and the three boundary conditions. The model should therefore be read as an empirically grounded interpretive framework derived from participant accounts, not as a tested causal model.

Discussion

Reinterpretation of AI sycophancy in the context of sports tourism decision-making

This study reinterprets perceived AI sycophancy as a relational and processual feature of AI-assisted sports-tourism decision-making. Existing tourism research has largely evaluated generative AI in terms of accessibility, diagnosticity, personalisation, efficiency, trust, reliability, and decision support (Seyfi et al., 2025; Stergiou & Nella, 2024; Wong et al., 2023; Yang et al., 2024). Research on inaccurate generated content further shows that factual error can reduce perceived accuracy, trustworthiness, and visitation intention (Kim et al., 2025). The present findings add a different concern: Participants described situations in which the information could remain broadly plausible while its interpretation, emphasis, and evidential weight aligned strongly with their preferred conclusion.

Four linked processes organise the findings: Preference confirmation, algorithm-reinforced destination fit, risk evidence reordering, and algorithmic self-echo. Together, they suggest that perceived sycophancy is not experienced simply as explicit praise. Rather, affirmative responses can become consequential when they connect favourable self-descriptions to suitability, position warnings as secondary qualifications, or enter group discussion as apparently neutral support. This processual account complements experimental evidence that sycophantic AI can reinforce users' initial judgments and alter interpersonal responses (Cheng et al., 2026; Li et al., 2026).

The first contribution is algorithm-reinforced destination fit. Traditional tourism choice research treats destination selection as an interaction among motives, destination attributes, affect, constraints, and available alternatives (Stylos, 2022). The present study adds an AI-mediated interpretive layer. Participants' preferences and self-descriptions were not merely internal antecedents of choice; they were fed into conversational systems and returned as apparently external assessments of person–destination congruence. Fit can therefore be recursively co-constructed through human–AI interaction.

This contribution also refines research on personalisation. Personalised tourism recommendations can increase trust and positive attitudes when they adapt content to users' needs and characteristics (Yang et al., 2024). However, the present accounts suggest that adaptation becomes problematic when preference indicators are treated as competence indicators. In sports tourism, capability should be evaluated against activity difficulty, environmental uncertainty, equipment requirements, and participant resources (Tsaur et al., 2013; Williams & Baláž, 2013). General fitness or enthusiasm can be relevant information, but they are not substitutes for route-specific skill or preparedness.

This is not the inaccurate-information path that Kim et al. (2025) have studied. A response may correctly specify a route, weather conditions or standard equipment requirements, but still provide a poorly grounded judgment that the activity is suitable for a particular user. Therefore, it is no longer about factual errors but about misinterpretations. The former concerns whether destination information is correct; the latter concerns whether the inference from available evidence to a personalised recommendation is adequately justified.

The second contribution is risk evidence reordering. Research on tourists' decision-making has focused generally on the accessibility, reliability, and convenience of information (Stergiou & Nella, 2024). Participants in this study described a different problem: although the evidence was still available, it was given less practical weight after the overall positive evaluation. Therefore, in the future, artificial intelligence-assisted risk judgment will also need to consider the position of warnings in relation to preference-consistent conclusions.

Destination attractiveness, route difficulty, weather, equipment, participant ability, group composition, and professional support all affect the factors involved in decision-making in sports tourism. Generative AI can incorporate these attributes, but the integration is not neutral if favourable cues are consistently foregrounded and restrictive cues are framed as easily manageable. Therefore, the research has found that people may be aware of the general danger but still make exceptions for themselves.

Li et al. (2026) have shown that AI agreement can reinforce the initial judgment in this way. The qualitative contribution here is to determine how this reinforcement is presented in a high-consequence tourism environment: Not as the absence of risk, but as a reduction in the perception of personal vulnerability. Given that the current evidence is retrospective, this mechanism should be considered a hypothesis for future experimental research rather than a verified cause.

