Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning

Abstract

This study aims to cultivate an initial understanding of travelers' engagement with generative artificial intelligence (GAI) during the travel planning phase. It focuses on its influence on decision-making and intentions for continuous usage in planning tourism activities. Utilizing the stimulus-organism-response framework and domain literature, data were gathered through semi-structured interviews (UK) and scenario-based questionnaires (USA). The study reveals complex aspects of travelers' behavior, uncovering that while GAI recommendations mitigate the risk of information overload, their influence does not necessarily streamline decision-making. Trust and information retrieval skills surfaced as moderate determinants of the relationship between recommendations and information overload. This work is a pioneer in empirically exploring and quantifying continuance intentions of generative artificial intelligence (GAI) usage, contributing novel insights to electronic Word of Mouth and decision-making literature.

Keywords

recommendation quality, decision satisfaction, information overload, travel, hospitality, generative artificial intelligence

Introduction

The rapid advancement of generative artificial intelligence (GAI) has begun to transform how travelers engage with information during trip planning (Mladenović et al., 2024). Unlike earlier digital tools that aggregated or ranked information, GAI (e.g., ChatGPT) autonomously synthesize heterogeneous information sources—including online reviews, travel blogs, official websites, forums, expert recommendations, and real-time advisories—

into coherent, natural language responses tailored to individual user queries (Carvalho & Ivanov, 2024; Dwivedi et al., 2023; Hsu et al., 2024). This capability represents a fundamental shift in online travel information processing as travelers increasingly interact with conversational agents capable of complex reasoning and personalized synthesis (Saleh, 2025) - opposed to manually parsing fragmented information from multiple digital platforms. For example, rather than reading dozens of reviews and comparing websites, a traveler may now prompt ChatGPT to generate a customized itinerary that simultaneously considers personal constraints such as accessibility needs, budget, or schedules.

This shift introduces both conceptual and practical challenges for understanding decision-making in the travel planning phase. Traditionally, research has emphasized electronic Word of Mouth (eWOM), particularly user-generated online reviews, as the dominant form of travel information influencing consumer behavior (Arenas-Márquez et al., 2021; Filieri et al., 2021). However, GAI-curated content departs from classical eWOM in two fundamental ways (Tassiello et al., 2024). First, GAI integrates multiple data beyond peer-to-peer reviews, including structured databases, professional sources, and historical knowledge bases, thus producing hybrid recommendations that do not exist in original form elsewhere (Kim et al., 2023; Kirshner, 2024). Second, the information is algorithmically composed rather than directly authored by consumers, raising questions about transparency, trust, and user interpretation. This raises an important conceptual question: to what extent does GAI represent an evolution of eWOM or the emergence of a qualitatively distinct information source requiring new theoretical treatment? Existing literature provides little empirical evidence on how travelers cognitively process, evaluate, or rely on these synthesized GAI-generated outputs.

Despite growing interest in GAI's role in consumers' decision making (e.g., Ali et al., 2023; Kim et al., 2023; Kim et al., 2025; Kirshner, 2024), most scholarship remains conceptual, often outlining potential use cases, ethical concerns, or technological capabilities (Fakfare et al., 2025; Kshetri et al., 2024). While important, such works offer limited insight into real-world user experiences and behaviors when interacting with GAI during travel planning. For instance, little is known about how travelers experience recommendation quality, information overload, decision difficulty, and satisfaction when using GAI-generated content, nor about the psychological mechanisms through which these outcomes unfold. One important gap concerns information overload - a well-established issue in online travel research (Dwivedi et al., 2023; Kirshner, 2024; van Dis et al., 2023) - but largely unexamined in GAI contexts. Traditional review platforms often overwhelm users with redundant, conflicting, or excessive information, impairing decision quality and increasing cognitive strain. GAI could potentially mitigate these effects by filtering and synthesizing vast datasets into focused recommendations, but might also introduce new forms of opacity or over-reliance depending on information transparency and perceived credibility (Carvalho & Ivanov, 2024; Hsu et al., 2024). At present, empirical evidence remains limited regarding whether GAI reduces or exacerbates travelers' information overload during real planning activities.

Furthermore, individual differences are likely to shape how travelers experience GAI-generated recommendations. Constructs such as trust in AI content (Amos & Zhang, 2024; Solakis et al., 2024) and information retrieval skills (Wu et al., 2024) may moderate users' ability to process GAI outputs. For example, less digitally skilled users may benefit from GAI's synthesis capabilities, while highly skilled users may remain critical or prone to further verification. Similarly, users who trust AI may experience lower cognitive effort, while skeptics may engage in additional data validation (Ali et al., 2023). These contingent processes remain empirically underexplored. Collectively, these conceptual and empirical gaps lead to the pending question: how does generative AI (re)shape cognitive and behavioral decision processes during trip planning, and under which conditions does it facilitate or prevent effective decision-making? Fundamentally, addressing this is both theoretically and practically significant. Theoretically, it extends existing frameworks such as information overload theory (Kim et al., 2025; Seyfi et al., 2025) and stimulus-organism-response models (Mladenović et al., 2023) into the emerging domain of GAI-mediated travel decisions. Practically, it informs the design of AI-based travel platforms that balance personalization, cognitive load, trust-building, and user satisfaction. Accordingly, this study seeks to address these issues through a multi-method empirical approach, guided by the following research questions: ***RQ1:*** *How do travelers engage with GAI in planning their itineraries?,* ***RQ2:*** *What is the influence of GAI on travelers' decision-making, particularly in terms of information overload, decision difficulty, and satisfaction? and* ***RQ3:*** *What are travelers' intentions to continue using GAI for travel planning in the future?*

In addressing these questions, this study offers several concrete contributions. First, it moves beyond adoption-focused studies by empirically examining GAI's cognitive effects on travelers during active planning scenarios, including recommendation quality, information overload, decision difficulty, and satisfaction. Second, it employs a sequential mixed-methods design—combining qualitative interviews and scenario-based quantitative testing—to capture both contextual depth and generalizability. Third, it conceptualizes GAI not merely as eWOM but as a synthesizing mechanism integrating diverse digital content into algorithmic recommendations, extending existing theories of online information processing. Finally, it introduces and empirically tests the moderating roles of user trust and information retrieval skills—two boundary conditions rarely investigated in current GAI tourism research.

Theoretical Background

Travelers' Reliance on Online Reviews in Travel Planning

Online review platforms transformed how travelers plan, evaluate, and make travel-related decisions (Assaker, 2020). Travel decision-making involves a complex process that includes destination choice, selection of accommodation, activity, and transportation planning, to name a few (Sigala et al., 2024). In recent years, travelers have increasingly relied on online reviews as a primary source of information during their decision-making process. Online reviews provide travelers with real-time, user-generated content (Filieri et al., 2021; Shang & Pan, 2024). Early studies examined the role of online reviews in travel decision-making (Aureliano-Silva et al., 2021; Nilashi et al., 2021). For instance, Filieri et al. (2021) found that visit intentions are greatly affected by online reviews and user-generated content.

However, recently, artificial intelligence-based recommendation platforms (e.g., ChatGPT, Gemini, Grok) have gained popularity - primarily because they provide above-average and very personalized user and travel experiences (Ashfaq et al., 2020; Meng et al., 2023; Sivathanu & Pillai, 2023). According to Shi et al. (2021), these platforms may induce higher satisfaction, loyalty, and advocacy levels. For instance, ChatGPT could help travelers confidently make bookings. Ali et al. (2023) found that the perceived relevance and intelligence of the personalized (travel recommendations) generated by GAI significantly affect travelers' trust and intention to use GAI in the travel planning phase.

While online reviews remain an important source of user-generated content in travel planning, GAI platforms fundamentally alter how such information is accessed and utilized. Namely, GAI incorporates eWOM as one of multiple input sources—alongside official websites, expert articles, travel blogs, and third-party data—generating synthesized outputs tailored to individual traveler needs (Mladenović et al., 2024; Tassiello et al., 2024). This synthesis reduces the burden of manual search but also introduces new cognitive and trust-related challenges, as users engage with aggregated content they did not directly retrieve themselves (Saleh, 2025). Accordingly, studying AI-generated recommendations provides an important extension to existing eWOM research by exploring how travelers interact with information that partially derives from peer reviews but is algorithmically reformulated.

Recent studies have examined ChatGPT and GAI in tourism using frameworks such as TAM (Solomovich & Abraham, 2024; Christensen et al., 2024), S-O-R (Xu et al., 2024; Pham et al., 2024; Wang et al., 2025), and other lenses like affordance-actualization (Li & Lee, 2025) or parasocial interaction theory (Duong et al., 2024). While valuable, these studies largely focus on attitudes, trust, or usage intentions, with limited attention to cognitive mechanisms like information overload or decision difficulty.

