

# From Search to Co-Planning: How Vietnamese Independent Travelers Use, Verify, And Act on Generative Ai Recommendations

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## **Abstract**

*Generative artificial intelligence (GenAI) is reshaping how travelers search for information and plan trips, yet much of the existing research still focuses on technology adoption, trust, or continuance intentions rather than on the process through which an AI recommendation is checked and translated into an actual decision. This study explores how Vietnamese independent travelers use GenAI in trip planning, how they evaluate and verify AI outputs, and how they decide whether to accept, modify, or reject those recommendations. An exploratory qualitative design was employed, involving 28 participants who had used GenAI to plan a specific independent trip. Data were collected through semi-structured in-depth interviews and analyzed using the Gioia methodology. The findings suggest that GenAI is shifting from a search tool toward a co-planning partner; however, its outputs are rarely received entirely passively. Travelers engage in selective verification depending on perceived risk, information volatility, and decision reversibility, while calibrating their trust according to the task and prior experience. Four ways of integrating AI recommendations into travel decisions were identified: direct acceptance, acceptance after verification, modified acceptance, and rejection. The study therefore proposes the concept of “verified co-planning” and develops a process model in which verification and trust calibration connect AI recommendations with action. These findings extend process-based understanding of GenAI in tourism and clarify how travelers preserve agency as AI becomes more deeply embedded in travel planning.*

**Keywords:** *generative AI; independent travelers; travel planning; information verification; trust; decision-making*

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## **I. Introduction**

Trip planning is a complex information-processing process in which travelers continuously search for, evaluate, and combine information about destinations, transportation, accommodation, sightseeing activities, food, budgets, and personal constraints. Research on online information search has shown that vacation planning is not a single act but consists of multiple “episodes” and “chapters” corresponding to specific problems to be solved, ranging from destination choice to hotels, restaurants, and on-site activities (Pan & Fesenmaier, 2006). At a broader level, Smallman and Moore (2010) argue that tourist decision-making should be understood as a process unfolding over time, shaped through sequences of actions and adjustments rather than merely as the outcome of a set of variables acting on a final choice.

The diffusion of generative artificial intelligence (GenAI), particularly conversational systems based on large language models such as ChatGPT, Gemini, and Claude, is changing the structure of this process. With conventional search engines, travelers typically enter keywords, visit multiple sources, filter information themselves, and assemble fragmented information into a plan. GenAI enables a different form of interaction: users can describe their needs in natural language, request a relatively complete itinerary, add constraints concerning budget, time, preferences, or travel companions, and then continue to provide feedback so that the system revises the proposed plan. The role of technology may therefore shift from supporting information retrieval to participating directly in the formation and refinement of travel plans.

The literature on GenAI in tourism has expanded rapidly in recent years. Reviewing 170 empirical studies published between 2022 and 2024, Li et al. (2025) identify three broad streams concerning antecedents of GenAI use, impacts and applications, and technical issues. They also note that tourism research tends to rely heavily on quantitative designs and theories borrowed from other fields. A more specialized review by Halibas et al. (2026), covering 39 empirical studies on GenAI in travel planning, similarly concludes that the field remains substantially shaped by cognition-utility models and technology-adoption questions.

At the empirical level, Ali et al. (2023) show that the relevance, reliability, usefulness, and perceived competence of personalized travel recommendations provided by ChatGPT are positively associated with

travelers' trust and behavioral intentions. In Vietnam, Pham et al. (2024), using a sample of 606 respondents recruited at high-traffic tourist destinations, report that perceived warmth, communication speed, and perceived competence of ChatGPT are associated with trust, attitudes, satisfaction, and continuance intentions for travel services. These studies establish the importance of trust and perceived system characteristics, but they primarily focus on the antecedents and consequences of AI use.

More recent studies have begun to adopt a more process-oriented perspective. Drawing on qualitative data from 104 people who had used large language models for travel advice, Kuhail et al. (2026) show that users value efficiency, clarity, and decision support while employing prompting strategies that range from highly specific instructions to exploratory and conversational interaction. Notably, large language models may be experienced as a "co-planner". Mladenović et al. (2026) likewise show that GenAI recommendations can reduce the risk of information overload but do not automatically simplify decision-making; trust and information-retrieval skills remain consequential.

These findings point to an important gap after an AI recommendation has been generated. Recommendations about itineraries, hotels, restaurants, transportation, or attractions do not automatically become actual decisions. Users must still judge whether the information is plausible, current, and appropriate to their needs; decide what needs to be checked; select verification sources; and only then accept, modify, or reject an option. The research gap therefore lies less in demonstrating that travelers use GenAI than in understanding the process through which AI outputs are evaluated, verified, and translated into action.