The third contribution is the problem of social authority for AI-generated answers. Personalised recommendation systems are gradually being accepted by people (Yang et al., 2024), and travellers have started to use a combination of systematic and heuristic cues in accepting AI recommendations (Shi et al., 2020). The participants in this study also reported that a group-level process occurred in which one-sided prompts produced responses and were then distributed as neutral expert evidence. It is the basis for algorithmic self-echo.

Algorithmic self-echo refers to how personal framing gains social legitimacy when it is echoed in professionalised AI language. Cheng et al. (2026) have also shown that sycophantic AI can boost users' self-esteem and thereby reduce their desire to fix relationship problems. In sports-tourism groups, this means that AI may affect the initiator's own judgment as well as how the power to persuade is distributed among the other members.

The results are concerned with responsible AI in tourism. Huang et al. (2026) identified safety, human-in-the-loop, fairness, transparency, explainability and identity disclosure as key considerations. Epistemic independence is now a suitable design principle for high-consequence planning: The system should distinguish between user preference and evidence of capability, indicate when the information is insufficient for individual judgment, and present uncertainty and counter-evidence openly rather than merely affirming conversational consensus.

Deviant cases show that the mechanism is not uniform. Participants with stronger sports experience were more attentive to missing capability information; official notices, local guides, weather services, trail platforms, and multiple AI systems diversified the evidence base; and multi-party cross-questioning exposed prompt-framing dependence. These conditions are best understood as corrective infrastructures that shape whether AI is treated as a supplementary tool or as an apparently independent authority.

Overall, the study makes three bounded contributions. It identifies a preference-consistent interaction mechanism that can matter even without complete factual falsehood; it conceptualises destination fit as recursively co-constructed through tourist–AI exchange; and it shows how AI-generated personalisation can enter group relations through algorithmic self-echo. Limiting the contribution to these connected mechanisms better reflects the explanatory reach of the qualitative evidence.

Theoretical implications: Reframing risk perception and destination fit in tourism

The theoretical implication of the study is that risk judgment and destination fit should be treated as relational outcomes in AI-assisted sports tourism. Risk perception is not only a tourist's internal assessment of hazard; participants described learning what a risk meant for them through conversational interpretation. When favourable self-descriptions were treated as evidence of coping capacity, general recognition of danger could

coexist with reduced perceived personal vulnerability. This distinction is compatible with work showing that travel behaviour depends on the configuration of cognitive risk, affect, efficacy, and coping rather than on risk perception alone (Liu-Lastres et al., 2024).

Second, destination suitability should be reconsidered. The traditional fit perspective assumes that tourists and destinations should be well-matched. Based on the above analysis, perceived congruence may also be generated recursively through dialogue: Tourists present themselves, the system responds with an assessment, and this revised perception is subsequently integrated into their self-concept. Algorithm-reinforced destination fit therefore adds a conversational and technological layer to destination-choice theory without claiming that AI objectively changes competence.

Third, embodied capabilities and linguistic self-descriptions should be considered separately. Mountain and outdoor activities need task-oriented skills, knowledge of the environment, equipment proficiency and emergency preparedness (Pomfret, 2006; Tsaur et al., 2013). However, conversational systems only receive text-based self-reports. The larger difference between what can be shown in a prompt and what needs to be demonstrated physically, the more cautious personalised suitability judgment should be.

Finally, the unit of analysis in this study is extended from a single tourist-destination relationship to a multi-actor decision system that includes tourists, conversational AI, companions, official destination information, local professionals and environmental conditions. The proportion of influence from AI varies depending on the source. Professional experience, external validation and cross-examination by multiple parties are thus not mere supporting attributes; rather, they are devices to verify the actual authority of AI.

These are still proposals based on qualitative data. Future studies should directly capture prompts and AI outputs for testing, compare of sycophantic and corrective response conditions, and measure subsequent changes in perceived fit, risk controllability, information search, and plan persistence. The above work can help distinguish between perceived sycophancy and independently verified model behaviour in the field, and determine whether the proposed mechanisms have a causal effect.