The Information Overload Phenomena

Various information online (including electronic Word of Mouth) can lead to information overload (Mladenović et al., 2023). The negative consequences of information overload include confusion, reduced ability to set priorities, poor decision-making, reduced purchase intention, and high perceived risk (e.g., Hu & Krishen, 2019; Wu et al., 2024). A psychological state of information overload may be triggered by numerous factors: the number of alternatives, product attributes, or perceived information quality (Hu & Krishen, 2019). For example, the quality and quantity of online reviews negatively affect decision-making and, consequently, induce information overload. To date, little research exists on the interplay between information overload and decision-making (Hu & Krishen, 2019). As per cognitive load theory, individual differences (e.g., inner motivation, prior knowledge, etc.) can affect the cognitive effort required to reach a decision (Bermes, 2021; Hu et al., 2023).

However, previous studies did not consider other factors, such as trust and information retrieval skills.

Integrating the S-O-R Model and Cognitive Load Theory

The Stimulus–Organism–Response (S-O-R) model is a psychological framework used to understand how external stimuli (S) influence internal cognitive and emotional processes (O), leading to specific behavioral responses (R) (Sherman et al., 1997). This model has been widely adopted in fields such as consumer behavior, human–AI interaction, and tourism to explain how environmental factors shape individuals' perceptions, emotions, and behaviors (e.g., Mim et al., 2022; Mladenović et al., 2023). In the present study, perceived GAI recommendation quality is conceptualized as the stimulus (S). The organism (O) refers to users' internal cognitive states, particularly information overload and decision difficulty, while the response (R) includes both psychological outcomes (satisfaction) and behavioral intentions (continued use of GAI for travel planning).

The "organism" in the S-O-R framework encompasses all intervening internal processes, including affective, perceptual, and cognitive states. Information overload, defined as a user's subjective experience of cognitive strain when processing excessive or disorganized content, fits this category as it reflects an internal processing response to external stimuli (Eppler & Mengis, 2004). Empirical S-O-R-based studies have similarly treated cognitive overload, anxiety, and decision difficulty as organismic constructs in online recommendation contexts (e.g., Mladenović et al., 2023; Zheng et al., 2023). For instance, Pham et al. (2024) applied it to explore how ChatGPT's anthropomorphic cues influence trust and behavioral responses. However, a key limitation of the S-O-R framework is its treatment of the organismic state as a holistic, undifferentiated black box. According to Wang et al. (2025), this limits its capacity to distinguish between specific cognitive and emotional mechanisms, particularly in complex digital decision environments.

To overcome this limitation, the present study integrates CLT into the S-O-R framework. CLT posits that individuals have a limited capacity for processing information, and excessive cognitive demands can hinder decision-making effectiveness (Sweller, 1988; Paas et al., 2003). When consumers encounter recommendations that are fragmented, unstructured, or ambiguous, their cognitive load increases, making it more difficult to process and utilize information effectively. This perspective is particularly relevant in the context of generative AI-driven recommendations, where variations in information quality can influence cognitive effort, information overload, and decision difficulty.

In this combined model, GAI recommendation quality (stimulus) affects users' extraneous cognitive load, which in turn contributes to feelings of information overload and decision difficulty (organism). These organismic states influence both decision satisfaction and continuous usage intention (response). Moreover, integrating CLT enables us to conceptualize how individual differences, such as trust in AI and information retrieval skills, moderate the cognitive processing of GAI content.

Within this framework, the three core forms of cognitive load (Sweller et al., 2011) can be directly linked to the processes examined in this research. Intrinsic load reflects the inherent complexity of the travel-planning task, such as comparing multi-destination routes or balancing several booking constraints; this element underlies travelers' baseline decision difficulty. Extraneous load arises from the way information is presented. Here, from unstructured or poorly organized GAI outputs, which leads to perceived information overload. Germane load captures the productive mental effort invested in interpreting and applying GAI recommendations to one's personal situation, which in this study is expressed through decision satisfaction and continuance intention. By positioning these loads within the S-O-R structure, recommendation quality acts as the stimulus influencing both extraneous and germane processing, while intrinsic task demands shape the overall organismic state that drives behavioral responses.

Study 1: Explorative Interpretative Phenomenological Study

The first study, grounded in an interpretative phenomenological approach, aims to provide in-depth insights into how travelers perceive and experience the use of GAI during travel planning. This exploratory phase not only revealed individual meaning-making processes but also revealed recurring patterns related to trust, information overload, perceived recommendation quality, and decision confidence. These themes, while emergent and inductively derived, echoed key constructs identified in prior literature, reinforcing their conceptual relevance and salience in AI-mediated decision-making contexts. Importantly, Study 1 preceded the quantitative phase and served as a contextual foundation for refining the focus of Study 2. In this way, the two studies form an integrated whole: the qualitative inquiry captures the lived complexity of user interactions, while the quantitative study tests generalizable patterns of those interactions across a broader population. This sequential mixed methods design thus enhances the validity, interpretive depth, and theoretical coherence of the research as a whole.

Sample and Participant Recruitment

Data for the first study were collected through semi-structured interviews with UK residents actively planning their holidays. Given the exploratory nature of the study, a multi-pronged sampling strategy was employed, combining purposive and snowball sampling to recruit information-rich participants likely to offer diverse perspectives on the use of GenAI for travel planning (Patton, 2015). Participants were recruited through social media platforms and personal referrals. To ensure relevance to the research objectives, inclusion criteria required that participants be aged 18 or over, reside in the UK, be planning a leisure trip within the next three months, and have used or expressed an intention to use GAI tools (e.g., ChatGPT, Gemini) during their travel planning. A total of 27 individuals expressed interest in participating. From this group, 19 participants were selected for interviews. The final selection was based on maximum variation sampling, ensuring a mix of age, digital proficiency, travel frequency, and GAI familiarity. This diversity allowed the study to capture a broad spectrum of perspectives while maintaining depth in individual experiences. Recruitment continued until thematic saturation was reached - that is, no new codes or meaningful insights were emerging from the data (Levitt et al., 2017). The final sample size is consistent with standards for Interpretative Phenomenological Analysis (IPA), which emphasizes rich, detailed accounts over large sample sizes to explore lived experience meaningfully. A demographic summary of the participants is presented in Table 1.

Table **1** Demographic Overview of Participants

Participants	**Gender**	**Age**	**Occupation**
P1	Female	18-21	Healthcare
P2	Female	18-21	Education
P3	Female	22-25	Marketing
P4	Female	26-30	Healthcare
P5	Female	26-30	Information Technology
P6	Female	31-35	Healthcare
P7	Female	31-35	Manufacturing
P8	Female	36-40	Healthcare
P9	Male	18-21	Healthcare
P10	Male	18-21	Healthcare
P11	Male	18-21	Information Technology
P12	Male	22-25	Information Technology
P13	Male	22-25	Marketing
P14	Male	26-30	Education
P15	Male	26-30	Education
P16	Male	31-35	Education
P17	Male	31-35	Human Resources
P18	Male	31-35	Sports Management
P19	Male	36-40	Transport and Logistics

Data Collection and Analysis

Qualitative data for the study were collected through semi-structured online interviews using Teams. Participants were assured of confidentiality, anonymity, and their right to withdraw at any point without explanation. Interviews lasted on average of 48 minutes. An interview guide (Appendix 3) was used to structure the conversation while allowing flexibility to follow emerging topics. Data collection continued until thematic saturation was reached, that is, when additional interviews no longer produced new insights (Levitt et al., 2017). The interviews were transcribed using the Otter speech-to-text application, with manual verification to ensure accuracy. Transcripts were imported into NVivo for coding and analysis. We followed a six-phase reflexive thematic analysis framework, which emphasizes an interpretive and iterative approach to theme development. Analysis began with repeated reading of the transcripts to ensure immersion in the data. During this phase, we engaged in open, inductive coding using both in vivo and descriptive labels that captured participants' meanings and language.

Although a formal codebook was not developed at the outset, codes were documented, refined, and grouped through continuous memo writing and discussion. As patterns began to emerge, initial codes were clustered into conceptually related sub-themes. These sub-themes were then reviewed and refined to ensure internal coherence and distinctiveness. The process was collaborative, involving regular peer debriefing sessions to challenge assumptions and enhance analytical rigor. Ultimately, nineteen sub-themes were identified and consolidated into four overarching themes, each aligned with the research objectives and forming the basis for a typology of traveler engagement with GAI. Dormant or weakly supported codes were excluded to maintain analytical clarity. To enhance transparency, illustrative quotes supporting each theme are included in the findings section.

Credibility of Data Collection

Voluntary participants were recruited, respecting their willingness to share information and upholding their autonomy by allowing withdrawal. To enhance trustworthiness, member checks were conducted, and participants verified the accuracy of their representation. Their voices were preserved authentically through the use of their exact words. Ongoing researcher reflexivity addressed biases and decision-making. Regular debriefing sessions with the research team ensured comprehensive data capture and understanding. A table of themes in Appendix 4 showcased the rigorous process of merging themes, confirming the robustness and validity of the thematic analysis in answering the research question.