This gap is particularly relevant among independent travelers. Because they do not rely entirely on packaged tours, they directly search for information, build itineraries, select services, and bear the consequences of final decisions. They simultaneously act as the person delegating tasks to AI, the evaluator of its recommendations, and the decision-maker who determines which source deserves greater authority in a given situation. Studying independent travelers therefore allows closer observation of how GenAI is integrated into an information ecosystem that includes search engines, digital maps, online travel agencies (OTAs), social media, official websites, and interpersonal sources.

Accordingly, this study explores how Vietnamese independent travelers use GenAI during trip planning, how they evaluate and verify information and recommendations generated by AI, and how those recommendations are accepted, modified, or rejected. Three research questions guide the study: RQ1, how do Vietnamese independent travelers use GenAI in the trip-planning process? RQ2, how do they evaluate and verify the information and recommendations provided by GenAI? RQ3, how do they decide whether to accept, modify, or reject GenAI recommendations in the course of travel decision-making?

The study makes three connected contributions. First, it shifts attention from technology adoption to actual use processes, thereby explaining how AI is embedded in sequences of planning actions. Second, it places verification at the center of the relationship between AI recommendations and decisions, enabling closer examination of how users distribute trust across AI and other information sources. Third, it examines user agency through the ways travelers delegate tasks, limit the scope of reliance on AI, and ultimately accept, revise, or veto AI outputs. On this basis, the study advances the notion of "verified co-planning", in which AI participates deeply in option generation while final decision authority is maintained through human judgment and verification.

## **II. Literature review and theoretical background**

### **2.1. Generative AI in travel planning**

GenAI differs from conventional search engines in its ability to maintain dialogue, integrate multiple constraints, and generate new options rather than merely return lists of links. In trip planning, these features allow users to move from gathering fragmented pieces of information toward asking a system to structure the problem, generate an itinerary, compare alternatives, and revise options in response to feedback. Li et al. (2025) show that GenAI research in tourism is developing rapidly, with substantial attention devoted to adoption antecedents and technological impacts. Halibas et al. (2026) likewise characterize the travel-planning literature as fragmented and constrained by repeated reliance on technology-adoption theories.

Kuhail et al. (2026) provide qualitative evidence that users employ large language models not only to complete discrete tasks but also in exploratory, iterative, and collaborative ways, enabling AI to function as a co-planner. Co-planning, however, does not necessarily imply transferring decision authority. An AI-generated option must still be situated within the user's resources, experience, preferences, and perceived risk. Research on GenAI in tourism therefore needs to move beyond asking whether AI is useful and examine what users do with recommendations after they appear.

### **2.2. Information search and a process perspective on independent travelers' decision-making**

Pan and Fesenmaier (2006) show that vacation information search has a dynamic structure composed of multiple episodes and chapters linked to problems that need to be solved. This perspective implies that travel

planning is adaptive: when new information emerges, users redefine the issue under consideration and switch information sources. At the theoretical level, Smallman and Moore (2010) extend this argument by distinguishing variable-based from process-based research. They argue that relationships among variables alone are insufficient to explain how decisions emerge; instead, researchers need to follow the sequences of actions and events through which choices are progressively formed.

In a GenAI environment, a process perspective becomes particularly useful. An initial need can be decomposed into multiple tasks: generating ideas, creating an itinerary, adjusting a budget, reducing travel time, changing locations, or resolving new constraints. AI can assume a larger share of exploration and synthesis, while users shift toward feedback, refinement, and verification. Mladenović et al. (2026) show that AI can reduce information overload without eliminating the need for information processing. This suggests a redistribution of cognitive work between humans and technology rather than a complete substitution of human search.

### **2.3. Information quality, verification, and trust calibration**

The ability to produce fluent and personalized responses is one of GenAI's main advantages, but a plausible-sounding answer does not guarantee that information is accurate, current, or contextually appropriate. Evaluating 4,800 tourism-related responses from three GenAI platforms, Dong et al. (2026) show that information quality varies by platform, prompting strategy, and question type. They frame this as conditional trustworthiness, emphasizing that AI reliability is not a fixed property. Won and Lee (2026) similarly show that perceived information quality and users' AI literacy are related to continued use of AI for travel planning, with critical evaluation skills helping users manage lower-quality outputs.