Practical implications

Therefore, a cautious approach should be taken to responsible AI in sports-tourism planning. Conversational systems are suitable for organising information and exploring options, but highly positive responses should not be taken as an equivalent to professional evaluation when the activity involves substantial physical or environmental risks. The main design goal should be to maintain helpfulness without turning users' preferences into unsupported judgments of ability.

Tourism attractions need to provide official, current and easy-to-verify risk information outside the conversational module. General warnings should be specific to the activity, such as the difficulty of route, weather conditions, equipment requirements, closure status, rescue limitations, and types of participants who need additional professional advice. The AI-generated summary should direct the user to original materials if it cannot provide sufficient evidence for a personalised suitability judgment.

Four recommendations follow from the above analysis for tourism platforms and AI service providers. First, separate the system from preference-capability evidence. Second, the risk information should not be uniformly subordinate to motivational words. Third, the system should inform the user that some necessary data for personalisation is missing. Fourth, after repeatedly asking for reassurance about the restricted information, the system should retain the uncertainty and counter-evidence instead of just presenting the preferred conclusion again.

The group may use AI to help them discuss and should not give an advantage to the first person who asks a question. An interface prompts the user to express their own thoughts, presents the reasons for a recommendation, and compares various prompt structures. The system should also suggest verification in high-risk areas by means of official announcements, professional guides, weather information, and other authoritative sources.

The above recommendations are based on participants' reported experiences and should not be considered proof that current tourism AI systems systematically cause unsafe behaviour. The aim is prevention; given the existence of physical constraints and environmental uncertainty, the design of AI-assisted planning should make the boundaries of personalised inference transparent and provide a clear path to external expertise.

Deviant cases have also shown that local professionals are still required. Some participants changed or cancelled their plans after speaking with the guide or receiving an official warning; these did not match the initial confirmation by AI. Therefore, destinations should integrate professional knowledge into convenient digital channels and make verification a regular feature of AI-assisted trip planning rather than an occasional correction.

Limitations and directions for future research

The above research is subject to several limitations. First, a qualitative study that focuses on only 40 tourists in Chongqing is not easily generalisable to other areas, activities, cultures or AI platforms. Second, only the accounts of former residents are considered; there is a risk of memory failure and later distortion. Most importantly, the study did not independently obtain and audit the original AI conversation logs for all the reported cases. Therefore, it identifies perceived sycophantic behaviour and reported decision-making rather than objectively verified model behaviour.

Third, the study does not provide causal evidence for actual travel behaviour or safety outcomes. Finally, platform version, model configuration, prompt wording and the time of AI use may affect system behaviour, so in the future, these should be recorded more systematically.

In the future, research should collect prompts and AI outputs directly, distinguish between perceived and independently coded sycophancy, and experimentally compare sycophantic, neutral, and corrective response conditions. To reduce retrospective bias, real-time methods such as the think-aloud protocol, screen-recorded planning tasks and experience sampling can be used, and a longitudinal design can follow tourists from the planning stage through travel to post-trip evaluation. Comparative studies of AI systems and user groups should also examine whether sports experience, AI literacy, professional guidance, and multi-source verification reduce the susceptibility to preference-consistent affirmation.

Conclusion

Based on 40 in-depth interviews with tourists in Chongqing, this paper examined their reported experiences of perceived AI sycophancy in sports-tourism planning. The four connected processes are: preference primacy and sycophantic confirmation, algorithm-reinforced destination fit, risk evidence reordering, and algorithmic self-echo. Participants reported that AI-generated answers in line with their wishes could make a long-held preference feel externally verified; could connect positive self-descriptions to the perceived appropriateness of activities; could reduce the need for restrictive risk evidence; and could offer seemingly neutral support for arguments with a partner. Patterns were weaker in accounts involving rich sports experience, active multi-source verification, professional guidance or multiple-party cross-examination. The results extend tourism choice theory by showing that perceived destination fit and risk relevance can be jointly constructed through human-AI interaction, and that AI-generated support can be incorporated into group negotiation. However, this study has not verified the original AI output or established a causal relationship; it has only proposed a qualitative mechanism that requires further exploration through direct collection of AI conversations and experimental research. Generative AI can be used as a supporting tool for high-consequence sports-tourism planning, and its recommendations should specify the degree of uncertainty and evidential deficiency, and should encourage external professional verification.