Findings and Discussion

Topic 1: Interplay Between ChatGPT Usage and Awareness Levels. The qualitative data analysis reveals that travelers' willingness to engage with GAI for travel inquiries is influenced by their level of awareness about technology. There was a notable variation in familiarity with GAI. Most participants (n=17) were familiar with ChatGPT, while some mentioned using Google Gemini (n=2). These individuals shared their experiences and concerns, drawing comparisons between traditional chatbots and GAI regarding conversation style and level of detail provided. They preferred GAI due to its advanced capabilities in generating responses that closely align with their needs. However, some participants had reservations. Three raised concerns, referring to technology as a '*Black box.*' Despite this, the participants acknowledged becoming more accustomed to the technology and its benefits. Although uncertainty and lack of trust could be linked to information quality, participants often attributed their mistrust to not fully understanding how the AI worked, describing it as a "black box." This mistrust was therefore more deeply rooted in their awareness levels than in the content accuracy alone.

The findings indicate that the level of awareness and familiarity with GAI has significant implications for shaping travelers' willingness to adopt it. As participants become more informed about capabilities and potential, their trust and confidence in engaging with GAI will likely increase, leading to greater adoption. To address these concerns, companies need to be transparent about their artificial intelligence, explain how information is generated, and ensure data privacy and security to foster user confidence.

Topic 2: Travel planning starts with GAI. Individuals who have developed confidence in GAI view it as an exciting and promising starting point for their travel inquiries. These participants know the growing trends and are eager to explore their capabilities. Using GAI for travel queries has become an engaging and fun activity for these participants, and they enjoy experimenting with it, exploring its abilities using different prompts, and discovering the insights it provides. Artificial intelligence's ability to offer exciting and relevant suggestions (e.g., flights and on-site solutions) allows it to consider options it might not have considered before. It is worth noting that the participants showed a particular interest in using text-based GAI for their travel inquiries. They found asking questions and receiving responses about travel options was convenient and user-friendly. This personalized and interactive experience makes the trip-planning process less stressful and enjoyable.

For those open to embracing GAI as a starting point for their travel queries, the technology is a valuable tool for exploring and discovering new possibilities. Its ability to provide relevant insights and personalized suggestions about travel options enhances decision-making and opens up a world of exciting opportunities.

Topic 3: Urge to verify GAI-based recommendations. Despite the concerns raised by participants about information overload and the need to verify the accuracy of the data, they still appreciated the vast amount of information provided by GAI. They recognized that the artificial intelligence system was a valuable starting point for their travel inquiries. However, participants were also responsible for verifying the information, recognizing that the machine has limitations and that human judgment is still essential. To ensure the accuracy of the information, participants took proactive measures to verify the data from multiple sources. For example, one participant who raised concerns about the opening times of a tourist attraction cross-referenced the information provided by ChatGPT with the official website. Others used search engines, relied on TripAdvisor, and checked social media for up-to-date information. Participants acknowledged that the verification process added extra work and were cautious not to solely base their decisions on GAI-generated information.

As a potential remedy, some participants suggested the development of a specialized GAI tool focused solely on tourism. Such a tool could provide more targeted and accurate information - streamlining the travel planning process. Overall, participants recognized the benefits of GAI but acknowledged its limitations. The need for human verification and cross-referencing of data was seen as necessary to ensure the information's reliability and currency. While there were challenges, the potential for artificial intelligence to become an even more valuable travel planning tool was evident, with participants expressing interest in specialized tools tailored to tourism needs. As technology continues to evolve, addressing these concerns will be essential to optimize its utility in the tourism industry.

Topic 4: Travelers' concerns regarding GAI-generated recommendations. Many participants expressed concerns regarding information overload and the need to filter through vast amounts of data that artificial intelligence provides. They found it challenging to manage the volume of information and felt the need to work around the prompts to narrow down and focus their queries. However, this approach could be distracting, making it difficult to achieve precise results. Participants acknowledged that using prompts required specific expertise (those unfamiliar with the proper prompts raised concerns about the random information generated). This lack of control over the output led to doubts about the relevance of the information, undermining trust in GAI as a reliable source. Another significant concern raised by users was the currency of the information provided by GAI systems. Comparisons were drawn with Gemini and Grok, highlighting that data might be outdated, as it could have been captured years ago. For instance, participants expressed concerns about the accuracy of hotel ratings, entrance fees for tourist attractions, opening hours, and transportation routes. Such time-sensitive information is crucial for evaluating travel options, and uncertainty about its accuracy can lead to hesitancy in relying on GAI.

These concerns reflect the need for further refinement and improvement in GAI. Enhancing user control and guidance during interactions and providing up-to-date and verified information will be essential for building user trust and confidence in technology. Additionally, clear communication about the limitations and strengths of GAI can help travelers make more informed judgments about its suitability for their planning needs.

Figure 1 provides a thematic structure linking qualitative insights to the overarching conceptualization of ChatGPT's role in travel planning. It visually organizes the second-order and first-order themes that emerged from participant narratives into four interrelated thematic clusters. These clusters reflect the nuanced ways users engage with, assess, and adopt GAI in their travel planning journeys. The figure illustrates how these themes collectively shape perceptions of ChatGPT - from initial awareness and curiosity to ongoing usage, critical evaluation, and trust-building. By mapping these dynamics, the figure underscores the complex, evolving relationship between travelers and GAI technologies, offering a structured foundation for interpreting the broader implications of GAI-enabled travel planning.

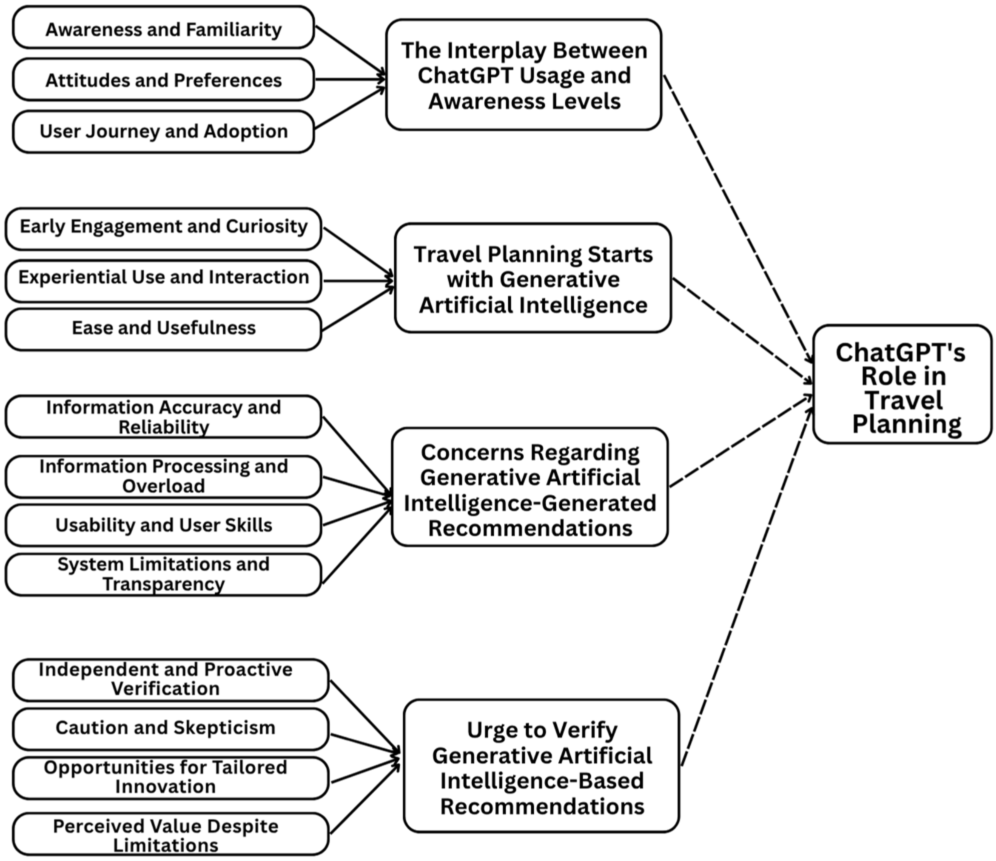

Figure 1: Thematic Structure Linking Qualitative Insights to ChatGPT's Role in Travel Planning

Study 2: Travelers' decision satisfaction and continued use intention

Study 2 builds on the qualitative insights from Study 1. The mixed-method sequence follows an exploratory-to-confirmatory logic: the first study identified the most significant constructs in travelers' experiences with GAI—information overload, decision difficulty, trust, and verification behavior, while the second empirically tests their relationships on a larger sample. Specifically, Study 1 revealed that travelers' trust in GAI and their information-retrieval skills shape how they process recommendations, and that satisfaction and future-use intentions emerge as key behavioral outcomes. These insights guided the selection of constructs, the development of hypotheses, and the design of the scenario-based task in Study 2. This integration ensures the two studies collectively form a coherent investigation of how GAI influences decision-making in travel planning.