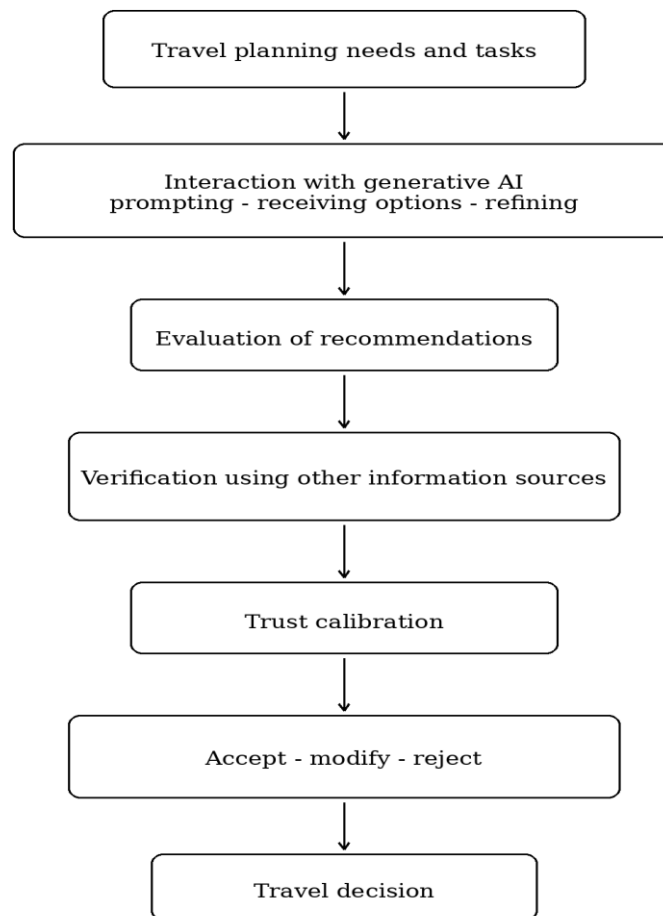
From a human-AI interaction perspective, the goal is not to maximize trust in AI. Mehrotra et al. (2024) show that concepts such as appropriate trust, calibrated trust, and appropriate reliance all emphasize alignment between reliance and the system's actual capabilities. Overtrust can lead users to accept erroneous outputs, whereas undertrust can cause them to forgo useful assistance. Applied to tourism, the same individual may rely heavily on AI for a broad itinerary but much less for fares, transportation schedules, or entry regulations. Trust is therefore better understood as something updated according to the task, prior experience, and verification outcomes.

In this study, verification refers to the process of seeking additional evidence or cross-checking an AI recommendation against another source to assess its accuracy, currency, or personal suitability before acting. Recent research has begun to document cross-checking behaviors and the role of information-retrieval skills (Kuhail et al., 2026; Mladenović et al., 2026), but it provides limited explanation of what users verify, what triggers verification, which sources they select, and how verification changes subsequent decisions. Verification is therefore treated here as a behavioral mechanism that may connect AI recommendations with actual decisions.

### **2.4. Delegation to AI and the guiding conceptual framework**

Using AI is not equivalent to delegating the entire decision to AI. Roy et al. (2026) distinguish three levels of decision delegation in travel planning: identifying attributes, forming a consideration set, and participating in the final decision. Their findings indicate that reliability and accountability are important signals shaping willingness to delegate. This distinction helps explain why users may delegate substantial cognitive work to AI while retaining the right to confirm or veto an option before acting.

**Figure 1. Guiding conceptual framework**



*(Source: Authors' conceptualization informed by Pan and Fesenmaier (2006), Smallman and Moore (2010), Mehrotra et al. (2024), and Roy et al. (2026))*

Building on two foundations - a process perspective on tourist decision-making and a trust-calibration perspective in human-AI interaction - the study employs a guiding conceptual framework comprising planning needs, interaction and co-planning with AI, evaluation of recommendations, verification through other sources, trust calibration, responses to recommendations, and travel decisions. The framework is not a causal model and is not used to formulate hypotheses; it serves only to sensitize the analysis. The actual sequence, mechanisms, and feedback loops are developed from the qualitative data.

### **III. Method**

#### **3.1. Research design**

The study used an exploratory qualitative design to reconstruct how Vietnamese independent travelers use, evaluate, verify, and act on GenAI recommendations. A qualitative approach was appropriate because the aim was not to estimate relationships among variables, but to clarify sequences, mechanisms, and the meanings users attach to decisions in specific experiences. The analysis centered on a concrete travel-planning episode in which participants had used GenAI, thereby reducing speculative responses and encouraging reconstruction of the sequence from the emergence of a need to the final decision.

#### **3.2. Participants and data collection**

Participants were selected using criterion-based purposive sampling combined with maximum variation. Eligibility required participants to be Vietnamese citizens aged 18 or older, to have completed at least one independent trip within the previous 12 months, to have directly participated in planning or revising the trip, and to have actually used at least one GenAI tool - such as ChatGPT, Gemini, Claude, Copilot, or an equivalent system - for that trip. The final sample comprised 28 participants and was varied in age, gender, travel format, domestic versus international destination, travel experience, and level of AI proficiency. Sample size was guided

by the information-power principle proposed by Malterud et al. (2016), according to which qualitative sample adequacy depends on the specificity of the research aim, the specificity of the sample, dialogue quality, and the analytic strategy.