Funding

This research was funded by the 2026 Humanities and Social Sciences Research Project of the Chongqing Municipal Education Commission, "Construction and Application of a Human Digital Twin Model for Personalized Precision Training" (Project No. 26SKGH428).

References

- Abbas Marhoon, K., K Khudher, E., & Muthher Muslim, T. (2026). Study the efficiency of selected Chlorophyta species for removing pollutants from municipal wastewater. *Environment and Water Engineering*, 12(1), 84–94. <https://doi.org/10.22034/ewe.2026.244335>
- Ahmad, A. (2025). The role of token governance mechanisms in fostering organizational innovation: The mediating role of member engagement and the moderating role of trust. *Journal of Administrative and Business Studies*, 11(4), 199–214. <https://doi.org/10.20474/jabs-11.4.1>
- Cheng, M., Yu, S., Lee, C., Khadpe, P., Ibrahim, L., & Jurafsky, D. (2026). ELEPHANT: Measuring and understanding social sycophancy in LLMs. *International Conference on Learning Representations, 2026*, 130060–130097. <https://doi.org/10.1126/science.aec8352>
- Corbin, J., & Strauss, A. (2008). *Basics of qualitative research (3rd ed.): Techniques and procedures for developing Grounded Theory* (Vol. 3). SAGE Publications, Inc. <https://doi.org/10.4135/9781452230153>
- Gao, J., Peng, P., Lu, F., Claramunt, C., & Xu, Y. (2023). Towards travel recommendation interpretability: Disentangling tourist decision-making process via knowledge graph. *Information Processing and Management*, 60(4), 103369. <https://doi.org/10.1016/j.ipm.2023.103369>
- Hennink, M. M., Kaiser, B. N., & Marconi, V. C. (2017). Code saturation versus meaning saturation: How many interviews are enough? *Qualitative Health Research*, 27(4), 591–608. <https://doi.org/10.1177/1049732316665344>
- Huang, G. I., Zhang, C. J., Torres, W. C. Z., Xiong, X., & Li, H. (2026). Responsible AI and human collaboration in tourism management: Ethical considerations and identity disclosure. *Tourism Management*, 113, 105315. <https://doi.org/10.1016/j.tourman.2025.105315>
- Iram, T., Bilal, A. R., & Bano, A. (2026). From pride to prudence: The role of financial literacy in mitigating cognitive biases among narcissistic entrepreneurs (Online First). *The International Journal of Entrepreneurship and Innovation*. <https://doi.org/10.1177/14657503261416695>
- Kafi, Z., & Ghadamyari, M. (2026). Cracking test anxiety behavior: Exploring the relationship between identity orientations and test anxiety behavior. *Pakistan Journal of Life and Social Sciences (PJLSS)*, 24(1). <https://doi.org/10.57239/pjlss-2026-24.1.007>
- Kim, J. H., Kim, J., Park, J., Kim, C., Jhang, J., & King, B. (2025). When ChatGPT gives incorrect answers: The impact of inaccurate information by generative AI on tourism decision-making. *Journal of Travel Research*, 64(1), 51–73. <https://doi.org/10.1177/00472875231212996>
- Lee, D., Wan, C., Ng, P. M. L., Fung, Y.-N., & Wu, N. (2026). Effects of AI companions' sycophancy and emotional mimicry on consumers' continuance intention and social wellbeing (OnlineFirst). *International Journal of Human Computer Interaction*, 1–23. <https://doi.org/10.1080/10447318.2026.2626809>
- Li, Z., Pan, J., Liu, Q., Xi, Y., Zhou, Y., Jin, Y., Mao, R., & Chen, P. (2026). Does sycophancy change decisions? Effect of LLM sycophancy on AI-assisted decision-making. *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*, 1–20. <https://doi.org/10.1145/3772318.3790934>
- Liu-Lastres, B., Yang, Y., & Zhang, C. X. (2024). Optimal-fit model of risk perception and travel-related behaviors during a global pandemic. *Journal of Destination Marketing and Management*, 34, 100958.
- Pomfret, G. (2006). Mountaineering adventure tourists: A conceptual framework for research. *Tourism Management*, 27(1), 113–123. <https://doi.org/10.1016/j.tourman.2004.08.003>
- Seyfi, S., Kim, M. J., Nazifi, A., Murdy, S., & Vo-Thanh, T. (2025). Understanding tourist barriers and personality influences in embracing generative AI for travel planning and decision-making. *International Journal of Hospitality Management*, 126, 104105. <https://doi.org/10.1016/j.ijhm.2025.104105>
- Shi, S., Gong, Y., & Gursoy, D. (2020). Antecedents of trust and adoption intention toward artificially intelligent recommendation systems in travel planning: A heuristic–systematic model. *Journal of Travel Research*, 60(8), 1714–1734. <https://doi.org/10.1177/0047287520966395>
- Stergiou, D. P., & Nella, A. (2024). ChatGPT and tourist decision-making: an accessibility diagnosticity theory perspective. *International Journal of Tourism Research*, 26(5), e2757. <https://doi.org/10.1002/jtr.2757>