Hypotheses Development

Implications of GAI-recommendations on Information Overload and Decision Difficulty

According to CLT, structured and coherent recommendations reduce cognitive load, allowing consumers to allocate their cognitive resources to essential decision-making processes (Sweller et al., 2011). Theoretically, perceived lower-quality online reviews should require higher cognitive effort for consequent processing (Kumar et al., 2023). Recommendations that are unstructured and with interrupted information flow should likely induce higher cognitive loads. Higher perceived information quality positively influences information selection (Metzger & Flanagin, 2013), potentially reducing information overload. Recently, Hu and Krishen (2019) found that recommendation quality is negatively linked to information overload. Recent work indicates that when users perceive high-quality AI-generated content, their cognitive effort diminishes. For example, EEG research shows that interacting with well-designed LLM outputs is associated with reduced cognitive load (Leung et al., 2025). Thus, when travelers perceive the quality of reviews to be higher, they should be less overloaded with information.

H1: Review (recommendation) quality is negatively related to information overload.

While information quality affects decision-making processes (Houhamdi & Athamena, 2019), Hu and Krishen (2019) believe that recommendation quality is directly related to one's fluency in processing information. Fluency stresses the role of review (recommendation) quality as it interplays with the traveler's cognition (Filieri et al., 2018). According to the fluency heuristic, information (reviews) that is more easily processed is preferred compared to the ones requiring more significant cognitive effort (Chiu et al., 2014). Higher levels of fluency should result in more affirmative perceptions by travelers and imply lower difficulties in the decision-making process. Additionally, prior research emphasized the importance of perceived information quality in reducing uncertainty (Mladenović et al., 2023), which is closely related to decision difficulty (Mladenović et al., 2025). Hypothetically, when travelers find the information trustworthy, they are more confident in their decision-making abilities, thus reducing decision difficulty. Therefore:

H2: Review (recommendation) quality is negatively related to decision difficulty.

How Does Information Overload Implicate Decision Difficulty and Decision Satisfaction?

Information overload has emerged as a critical barrier to effective decision-making in digital and consumer behavior contexts. It reduces individuals' capacity to extract key elements from the data they encounter (Hu & Krishen, 2019; Kirshner, 2024; Mladenović et al., 2023), often leading to cognitive confusion (Kirshner, 2024) and emotional strain, such as frustration and anxiety (Peng et al., 2021). Those overwhelmed by information tend to make decisions less effectively and efficiently. This phenomenon is particularly pronounced in digital environments, where users are often inundated with excessive or poorly organized content (Bermes, 2021). According to CLT, human cognitive processing capacity is limited and can be overwhelmed when confronted with excessive or poorly structured information. One of the core tenets of CLT is that extraneous cognitive load—arising from unnecessary or disorganized information—can interfere with a person's ability to make decisions effectively. In digital environments, this manifests as information overload, a condition in which users receive more data than they can meaningfully process (Eppler & Mengis, 2004).

In decision-making contexts, especially those involving GAI outputs, information overload has been shown to undermine users' ability to evaluate options efficiently, thereby increasing decision difficulty. Empirical studies support this link: Xu et al. (2022) found that information overload erodes individuals' confidence in their decision-making abilities, while Peng et al. (2021) demonstrated that overload leads to inferior decision quality. However, this relationship remains underexplored in the context of GAI-generated travel recommendations, which often present users with a vast yet variable-quality dataset. From a CLT perspective, information overload increases the cognitive burden, thereby reducing clarity and increasing effort during the decision-making process. Accordingly, we hypothesize:

H3: Information overload is positively related to decision difficulty.

In line with CLT, increased cognitive load not only increases decision difficulty but also induces negative affective responses, such as frustration and dissatisfaction (Hu et al., 2023). For instance, Xu et al. (2022) found that information overload eroded one's confidence in their ability to make informed decisions. On this note, Peng et al. (2021) found initial traces of how information overload affects consumers' decision-making, resulting in poor decision quality. From a cognitive load perspective, an excessive information burden (high extraneous load) should diminish decision confidence and satisfaction (Gandhi et al., 2023). When users feel mentally overwhelmed, their satisfaction with the process diminishes, regardless of the outcome, because the cognitive effort required outweighs the perceived value of the result. In AI-based decision environments, this becomes particularly relevant: although the system may provide actionable suggestions, the user's processing experience may still be dissatisfying due to the mental load involved. Hence, we propose:

H4: Information overload is negatively related to decision satisfaction.

The Complex Interplay Between Decision Difficulty and Satisfaction

It is essential to notice that process satisfaction is connected to the decision-making process, not the choice itself (Ashfaq et al., 2020). CLT suggests that when cognitive resources are heavily utilized, decision difficulty increases, reducing users' sense of control, confidence, and efficiency, all of which are vital for positive evaluations of the decision-making process. Several studies reported decision difficulty as a solid predictor of lower satisfaction (e.g., Hu & Krishen, 2019; Wang & Shukla, 2013). Hypothetically, if travelers are satisfied with decision-making (e.g., effectiveness, speed, convenience, etc.), higher adoption and continuance intention rates are expected (as suggested by Lee & Koo, 2015). Thus, the following:

H5: Decision difficulty is negatively related to decision satisfaction.

Will those satisfied with GAI keep using it?

Prior literature has examined the satisfaction-intention link in various contexts (e.g., Hoyer et al., 2020; Lim & Kim, 2020). For example, Ashfaq et al. (2020) found that satisfied users are more inclined to continue using. Another study by Lee et al. (2015) found that decision satisfaction leads to a continuous intention to use in the context of ubiquitous decision support systems. Given the assumed link that perceived satisfaction positively affects the continuance intention, the following is proposed:

H6: Decision satisfaction is positively related to GAI's continuous intention to use.

This relationship is grounded in the well-established post-adoption behavior theory, which posits that user satisfaction serves as a key antecedent to ongoing engagement (Fazal-e-Hasan et al., 2021). In the context of GAI, where users are often navigating novelty, uncertainty, and varying degrees of quality, satisfaction signals not only task success but also trust in the tool's utility and reliability. As such, satisfaction reflects a cognitive and emotional endorsement of the AI's role in decision-making, which is likely to reinforce the user's willingness to continue using the system.

Does Travelers' Trust Make Recommendations More Impactful?

Trust is a critical factor in shaping consumer behavior, particularly in how individuals evaluate online reviews (Nilashi et al., 2022). In digital environments, trust in online content enhances users' confidence in the reliability and usefulness of the information provided (Filieri et al., 2018; Mladenović et al., 2025). Specifically, trust has been identified as a contextual factor, a belief that varies across domains and systems, capable of exerting moderating effects on users' decision processes (Hatamleh et al., 2023; Kim & Lee, 2019). In the context of GAI-generated recommendations, when users perceive high recommendation quality and trust the source, they are less likely to feel overwhelmed and more likely to find the decision-making process less cognitively demanding (Kim et al., 2023; Shi et al., 2021).

Expanding on this, trust in GAI is best conceptualized as a contextual trait - a relatively stable belief about the system's reliability, competence, and integrity formed within a specific context, such as AI-assisted travel planning (Glikson & Woolley, 2020).

Users with high trust in GAI are inclined to accept recommendations at face value, which reduces the need for intensive scrutiny or information cross-checking. This leads to lower cognitive load and facilitates smoother decision-making. Conversely, low-trust users may approach AI outputs with skepticism, engage in more cognitive verification, and ultimately experience higher levels of information overload and decision difficulty (Choi et al., 2021; Gursoy et al., 2019; Ngo, 2025). Hypothetically, a higher level of trust may result in greater confidence, reducing decision difficulty. It is assumed that trust moderates the effects of perceived recommendation quality on cognitive outcomes such as information overload and decision difficulty. Specifically, the negative impact of high-quality recommendations on overload and decision strain should be stronger among users with higher levels of trust. In other words, a trust may amplify the cognitive relief afforded by credible, well-articulated AI-generated suggestions, while users with low trust may remain skeptical and thus less affected by improvements in recommendation quality. Therefore:

H7: User trust moderated the relationship between a) perceived recommendation quality and information overload and b) perceived recommendation quality and decision difficulty.

Does Retrieval Skill Induce Information Overload and Decision Difficulty?