Data were collected through semi-structured in-depth interviews lasting approximately 45-60 minutes. Participants were asked to focus on one specific trip and describe in sequence how AI was used, how its outputs were evaluated and verified, and why particular recommendations were accepted, modified, or rejected. When participants voluntarily retained relevant material, selected chat excerpts or prompts were used as memory aids; identifying information was removed. Interviews were audio-recorded with consent, transcribed verbatim, and anonymized using participant codes P01-P28.

### **3.3. Data analysis**

Data were analyzed using the Gioia methodology, a systematic approach to developing concepts and theory from qualitative data (Gioia et al., 2013). Analysis proceeded alongside data collection. In the first cycle, transcripts were coded into first-order concepts that remained close to participants' language. In the next cycle, similar concepts were compared and grouped into more abstract second-order themes. Finally, second-order themes were integrated into aggregate dimensions. Constant comparison across cases was used to identify both dominant patterns and discrepant cases. Once the data structure stabilized, the analysis examined sequences and relationships among aggregate dimensions to build a process model explaining how AI recommendations move from technological outputs to travelers' decisions.

### **3.4. Research quality and ethics**

Analytic rigor was strengthened by anchoring interviews in concrete episodes, maintaining coding records and analytic memos, deliberately examining cases that contradicted dominant patterns, and presenting illustrative quotations for key themes. The reporting of the qualitative methods was informed by the Consolidated Criteria for Reporting Qualitative Research (COREQ) (Tong et al., 2007). Participation was voluntary and confidentiality and anonymity were maintained; participants could decline to answer any question or stop the interview. Identifying information, financial details, booking codes, and private content unrelated to the study were excluded from the analytic dataset.

## **IV. Findings**

### **4.1. Participant characteristics and data structure**

The sample comprised 28 Vietnamese independent travelers aged 20-49, including 17 women and 11 men. Fifteen participants recalled a domestic trip and 13 an international trip. Travel-party configurations included solo travel, travel with friends, travel as a couple, and family travel. ChatGPT was the most commonly used tool, although some participants also used Gemini, Copilot, Perplexity, or other GenAI tools to compare or supplement information. Because participants could use more than one system, tool-use counts exceed the number of participants.

**Table 1.** Participant characteristics

| <b>Characteristic</b>  | <b>Distribution</b> |
|------------------------|---------------------|
| Number of participants | 28                  |
| Age                    | 20-49 years         |
| Gender                 | 17 women; 11 men    |
| Domestic trips         | 15                  |
| International trips    | 13                  |
| Solo travel            | 7                   |
| Travel with friends    | 8                   |
| Travel as a couple     | 8                   |
| Family travel          | 5                   |
| Used ChatGPT           | 25                  |
| Used Gemini            | 10                  |
| Used other GenAI tools | 7                   |

(Source: Authors' interview data)

The Gioia analysis generated four core aggregate dimensions: co-planning with GenAI, selective verification, trust calibration, and the integration of AI recommendations into travel decisions. In addition, a cross-cutting learning mechanism captured how prior outcomes recalibrated the scope of AI delegation in subsequent use. Table 2 presents the progression from first-order concepts to second-order themes and aggregate dimensions.

**Table 2.** Gioia data structure

| First-order concepts                                                                            | Second-order themes               | Aggregate dimensions                                  |
|-------------------------------------------------------------------------------------------------|-----------------------------------|-------------------------------------------------------|
| Asking for ideas; requesting itineraries; asking AI to integrate multiple conditions            | Delegating planning tasks         | Co-planning with generative AI                        |
| Rephrasing prompts; adding constraints; requesting alternatives; iterative refinement           | Interactive refinement of plans   | Co-planning with generative AI                        |
| Checking Maps, OTAs, social media, official websites; asking acquaintances                      | Multi-source verification         | Selective verification                                |
| Checking more carefully when information concerns times, prices, tickets, visas, or major costs | Risk-contingent verification      | Selective verification                                |
| Trusting AI for overall structure but not for prices or opening times                           | Task-contingent trust             | Trust calibration                                     |
| Increasing trust after good outcomes; decreasing trust after errors                             | Updating trust through experience | Trust calibration                                     |
| Using as given; checking then using; modifying before use; rejecting entirely                   | Responses to recommendations      | Integrating recommendations into decisions            |
| Knowing which tasks can be delegated and which sources must be checked                          | Learning and boundary setting     | Post-experience learning and delegation recalibration |

(Source: Developed from the interview data using the Gioia methodology)