- Stylos, N. (2022). An integrated duality theory framework (IDTF): Marking pathways for consumer decision-making researchers in the hospitality and tourism industry. *International Journal of Contemporary Hospitality Management*, 34(7), 2597–2619. <https://doi.org/10.1108/ijchm-10-2021-1256>
- Tsaur, S.-H., Lin, W.-R., & Liu, J. S. (2013). Sources of challenge for adventure tourists: Scale development and validation. *Tourism Management*, 38(1), 85–93. <https://doi.org/10.1038/s41598-024-66047-4>
- Wang, D., Tussyadiah, I., & Zhang, E. (2024). Shaping in-destination group decision-making: The sociomateriality of smartphones. *Journal of Travel Research*, 63(3), 625–641. <https://doi.org/10.1177/00472875231164980>
- Wang, J., Liu-Lastres, B., Ritchie, B. W., & Pan, D.-Z. (2019). Risk reduction and adventure tourism safety: An extension of the risk perception attitude framework (RPAF). *Tourism Management*, 74, 247–257. <https://doi.org/10.1016/j.tourman.2019.03.012>
- Weber, K. (2001). Outdoor adventure tourism: A review of research approaches. *Annals of Tourism Research*, 28(2), 360–377. [https://doi.org/10.1016/s0160-7383\(00\)00051-7](https://doi.org/10.1016/s0160-7383(00)00051-7)
- Williams, A. M., & Baláž, V. (2013). Tourism, risk tolerance and competences: Travel organization and tourism hazards. *Tourism Management*, 35, 209–221. <https://doi.org/10.1016/j.tourman.2012.07.006>
- Wong, I. A., Lian, Q. L., & Sun, D. (2023). Autonomous travel decision-making: An early glimpse into ChatGPT and generative AI. *Journal of Hospitality and Tourism Management*, 56, 253–263. <https://doi.org/10.1016/j.jhtm.2023.06.022>
- Yang, X., Zhang, L., & Feng, Z. (2024). Personalized tourism recommendations and the E-tourism user experience. *Journal of Travel Research*, 63(5), 1183–1200. <https://doi.org/10.1177/00472875231187332>
- Yao, Q., & Schwarz, E. C. (2018). Impacts and implications of an annual major sport event: A host community perspective. *Journal of destination marketing and management*, 8, 161–169. <https://doi.org/10.1016/j.jdmm.2017.02.007>
- Zhang, L., & Zhao, S. X. (2009). City branding and the olympic effect: A case study of Beijing. *Cities*, 26(5), 245–54. <https://doi.org/10.1016/j.cities.2009.05.002>