Information retrieval skill is considered a user-level digital competency - a stable but context-sensitive ability to effectively locate, evaluate, and apply digital content (Bronstein &

Tzivian, 2013; Wu et al., 2024). It is shaped by users' education, experience, and digital literacy, and reflects their capacity to handle complex informational environments like those encountered when interacting with generative AI (Hoyer et al., 2020). Users with higher information retrieval skills may be better equipped to filter and process information efficiently (Nilashi et al., 2022), including online reviews. Thus, the relationship between perceived recommendation quality and information overload may be moderated by information retrieval skills - whereby skillful travelers are less prone to information overload and are likely to be more adept at extracting relevant information (Filieri et al., 2018), including online reviews. Consequently, the influence of perceived recommendation quality on decision difficulty may be attenuated for users with superior information retrieval skills, as they can navigate and process the information effectively. In line with this reasoning, we expect that information retrieval skills moderate the impact of recommendation quality such that the benefits of high-quality recommendations in reducing overload and decision difficulty will be more pronounced among users with lower skills. For these individuals, the structure and clarity of the information provided serve as essentials for navigating complex choices. In contrast, high-skill users may rely more on their filtering capabilities, rendering the perceived quality of the content less critical in reducing cognitive strain. Thus:

H8: Information retrieval skills a) positively moderate the relationship between perceived recommendation quality and information overload and b) negatively moderate the relationship between perceived recommendation quality and decision difficulty.

The following figure (Figure 2) presents a theoretical framework.

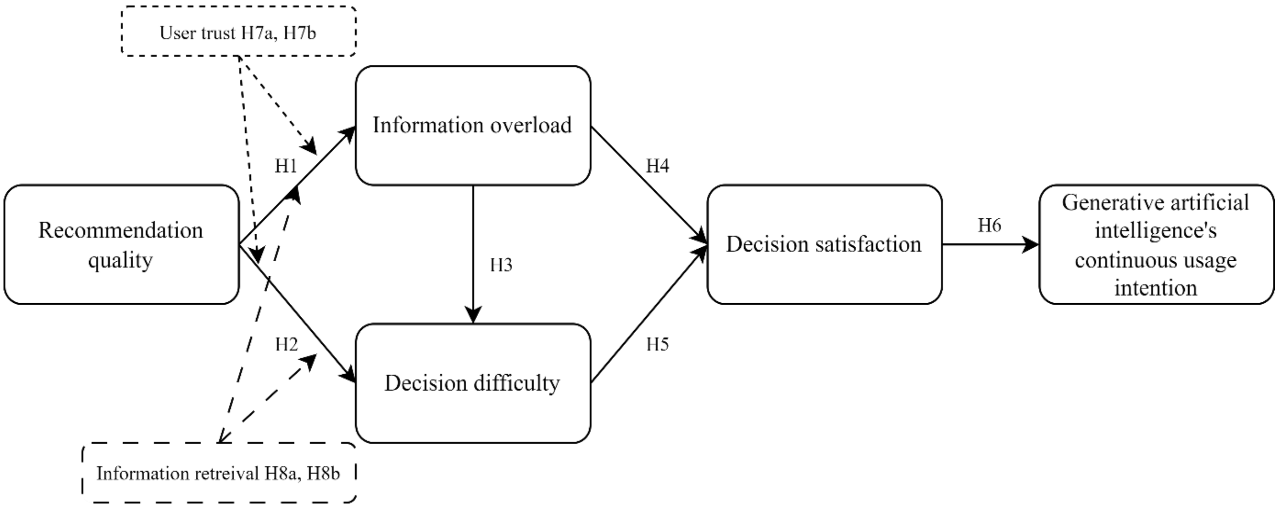

Figure **2** Study 2 - Research model showing relationships between recommendation quality, information overload, decision difficulty, decision satisfaction, trust, information retrieval skills, and continuance intention

Study Design, Measurements, and Research Context

The measurement model relied on validated multi-item constructs from prior literature, each rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Negatively worded items (e.g., "I found the process of deciding on the details of my trip frustrating") were reverse-coded before analysis. All item scores were averaged to form composite variables, where higher values indicate greater levels of the underlying construct (e.g., higher recommendation quality, stronger information overload, greater satisfaction). This coding procedure ensured conceptual alignment across constructs and mitigated potential interpretive inconsistencies. Data was collected through a scenario-based questionnaire to test the research model. To reduce potential issues related to social desirability bias, we stated the study's primary purpose, goals, and research context (Podsakoff et al., 2003). We employed the separation of measurements procedure (Podsakoff et al., 2012) to reduce the common method bias, as independent and dependent variables/items were measured in different sections of the questionnaire. The questionnaire was tested with a diverse group of fifty-two respondents encompassing frequent travelers, researchers, and marketers, resulting in minor technical and language refinements.

The scenario-based questionnaire (Appendix 1) aimed to simulate a hypothetical situation in which participants were asked to engage with GAI for a series of travel-related decisions about their upcoming trip to Paris. This destination was chosen due to its prominence as one of the top destinations in Europe and the high visitation rates (D'Acunto et al., 2023). This study relies on robust scales from the literature (7-point Likert scale; 1 - strongly agree, 7 - strongly disagree) (Appendix 2). Specifically, Hu and Krishen's (2019) scales for information overload, decision difficulty, decision satisfaction, and perceived GAI recommendation quality. Trust and continuance intention were measured using the scales developed by Balakrishnan and Dwivedi (2021), and information retrieval skills via scales developed by Bronstein and Tzivian (2013).

Procedure and Sample

To ensure data quality, respondents were filtered based on the guidelines of Kees et al. (2017) to include those with a survey completion rate higher than 95% and a minimum of 150 completed tasks. The sample consisted of participants from the United States, selected due to its status as the largest travel market in the World (Statista Research Department, 2025). The minimum sample size was determined using the a priori approach (Soper, 2023). With an effect size of 0.50 (Cohen, 1992), a target power level of 0.8, 7 latent variables, 25 observed items, and a probability cut-off level of 0.05, a minimum sample size of 131 was required. Based on two attention-checking questions (Oppenheimer et al., 2009), 39 disengaged respondents were removed. A T-test reported no differences in responses between early and late respondents.

Analyses and Results

In total, 496 valid responses have been received, of which 58% were male, 45% were between 26-45 years old, and around 55% traveled once every two months. Additionally, 26%

of respondents travel once a month. The reported frequency corresponds to the recent travel frequencies in the USA (Statista Research Department, 2025).

Measurement model assessment

The conceptual model is assessed using SmartPLS 4. Partial least squares (PLS) is chosen due to its robustness in handling smaller sample sizes and its flexibility, as it does not require multivariate normality assumptions (Hair et al., 2016). This makes it particularly appropriate for the objectives of this study. The evaluation process encompasses both the measurement and structural models, as outlined below. The model's measurement properties were evaluated for reliability and validity (Table 2). Each loading metric surpassed the 0.7 threshold, thereby signifying robust indicator reliability. The composite reliability was indicated by 'rho_c' values ranging between 0.7 and 1.0, which is consonant with established standards (Hair et al., 2019). In terms of convergent validity, the Average Variance Extracted (AVE) surpassed the minimum criterion of 0.5, confirming that the variable accounts for most of the variance in its indicators (Hair et al., 2019). We followed the procedure developed by Tehseen et al. (2017) to check for common method bias. An analysis indicated that the first unrotated factor accounted for 18.57% of the total variance, well below the conventional threshold of 50%, suggesting that CMB is unlikely to be a concern. Furthermore, following Tehseen et al. (2017), a full collinearity test was performed, and all variance inflation factor (VIF) values remained below 3.0, providing additional support that CMB is not substantially inflating the model estimates.

Table **2** Items’ validity and reliability

	Cronbach's alpha	rho_c	AVE
IO	0.837	0.889	0.608
DD	0.905	0.901	0.772
DS	0.888	0.905	0.695
RQ	0.891	0.907	0.885
TR	0.779	0.899	0.831
IR	0.901	0.932	0.731

CI	0.873		0.880	0.755

Note: IO-information overload; DD-decision difficulty; DS-decision satisfaction; RQ-recommendation quality; TR-trust; IR-information retrieval; CI-continuance intention

To evaluate the discriminant validity, a calculation of the heterotrait-monotrait (HTMT) ratio of correlations has been done (Table 3). The heterotrait-monotrait ratio must be below 0.85 (Henseler & Schuberth, 2020), and outputs indicate that all constructs met this condition.

Table **3** HTMT's ratios - test of discriminant validity

	IO	DD	DS	RQ	TR	IR	CI
IO	1						
DD	0.44	1					
DS	0.39	0.33	1				
RQ	0.28	0.31	0.23	1			
TR	0.20	0.55	0.75	0.44	1		
IR	0.49	0.47	0.29	0.41	0.38	1	
CI	0.47	0.28	0.44	0.39	0.29	0.22	1

Results

Firstly, a multicollinearity examination using VIF has been conducted (SmartPLS 4). VIF values remained below the upper limit (3.0), ruling out multicollinearity concerns. The model fit was assessed using standard PLS-SEM criteria (Hair et al., 2019). The standardized root mean square residual (SRMR) value was 0.053, indicating a good model fit (below the 0.08 threshold). The Normed Fit Index (NFI) was 0.914, and RMS_theta was 0.107, both within acceptable ranges. These values suggest that the model structure adequately represents the observed data and supports the reliability of the path estimates. Namely, perceived recommendation quality negatively affects decision difficulty and information overload (H1 and H2). Next, information overload negatively affects decision satisfaction and difficulty (H3 and H4). Interestingly, decision difficulty does not impact decision satisfaction (H5 disconfirmed), and decision satisfaction is strongly related to continuance intention to use GAI (H6) (Table 4).