#### **4.2. From information search to co-planning with generative AI**

GenAI was initially used as a starting point for narrowing the search space. Instead of opening many websites and synthesizing information from scratch, participants often asked AI to create an initial framework and then checked only what seemed necessary. P04 explained:

*"I used to spend half a day opening more than ten tabs just to see which places were worth visiting. This time I asked ChatGPT first and let it build a framework. Then I only checked the places that really needed checking". (P04)*

AI's role subsequently expanded from suggesting options to organizing travel constraints. Participants added the number of days, budget, age of travel companions, preferences, walking capacity, and must-see places. P11 noted:

*"At first I only asked for a four-day itinerary. Then I added that I was traveling with my mother, that she could not walk very much, and asked it to reduce the number of places each day. It revised the plan quite reasonably". (P11)*

Most participants did not accept the first proposal. They rephrased prompts, removed locations, added new requirements, and requested alternative plans. P08 described the first version as a "draft" and reported revising it through four or five rounds before the itinerary came close to what was wanted. P23 directly contrasted the experience with Google:

*"Google gives me results and I have to put them together myself. With ChatGPT, I tell it what is not quite right and it puts things together again. It feels more like discussing the trip with someone else". (P23)*

A coherent itinerary, however, was not necessarily a feasible one. P15 emphasized that AI may "think in terms of distance" without fully accounting for fatigue, waiting time, meals, or mood. The gap between the internal logic of an itinerary and its practical feasibility became an important reason why users continued to evaluate and verify recommendations rather than move directly from an AI output to action.

#### **4.3. Selective verification in the tourism information ecosystem**

Participants did not treat AI as a single authoritative source. After receiving an option, they turned to Google Maps, OTAs, social media, official websites, or acquaintances to confirm it. Verification, however, was not equally intensive across recommendations. Three factors consistently shaped the level of checking: information volatility, the consequences of an error, and the user's familiarity with the issue under consideration.

*“If it says I should spend three days in Kyoto, I can take that as a useful suggestion. But if it tells me the last train is at 10:20 p.m., I definitely have to check”. (P02)*

*“If a restaurant recommendation is wrong, it is not too serious - I can choose somewhere else. But if the visa rules, flight time, or train ticket are wrong, I cannot just trust ChatGPT”. (P17)*

These accounts show that verification is closely linked to consequences and decision reversibility. A low-risk suggestion could be used immediately or checked only superficially, whereas decisions involving bookings, transport schedules, substantial expenditure, or official rules had a higher verification threshold. Verification sources also varied by information type. Google Maps was prioritized for location and travel time; OTAs for prices and accommodation; social media for images and lived experience; and official websites for visas, regulations, and operating schedules.

*“ChatGPT helps me know what I should look for, but for visa information I go to the official authority’s website. I do not want to rely on important information from an answer when I do not know how up to date it is”. (P06)*

Verification also served two distinct functions. One was to confirm factual accuracy; the other was to assess experiential fit. P21 explained that a destination could be described accurately by AI yet still be rejected after watching real videos because it did not match personal preferences. Verification therefore answered not only “Is the AI correct?” but also “Is this recommendation right for me?”

**Table 3.** Verification patterns by information type and perceived risk

| Information / decision type                    | Typical verification level | Common verification sources        | Primary rationale                                     |
|------------------------------------------------|----------------------------|------------------------------------|-------------------------------------------------------|
| Destination ideas, food, optional activities   | Low                        | Quick search; social media         | Low risk and easy to change                           |
| Itinerary structure, distance, travel time     | Moderate                   | Google Maps; destination websites  | Need to assess practical feasibility                  |
| Accommodation, service prices, bookings        | Moderate to high           | OTAs; provider websites            | Cost implications and cancellation/change constraints |
| Train times, flights, visas, entry regulations | High                       | Official sources                   | Time-sensitive information and high cost of error     |
| Experiential fit                               | Situation-dependent        | TikTok, YouTube, Facebook, reviews | Assessing fit with personal preferences               |

*(Source: Authors’ analysis of interview data)*

An important consequence was that GenAI did not eliminate external search; it changed its structure. P13 described AI as narrowing the field to “five places,” after which the user needed to check only those five options rather than filter dozens of alternatives. Search therefore shifted from broad exploration toward targeted verification.

#### **4.4. Task-contingent trust and experience-based calibration**

Trust in AI did not appear as a stable system-level attitude. The same participant could rely on AI for one task while distrusting it for another. P10 explained:

*“For building an itinerary, I trust it quite a lot because it is fast and gives a good overall view. But for prices, I almost do not trust it because the prices have been wrong several times”. (P10)*

Trust was also updated through experience. When AI repeatedly produced useful options, participants reduced checking for similar tasks. In contrast, a serious error could reset the trust threshold. P07 recalled that after AI gave outdated information about a transport route, all subsequent transport-related information was checked. The error did not lead to abandoning AI; instead, it narrowed the scope of delegation.

The data also revealed a personalization paradox. When a response reflected a traveler’s budget, the age of companions, preferences, and desired pace, users were more likely to feel that the system “understood” them, which increased perceived trustworthiness. P18 described this experience:

*“When I told it very specifically that I was traveling with children, wanted a lunch break, and did not want to go too far, the answer matched what I wanted very well. At that point it was easier to trust because it felt like it understood me”. (P18)*

Personalization, however, did not guarantee factual accuracy. P03 encountered a highly persuasive itinerary that included a site closed on the intended day. “What fits me” and “what is factually correct” therefore constituted two different layers of evaluation. Through repeated use, participants developed bounded trust: they learned what AI was good at, what it should be used only to orient them toward, and what had to be verified through another source.

#### **4.5. Accepting, modifying, and rejecting generative AI recommendations**

Four primary response patterns were identified. Direct acceptance typically occurred when risk was low and the decision was easy to reverse. Acceptance after verification was common for decisions with clear implementation consequences, such as choosing an accommodation area or a transport option. Modified acceptance occurred when the AI-generated structure was useful but needed fewer attractions, a different order, or another mode of transport. Rejection occurred when a recommendation conflicted with a more authoritative source, lacked feasibility, or did not fit the desired travel experience.

*“AI usually tries to put too many places into one day. I still keep the overall structure, but I cut about one-third of it before it becomes realistic”. (P14)*

*“It tends to recommend the most famous places. I travel independently because I want to find places that are less crowded, so I often use its suggestions as reference points and then search in the opposite direction for something else”. (P22)*

**Table 4.** Responses to generative AI recommendations

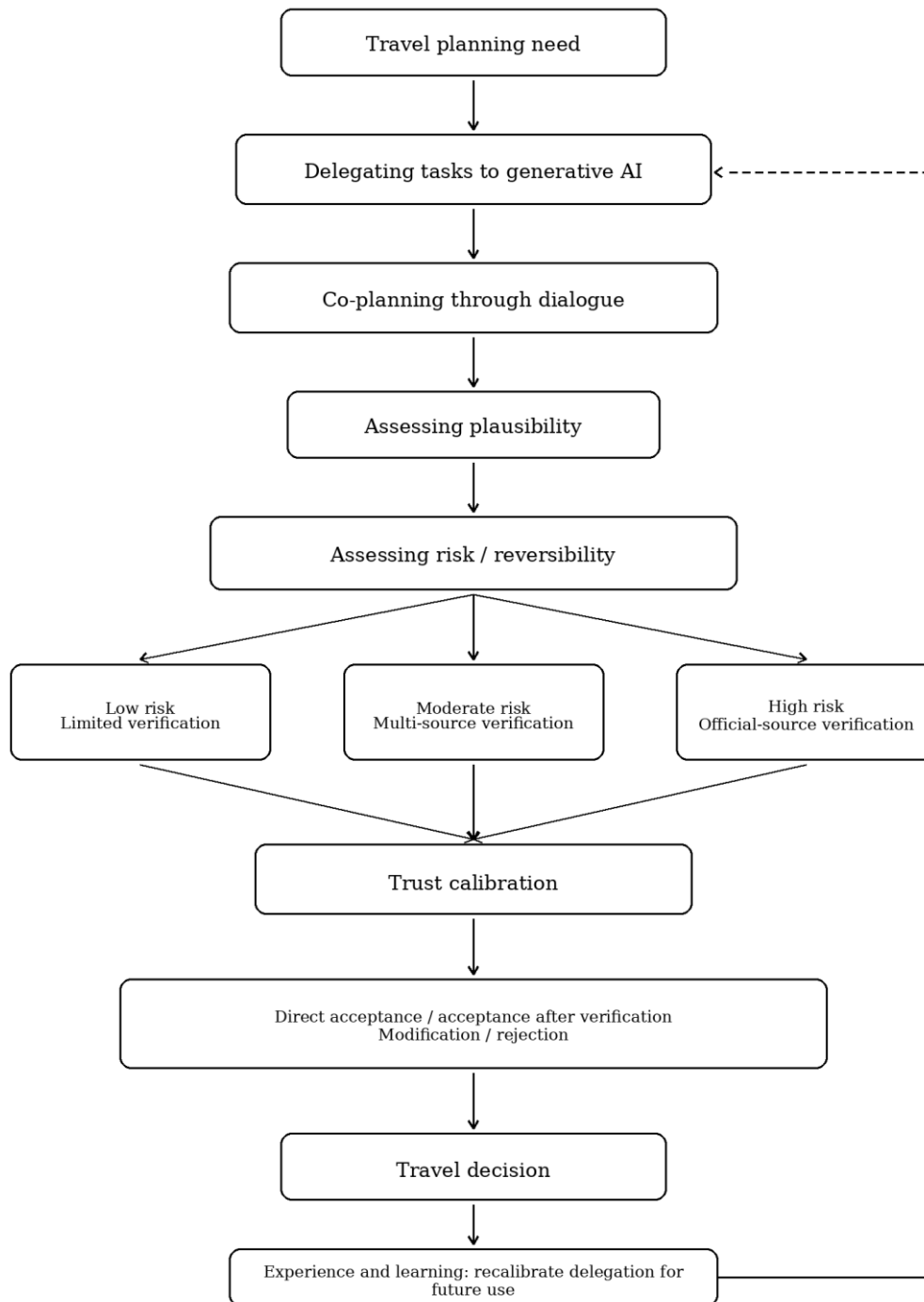
| <b>Response</b>               | <b>Typical condition</b>                                          | <b>Role of verification</b>                        |
|-------------------------------|-------------------------------------------------------------------|----------------------------------------------------|
| Direct acceptance             | Low risk, easy to change, mainly organizational                   | Low or none                                        |
| Acceptance after verification | Affects cost, time, or practical feasibility                      | High; external sources confirm the recommendation  |
| Modified acceptance           | Useful idea but not fully suited to the situation                 | Verification combined with personal experience     |
| Rejection                     | Incorrect, outdated, infeasible, or inconsistent with preferences | Another source or personal experience overrides AI |