Table **4** Results of the PLS analysis

Hypothesis	Path	β	t-value	p-value	Supported
H1	RQ → IO	-0.361 ***	5.874	<0.001	Yes
H2	RQ → DD	-0.312 ***	4.792	<0.001	Yes
H3	IO → DD	0.418 ***	6.013	<0.001	Yes
H4	IO → DD	-0.245 ***	4.163	<0.001	Yes
H5	DD → DS	0.054	0.894	0.372	No
H6	DS → CI	0.513 ***	7.052	<0.001	Yes

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

The PLS-MGA results (Table 5) highlight key differences in how trust and information retrieval skills moderate the impact of recommendation quality on information overload and decision difficulty. For trust, the low-trust group showed a significant effect of recommendation quality on reducing information overload (β = 0.21, p = 0.034) and decision difficulty (β = 0.19, p = 0.042). In contrast, the high-trust group exhibited non-significant effects on both outcomes, indicating that when users inherently trust AI recommendations, recommendation quality plays a smaller role in their decision-making process.

For information retrieval skills, the low-skill group significantly benefited from high-quality reviews to reduce information overload (β = 0.27, p = 0.013), while this effect was negligible for high-skill users (β = 0.01, p = 0.924). This supports the idea that users with weaker online search skills depend on well-structured AI recommendations, whereas skilled users can efficiently filter and assess information themselves. However, for decision difficulty, the moderation effect was weaker, with the low-skill group showing a marginal effect (β = 0.19, p = 0.072) and the high-skill group showing no significant influence (β = -0.09, p = 0.314), suggesting that skilled users navigate decision-making independently, regardless of recommendation quality.

Table **5** PLS-MGA results

Hypothesis	Group	Relationship	β Coefficient	Significance
H7a	Low Trust	RQ → IO	0.21*	p=0.034
H7b	Low Trust	RQ → DD	0.19*	p=0.042
H7a	High Trust	RQ → IO	0.03	n.s.
H7b	High Trust	RQ → DD	0.04	n.s.

H8a	Low IR Skill	RQ → IO	0.27*	p=0.013
H8b	Low IR Skill	RQ → DD	0.19†	p=0.072
H8a	High IR Skill	RQ → IO	0.01	n.s.
H8b	High IR Skill	RQ → DD	-0.09	n.s.

Note: S=Supported, NS=Not supported, **p≤0.01, *p≤0.05, † p < 0.10 (marginal significance) n.s. = not significant

Overall, these findings show that GAI recommendations are most valuable for users with low trust and weaker information retrieval skills, as they help mitigate overload and ease decision-making. However, as trust and skills improve, reliance on AI suggestions diminishes, emphasizing the need for customized AI interfaces that adapt to users' confidence and digital literacy levels.

In terms of R^2, the predictor variables posited in the model account for 49.6% of the variance in decision satisfaction and 56.6% in continuance intention to use GAI. According to Hair et al. (2019), the model has a substantial effect. Still, given the 50.4% and 43.4% residuals, the model's explanatory capacity could be enhanced by incorporating additional factors.

Discussion

The results confirm that higher perceived recommendation quality from GAI significantly reduces both information overload and decision difficulty. This finding indicates that concise, well-structured GAI recommendations lower cognitive strain and support more efficient decision-making rather than contributing to overload. For example, a comprehensive review detailing a destination's multiple features may help travelers understand its utility and prevent them, travelers, from seeking additional information elsewhere. Furthermore, information overload is related to perceived decision satisfaction and difficulty. This aligns with the notion that abundant information can result in a '*paralysis-by-analysis*' scenario (Mladenović et al., 2023), diminishing overall satisfaction. The concise, structured, and informative GAI recommendations (Dwivedi et al., 2024) may eventually do the opposite.

Intriguingly, the relationship between decision difficulty and decision satisfaction is not significant. Decision difficulty does not necessarily lead to lower satisfaction in the decision-making process. This diverges from early studies that found cognitive strain during decision-making generally reduces satisfaction (e.g., Hu & Krishen, 2019; Ali et al., 2023; Duarte Alonso et al., 2024). One possible explanation lies in GAI-curated content itself. Unlike traditional review-based decision-making, GAI delivers synthesized outputs that reduce the search task while still requiring cognitive effort to interpret, verify, or personalize results (Mladenović et al., 2024; Carvalho & Ivanov, 2024). In this context, users may experience decision difficulty not as a result of disorganized information, but rather as an outcome of deliberating among high-quality, context-rich alternatives. Hypothetically, difficulty may not signal frustration but rather careful consideration (Tassiello et al., 2024). This decoupling between difficulty and dissatisfaction may reflect automation-related trust effects (Ivanov & Webster, 2024), where users who trust the AI may feel that the process, while cognitively demanding, is still efficient. These possibilities suggest the presence of unmeasured moderators that condition the effect of difficulty on satisfaction (e.g., novelty of the tool, exposure to GAI, user expectations, etc). We encourage future research to explore such boundary conditions, particularly in emerging decision environments where traditional effort-satisfaction heuristics may not fully apply.

The robust connection between decision satisfaction and the intent to use GAI underlines the platform's capability to meet travelers' expectations and encourage repeated usage. Meanwhile, trust fortifies the link between perceived GAI recommendation quality and information overload - yet weakens the association with decision difficulty. Information retrieval skills also influence the relationship between recommendation quality and decision difficulty without affecting information overload. These factors suggest that the travelers' aptitude and confidence in navigating and interpreting GAI recommendations determine their future behavior.

General Discussion

Together, the two studies form a coherent mixed-method investigation in which qualitative exploration establishes conceptual depth and quantitative testing validates those insights across a larger sample. Study 1 attempts to decipher how travelers engage with GAI in planning their trips. Consequently, four significant topics emerged: awareness, verification, GAI being a starting point in planning, and concerns regarding information overload and implications on decision-making. While all four present promising prospects, the focus of study 2 is narrowed to verify the quality of GAI-generated recommendations and their implications on decision-making. Both studies indicate that travelers largely rely on GAI in travel planning. Central to the given research questions is that the higher perceived quality of artificial intelligence-based recommendations implies lower levels of information overload and decision difficulties, which increases decision satisfaction and GAI continuance intention.

Theoretical Implications

The following section clarifies not only how the study confirms existing theoretical models, but also how it extends and refines them. By combining S-O-R with CLT, this study distinguishes between intrinsic (task-driven), extraneous (presentation-driven), and germane (learning-driven) cognitive processes occurring when travelers use GAI. Study 1 qualitatively revealed how travelers struggle mainly with extraneous load (information overload and trust concerns), whereas Study 2 quantified how structured recommendations and user skills reduce that load and enhance germane engagement. This differentiation clarifies which type of cognitive load is most influenced by GAI design choices. By triangulating the phenomenon, the study reacts to vocal calls for more empirical studies in terms of GAI and its interplay within the travel sector (Ali et al., 2023; Dwivedi et al., 2023; Hsu et al., 2024; Jabeen et al., 2022; Kirshner, 2024). By answering the first research question, the results mapped out four research streams (level of awareness, GAI as a starting point in planning, need for verification, and major concerns) that need further exploration. Moreover, the present study ambitiously extends the model developed initially by Hu and Krishen (2019) in several ways. First, while their research focused on traditional eWOM and user-generated content, we adapt the framework to the novel context of generative AI (GAI)-generated recommendations, which introduce new cognitive and trust-related complexities. Second, beyond examining decision satisfaction, our study incorporates continuous intention to use GAI—a key behavioral outcome that reflects long-term user engagement. Third, we introduce and empirically test two critical moderators—trust in GAI and information retrieval skill—which capture individual-level variability in users' processing of AI-generated content. The inclusion of continuance intention further extends the theoretical model by linking satisfaction with post-adoption behaviors in the context of intelligent systems. This adds to existing decision and adoption models by showing that satisfaction with AI-generated recommendations is not solely driven by decision outcomes, but also by perceptions of the decision process itself—such as trust in system logic and perceived cognitive effort. This contributes to a multilayered understanding of how psychological mechanisms translate into ongoing technology use in AI-assisted environments.

Furthermore, the present study pioneers in mapping the moderating effects of trust and information retrieval skills on the relationship between GAI and information overload. The theoretical lens captures these factors' nuanced interplays and influences, thus providing a more detailed, holistic understanding of the dynamics that govern travelers' experiences and interactions with decision-support tools. The results facilitate a more prosperous understanding of how trust and competency in information retrieval can act as moderators, either amplifying or mitigating the experiences of information overload among travelers. To further deepen the explanatory power of this model, we integrated CLT, which allowed us to move beyond treating the 'organism' as a holistic black box. By doing so, we provided a more granular understanding of the internal cognitive processes. Specifically, information overload and decision difficulty mediate users' responses to AI-generated recommendations.

Our findings do not merely confirm the applicability of Information Overload theory in the context of GAI, but rather offer a conceptual refinement. Specifically, they suggest that overload in AI-mediated contexts may stem less from information volume and more from users' inability to trace the synthesis logic or source credibility behind presented outputs. This reframing contributes to the theory by expanding its scope to include a novel form of overload that is *algorithmically induced* rather than user-aggregated.

By extending the existing models and unearthing new moderating factors, we bolster the theoretical foundation, enabling it to be more reflective of the evolving landscapes of technology and travelers' engagement in decision-making processes.

Implications for Stakeholders and Travelers

The empirical results reveal several actionable and theoretically grounded implications for travel industry stakeholders and travelers. First, the study shows that higher recommendation quality significantly reduces information overload and decision difficulty. This implies that travel platforms should prioritize algorithmic transparency and structured content presentation. Service providers can translate this insight into practice by disclosing data sources and synthesis logic (e.g., “based on TripAdvisor and official tourism portals”). This builds trust and decreases users' cognitive burden—both validated moderators in our model. Secondly, results indicate that trust and information retrieval skills shape how users experience GAI recommendations. This indicates an important role for traveler education and interface design. Companies can integrate brief, embedded “prompt guides” or tutorial modes that enhance user literacy and empower low-skill users who benefit most from structured AI outputs. Such evidence-based design directly addresses cognitive asymmetries identified in this study.

Next, because decision satisfaction strongly predicts continuance intention, maintaining perceived reliability and enjoyment of interaction becomes a strategic priority. Rather than a generic “urge for improvement,” this recommendation reflects an empirically observed mechanism - satisfaction as a behavioral driver. Finally, our results suggest that travelers respond to GAI mainly through thinking and reasoning, not through emotions. In practice, this means travel companies should focus less on making AI tools sound “human” or emotional and more on helping users make clear and confident decisions. Features that explain how suggestions are generated, make choices easier to compare, and show that information is reliable will have a stronger effect on user satisfaction and continued use. This makes the technology both easier to trust and more useful in real travel planning.

These practical contributions should optimize the efficacy of GAI as a decision-support tool in travel planning, driving enhanced travelers' satisfaction and informed decision-making.

Limitations and Future Study Directions

As with any research, the present study needs some fixing. Although embracing a multi-method data collection approach, capping the needed ions was still impossible. Therefore, experimental design should be employed to triangulate the phenomenon comprehensively (Wu et al., 2024). The broad adoption of GAI is a recent phenomenon, implying that trust and information retrieval skills may be affected in due course. A longitudinal study would be beneficial to trace eventual deviations and changes over time in travelers' behavior (Maier et al., 2023). This study captured insights from two of the World's leading travel markets. As the perceptions may change due to cultural and socio-demographic variables, future studies should look at emerging travel markets (e.g., China, India, Brazil, etc.). The reported R^2 indicates that other factors may influence the travelers' decision satisfaction and continuance intentions. Therefore, future studies should look at various psychological elements that may assist in mapping this emerging domain (e.g., personality traits, cognitive load, risk-aversion, locus of control, social optimism, perceived transparency, etc.). Notably, scholars should empirically separate intrinsic, extraneous, and germane loads through experimental manipulations (e.g., varying task complexity or recommendation format) to test their distinct effects within the S-O-R pathway. A growing number of more specialized platforms and chatbots provide travel-related information (e.g., Expedia chatbot) (Ali et al., 2023; Gursoy et al., 2023). Future studies should capture these platforms and seek some deviations. Notably, the recent findings suggest that ChatGPT may suffer from intrinsic issues (e.g., hallucination, biases, misinformation, and inexplicability) (Kshetri et al., 2024) and user-related issues (e.g., over-reliance, copyright, ethics) (van Dis et al., 2023) - these present topics to be investigated within the travel sector.

Conclusions

The present study, anchored in the S-O-R model, explored the travel decision dynamics with a specific focus on GAI-generated recommendations. Through qualitative and quantitative study, we dived deeply into understanding the influences and outcomes of engaging with GAI recommendations. Consequently, we discovered four emerging research topics: level of awareness, the role of GAI as a starting point in planning, the need to verify artificial intelligence-based recommendations, and the major concerns. Central to our findings is that trust and retrieval skills significantly moderate the relationships between recommendation quality and information overload. We observed a pattern where enhanced GAI recommendation quality acts as a lever in reducing information overload and decision difficulties. This is a precursor to elevated decision satisfaction and amplifies the propensity for further GAI usage intentions.

Conclusively, research findings delineate a clear trajectory of influence, emphasizing that GAI recommendation quality alleviates information overload, facilitating more streamlined decision-making processes. This fosters an environment conducive to the continued and enhanced utilization of GAI tools like ChatGPT in travel planning. Considering robust findings, future research avenues are presented, inviting a deeper delve into further constructs that may unveil even more insights.

Data availability statement

Data is available on individual request.

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Appendix 1 - Study 2 - Scenario

Imagine you and a friend have recently purchased flights to go on a short holiday to Paris in France. Your trip will already be in two weeks; therefore, you need to decide on your itinerary, modes of transport, sights to visit, etc. To inform your decisions, you will use a novel conversational AI tool - ChatGPT4. Please initiate the ChatGPT session (https://chat.openai.com/chat) and follow the next steps.

Step 1: Please copy/paste this prompt to ChatGPT:
What is the best way to reach downtown Paris from the airport? Please consider the following facts: 1. I arrive at 11.30 PM 2. I use only public transport 3. The journey should not be longer than 1 hour

Step 2: Please copy/paste this prompt to ChatGPT:
Can you recommend a hotel in Paris's downtown area that meets most of the following criteria: 1. Costs less than 90 euros per night for two 2. Close to a metro station as I am arriving late at night 3. Offers late check-out 4. Has a rating of more than 4.5 on Tripadvisor and similar platforms 5. Is pet

friendly 6. One of the travellers is blind 7. Free cancellation option 8. Organises free city tours 9. Offers rooms with a view of the neighbouring park

Step 3: Please copy/paste this prompt to ChatGPT:
List at least five positive and negative online reviews for Hotel Le Petit Chomel.

Step 4: Please copy/paste this prompt to ChatGPT:
Can you recommend the best option for me to reach Barcelona from Paris if you consider the following criteria: 1. I prefer to travel early in the morning 2. The maximum cost should be at most 50 euros 3. I travel with a pet (cat) 4. I prefer reliable service providers with high ratings on review sites 5. I prefer a stopover (changing connections) to see places 6. The arrival time at Barcelona should be until 8 PM as I have dinner planned

Please take a moment to read and check the output ChatGPT provided, and do not close the ChatGPT window. We will ask you a couple of questions regarding the output on the following pages.

Appendix 2 - Study 2 - Utilized scales

Note: All scales used a 7-point Likert format (1 = strongly disagree, 7 = strongly agree). Items marked with "(R)" were reverse-coded so that higher values uniformly represent stronger perceptions of the construct.

Variable	Item	C	M	SD
Information overload	There was too much information provided by ChatGPT	IO1	3.82	0.912
	The information in ChatGPT completely flooded me	IO2	3.98	0.721
	There was so much information that I was unable to consider all of it	IO3	3.42	0.715
Decision Difficulty	It was not easy to decide on the details of my trip	DD1	4.01	0.821
	Based on ChatGPT's recommendation, I would need more time to decide on the details of my trip.	DD2	4.05	0.951