*(Source: Authors' analysis of interview data)*

These responses indicate that factual accuracy is only one component of the decision. Perceived risk, reversibility, fit with the desired experience, and the authority of the verification source jointly determine whether an AI recommendation is translated into action.

#### 4.6. Process model: from generative AI recommendations to travel decisions

**Figure 2.** Process model of using, verifying, and acting on generative AI recommendations



*(Source: Developed by the authors from the empirical findings)*

Taken together, the themes show that planning with GenAI is not a linear sequence from “asking” to “following”. The process contains steps that can recur: the emergence of a planning need; delegation of a task to AI; co-planning through dialogue; evaluation of plausibility; assessment of risk; selection of verification intensity and source; trust calibration; response to the recommendation; and, finally, a travel decision. Experience with the resulting outcome then feeds back into how users delegate and verify tasks in subsequent use.

Within this model, perceived risk operates as a branching mechanism for verification. Low-risk situations lead to limited checking; moderate risk often triggers multi-source verification; high-risk or time-sensitive information leads users to prioritize official sources. Two mechanisms lie at the center of the process:

verification and trust calibration. Verification provides evidence for evaluating AI outputs, whereas trust calibration determines the extent to which an output is allowed to influence action

## **5. Discussion**

### **5.1. From co-planning to verified co-planning**

The findings reinforce Kuhail et al.'s (2026) observation that large language models can be experienced as co-planners. The present study extends this idea by showing that co-planning does not end when AI produces an itinerary. Outputs still pass through user evaluation, cross-checking, and judgment. The human-AI relationship is therefore more accurately described as "verified co-planning": AI participates deeply in generating and structuring options but does not become the final source of authority.

This interpretation also helps explain Mladenović et al.'s (2026) finding that AI can reduce information overload without necessarily simplifying decision-making. AI lowers the cost of initial search but creates a new cognitive task: deciding which part of the output is trustworthy, which part needs checking, and which source has greater authority. AI therefore does not eliminate information processing; rather, it redistributes cognitive work from broad search and synthesis toward targeted evaluation and verification.

### **5.2. Selective verification and the role of perceived risk**

An important contribution of the study is the identification of selective verification. Users did not check every output with the same intensity. Instead, they appeared to conduct an implicit assessment of the cost of error and the reversibility of the decision. When an error was inexpensive and easy to correct, verification decreased; when it involved money, timing, or regulations, verification intensified. This mechanism adds a user-side perspective to Dong et al.'s (2026) concept of conditional trustworthiness: if AI quality is task-dependent, users' verification behavior is likewise task-dependent.

The findings also extend understanding of AI literacy. Won and Lee (2026) emphasize the role of AI literacy in critically evaluating and refining outputs. The present data suggest that, in tourism, competence also includes recognizing when to leave the AI environment, assessing the consequences of error, and selecting the appropriate verification source. A traveler may be proficient at prompting yet still be poorly equipped for a high-risk travel task if they do not know where to verify train schedules, fares, or visa requirements.

### **5.3. Task-contingent trust and the personalization paradox**

The findings suggest that trust should not be treated as a single evaluation of the system as a whole. Users formed task-specific "zones of trust": they could rely on AI to create an overall framework while distrusting real-time prices or schedules. This interpretation is consistent with appropriate-trust thinking in Mehrotra et al. (2024), according to which trust and reliance should correspond to a system's actual capability. The contribution here is that trust is updated through concrete experiences and leads to adjustments in delegation boundaries rather than simply to continued or discontinued use.