	Based on the recommendation provided by ChatGPT, I felt confident about which details (itinerary, modes of transport, sights to visit) of my trip to choose	DD3	3.78	1.02
Decision Satisfaction	I found the process of deciding on the details of my trip frustrating (R)	DS1	2.62	1.245
	I found the process of deciding on the details of my trip interesting	DS2	5.55	0.91
	I was satisfied with my experience of deciding which trip details to choose	DS3	5.22	0.875
Recommendation Quality	Recommendations provided by ChatGPT were understandable	RQ1	5.45	1.021
	The recommendations provided by ChatGPT were reliable.	RQ2	5.35	1.05
	Recommendations provided by ChatGPT were relevant to my purchase decision	RQ3	5.32	0.985
User trust	Recommendations provided by ChatGPT are reliable	TR1	5.10	1.03
	Recommendations provided by ChatGPT are trustworthy.	TR2	5.25	1.01
	Recommendations provided by ChatGPT are dependable.	TR3	5.20	0.99
GAI continuous intention	I want to continue using ChatGPT for travel-related queries	CI1	5.55	0.945
	I intend to continue using ChatGPT for travel queries rather than any alternative means	CI2	5.48	0.912
	I intend to continue using ChatGPT to process more travel-related queries in the future.	CI3	5.42	1.03
	I want to discontinue using chatbots for travel-related queries if I could.	CI4	2.15	1.315
Information retrieval	I can usually find information online that I need	IR1	5.41	0.855
	Searching for information online is easy for me	IR2	5.35	0.892
	I understand how to search for information online	IR3	5.28	0.978
	I can solve most problems by investing the necessary effort when seeking information online.	IR4	5.15	0.899
	I can select the relevant information from the results of an online search.	IR5	5.45	0.812
	I feel comfortable when searching for information online	IR6	5.32	0.94
	I enjoy searching for information online.	IR7	5.10	0.985
	Searching for information online can be frustrating	IR8	2.70	1.24

Note: M - Mean; SD - Standard Deviation; C – Code

Appendix 3 - Interview Guide: Travelers' Engagement with Generative Artificial Intelligence in Travel Planning

Introduction (Rapport and Consent)

Thank you for participating in this study. We're exploring how travelers like yourself use generative artificial intelligence tools—such as ChatGPT, Gemini, or similar platforms—during the travel planning process. We'll discuss how you engage with these tools, how they influence your travel decisions, and your future intentions. Your responses are confidential, and you're free to skip questions or stop at any time.

Section 1: Engagement with Generative AI

1. How did you first hear about or start using generative AI tools like ChatGPT or Gemini for travel planning?
2. What types of travel-related tasks do you typically use these tools for (e.g., destination ideas, hotel recommendations, itineraries)?
3. Can you walk me through a recent experience where you used a generative AI tool to plan part of a trip?
4. How would you compare the experience of using GenAI with traditional planning tools like Google Search or travel agents?
5. How confident are you in knowing how these tools work behind the scenes? Does that affect how you use them?

Section 2: Influence on Travel Decision-Making

6. Have any AI-generated recommendations influenced key decisions in your travel plans (e.g., where to go, where to stay, what to do)?
7. How do you assess the trustworthiness of the information you receive from these tools?
8. Do you take steps to verify the information they provide? If so, how?
9. Have you ever received inaccurate or outdated information from a GenAI tool? How did you handle it?
10. In your opinion, what are the main strengths and limitations of using GenAI for travel planning?

Section 3: Future Use Intentions

11. Do you intend to continue using generative AI tools for future travel planning? Why or why not?
12. What improvements or features would make you more confident in using these tools?
13. Are there specific types of travel decisions (e.g., time-sensitive bookings, local transport) you would or wouldn't trust AI to help with?
14. Would you recommend these tools to others? Why or why not?
15. Do you think AI will become an essential part of your travel planning in the future? Why?

Wrap-Up Questions

16. Is there anything else you'd like to share about your experience with generative artificial intelligence and travel planning?

Appendix 4 - Thematic Structure Linking Qualitative Insights to Main Themes on ChatGPT's Role in Travel Planning

Third-order themes	**Second-order themes**	**First-order themes**

Willingness influenced by awareness	**Awareness and Familiarity** “I’ve heard about ChatGPT, but I never felt confident using it until I saw my classmates try it. That made me curious.” **(P2 - Education, 18-21)** “If people don’t know what it can do, they will just ignore it. Awareness makes all the difference.” **(P6 - Healthcare, 31-35)**	**The Interplay Between ChatGPT Usage and Awareness Levels**
Variation in familiarity		
Majority familiar with ChatGPT		
Level of awareness matters		
Preference for Generative AI	**Attitudes and Preferences** “I prefer to use ChatGPT than Google sometimes. It’s faster and feels more tailored to what I am asking.” **(P5 - IT, 26-30)** “It sounds great, but can I trust it to give me accurate travel info? That’s where I hesitate, with all this hallucination, I am very sceptical of its promises.” **(P13 - Marketing, 22-25)**	
Reservations and concerns		
Uncertainty, lack of trust		
Confidence and trust		

Becoming accustomed Greater adoption expected Transparency and data privacy	**User Journey and Adoption** “At first it was strange, but the more I tried it, the more comfortable I got. Now I use it quite often.” **(P17 - Human Resources, 31-35)** “Give it a few years and everyone will be using it to plan trips. It’s too useful to ignore.” **(P12 - IT, 22-25)**	
Exciting and promising starting point Awareness of trends Curiosity to explore capabilities	**Early Engagement and Curiosity** “I wasn’t even planning a trip, but once I typed in a destination, it just kept giving me cool suggestions I hadn’t considered.” **(P3 - Marketing, 22-25)** “Everyone’s talking about using AI to plan stuff now. I wanted to see what the fuss was about.” **(P11 - Information Technology, 18-21)**	**Travel Planning Starts with Generative Artificial Intelligence**
Engaging and fun activity	**Experiential Use and Interaction**	

Experimenting	"It's surprisingly fun, it was like having a creative partner helping me dream up holiday ideas." **(P15 - Education, 26-30)**	
Interesting and relevant suggestions	"It recommended places that matched exactly what I was after." **(P6 - Healthcare, 31-35)**	
Sparks imagination		
Text-based		
Convenient and user-friendly	**Ease and Usefulness**	
Personalised and interactive experience	"I like how simple it is. You don't need to install anything or sign up. Just type and go." **(P1 - Healthcare, 18-21)**	
Enhances decision-making	"I used it to compare city options. It helped narrow things down quicker than browsing random websites." **(P18 - Sports Management, 31-35)**	
Exciting opportunities for travel planning		
Doubts about the accuracy and relevance of information	Information Accuracy and Reliability	**Concerns Regarding Generative Artificial Intelligence-Generated Recommendations**

Currency of data a significant concern	“Some of the hotel names it gave me didn’t even exist when I checked. How can I trust any other information its providing?” **(P7 - Manufacturing, 31-35**	
The accuracy of time-sensitive information	“The events listed were from last year. If it’s outdated, it defeats the whole purpose.” **(P10 - Healthcare, 18-21)**	
Comparisons with Google Gemini		
Concerns about information overload	Information Processing and Overload “It throws a lot of information at you all at once. You can imagine I had to scroll through so much just to find what I needed.” **(P8 - Healthcare, 36-40)**	
Challenges in filtering data		
Working around focused queries	“You really have to phrase your questions right. It’s not as smart if you're vague.” **(P13 - Marketing, 22-25)**	
Distractions and rigidity in the approach		
Expertise required for using prompts	Usability and User Skills “Unless you know how to ask it properly, you won’t get useful responses. It’s not intuitive for everyone.” **(P5 - Information Technology, 26-30)**	

Enhancing user control and guidance	“There should be tips or guided options. It feels too open-ended and that’s not helpful when you're in a rush.” **(P17 - Human Resources, 31-35)**	
Building user confidence		
Need for refinement and improvement	System Limitations and Transparency “It’s good, but you can tell it’s still learning. Sometimes the suggestions repeat or don’t make sense.” **(P2 - Education, 18-21)** “They should clearly say what it can and can’t do. I know there is a disclaimer at the bottom, but it should be well pronounced, so people don’t assume it’s always right.” **(P16 - Education, 31-35)**	
Providing up-to-date and verified information		
Clear communication about limitations and strengths		
Need to verify independently	Independent and Proactive Verification	

Proactive data verification	"I always double-check what ChatGPT suggests. I treat it like a draft, not the final answer." **(P6 - Healthcare, 31-35)**	Urge to Verify Generative Artificial Intelligence-Based Recommendations
Using search engines, TripAdvisor, and social media	"I wouldn't rely on it completely. I prefer to verify with official websites or people I trust." **(P11 - Information Technology, 18-21)**	
Human verification for reliability		
Caution in sole reliance	Caution and Skepticism "It's helpful, yes, but putting blind faith in it? Not a good idea for something as important as travel." **(P3 - Marketing, 22-25)**	
Acknowledgement of benefits and limitations	"It saves time but isn't always accurate. You have to know when to question its results." **(P15 - Education, 26-30)**	
Suggestion for a specialized tool for tourism	Opportunities for Tailored Innovation "Imagine if there was a ChatGPT version just for travel, it would know the right sites, flights, and trends." **(P9 - Healthcare, 18-21)**	

Interest in tailored tools for tourism	“There’s potential for a more refined tool. Something built with travellers in mind would make a difference.” **(P14 - Education, 26-30)**	
Continuous improvement		
Valuable starting point	Perceived Value Despite Limitations “It’s a good place to begin your search. It gives you direction even if not all the answers.” **(P4 - Healthcare, 26-30)** “It opens your eyes to places and tips you may not think to search for, though it is broad and useful.” **(P12 - Information Technology, 22-25)**	