The personalization paradox deserves particular attention. Recommendations that closely reflected users' preferences and constraints produced a stronger sense that "the AI understands me," yet perceived fit could be mistaken for factual accuracy. This extends prior work documenting positive relationships between personalized recommendations and trust (Ali et al., 2023). Personalization can simultaneously increase usefulness and weaken the motivation to verify. Research on trust in GenAI may therefore benefit from distinguishing at least three layers: perceived fit, perceived reliability, and behavioral reliance on a recommendation.

### **5.4. Traveler agency and the reconfiguration of the tourism information ecosystem**

GenAI did not make Google Maps, OTAs, social media, or official sources disappear. Instead, their functions changed. AI increasingly served exploration, synthesis, and option generation, while other sources shifted toward confirmation, updating, specialized checking, and evidence from lived experience. This pattern represents a reconfiguration of the tourism information ecosystem rather than simple substitution, and it helps explain why travelers may search less while searching more purposefully.

The four response patterns also demonstrate that traveler agency remains substantial. The findings are consistent with Roy et al. (2026), who distinguish levels of decision delegation to AI, but add an important distinction: delegating planning tasks is not equivalent to delegating final decision authority. Users can outsource substantial cognitive work to AI while retaining the right to confirm, revise, or veto its outputs. Co-planning is therefore a form of bounded delegation whose scope is dynamically calibrated according to task, perceived risk, and experience.

## **VI. Contributions and implications**

### **6.1. Theoretical contributions**

The study contributes to the literature on GenAI and tourism in three ways. First, it extends the understanding of AI as a co-planner through the concept of “verified co-planning”, emphasizing that AI may participate deeply in option formation while its outputs remain subject to human judgment. Second, it positions selective verification as a central mechanism connecting AI recommendations with actual decisions and highlights perceived risk and decision reversibility as conditions that trigger verification. Third, it shifts the conceptualization of trust from a general evaluation of AI toward task-contingent trust that is recalibrated through experience, explaining why the same user may rely heavily on AI for one task and hardly at all for another.

### **6.2. Practical implications**

For AI developers and travel platforms, the findings suggest that system value lies not only in generating attractive itineraries but also in supporting verification. Systems should distinguish time-sensitive information, regulatory information, and decisions with high consequences; where appropriate, they should direct users to official sources or display warnings about data currency. Source attribution, timestamps, and prompts to “verify before acting” may reduce the risk that users mistake response fluency for factual accuracy.

For tourism businesses and destination-management organizations, maintaining structured, current, and easily accessible official information becomes even more important in an AI-mediated environment. If travelers use AI as a starting point but return to official sources for confirmation, destination websites, transport operators, immigration authorities, and service providers become a high-value verification layer. Digital communication strategies should also recognize that social media, maps, and OTAs increasingly function not only as discovery channels but as confirmation channels after AI has narrowed the consideration set.

For travelers, competent GenAI use should be understood more broadly than prompt-writing skill. Responsible practice includes recognizing which information is likely to become outdated, considering the consequences of incorrect information, verifying high-risk decisions through an appropriate source, and retaining the authority to modify or reject a recommendation. Effective use of AI therefore requires both conversational skill within the system and information-evaluation skill outside it.

## **VII. Conclusion, limitations, and future research**

This study suggests that GenAI is changing independent travel planning not only by shortening information search but also by redistributing roles among travelers, AI, and other information sources. Travelers use AI to generate and refine options, yet they do not fully transfer decision authority to the system. They verify selectively according to risk, calibrate trust by task and experience, and then accept, modify, or reject AI outputs. The concept of “verified co-planning” therefore emphasizes a collaborative relationship in which the value of AI depends jointly on output quality and users’ capacity for judgment.

The study has several limitations. A qualitative design with 28 participants enables process depth but is not intended to statistically represent all Vietnamese travelers. The sample spans multiple trip types and AI systems, so it does not fully isolate differences between domestic and international travel or among platforms. Interview data rely primarily on retrospective accounts and may therefore be affected by recall bias. In addition, the rapid development of GenAI means that output quality, access to real-time data, and source-attribution mechanisms may change quickly over time.

Future research could systematically compare travelers by AI experience, trip type, or risk level; use digital diaries, chat histories, or direct observation to follow decision processes over time; and quantitatively test mechanisms suggested by the qualitative findings, particularly the roles of perceived risk, decision reversibility, verification, and task-contingent trust. Another promising direction is to examine how AI systems with real-time data access or direct integration with booking platforms shift the boundary between planning support and delegation of decision authority.

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