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Intention to Use Generative Artificial Intelligence for Hotel Selection Among Consumers: An Explanatory Sequential Investigation

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Abstract
Hotel choice is highly information-intensive, and generative AI (GAI) increasingly aggregates dispersed hotel data into personalized, conversational recommendations that reduce search and verification effort. Against this backdrop, this study examines consumers' intention to use such tools, adopting an explanatory sequential mixed-methods design and an integrated Technology Acceptance Model-Theory of Planned Behavior (TAM-TPB) framework. The quantitative phase comprises an online survey in China (N = 529; recruited and randomly distributed via a national panel) analyzed with maximum-likelihood structural equation modeling (SEM). The qualitative phase involves six follow-up interviews to interpret results. Findings show that perceived ease of use (PEU) increases perceived usefulness (PU) and attitude (ATT), while ATT and subjective norm (SN) strongly predict intention to use GAI; by contrast, perceived behavioral control (PBC) is non-significant. Interviews clarify a boundary condition: because conversational GAI is perceived as low in complexity, users prioritize information credibility and effort savings over feelings of control, which attenuates PBC's role-especially among experienced travelers who rely on effective existing routines. The study contributes to tourism research by specifying how classic adoption beliefs operate in GAI-assisted hotel choice and by delineating when PBC contributes little to intention. Practical implications are stakeholder-specific: for OTAs/AI vendors (product/data owners), design for verification-effort reduction and provenance/credibility transparency; for hotel managers/marketers, ensure accurate structured property data and activate credible social proof to reinforce ATT and SN. These insights inform the design and deployment of AI-assisted decision tools that help travelers choose hotels faster, with warranted confidence, in real tourism settings.

Key Words: generative Artificial Intelligence (GAI), hotel selection, tourist decision-making, Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), consumer behavior, mixed-method research, AI adoption in tourist consumption, intention to adopt GAI

JEL Classification: L83, D91, Z33

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1. Introduction

Generative artificial intelligence (GAI) is rapidly diffusing across tourism and hospitality (Alsaad, 2023; Yin et al., 2023), reshaping how travelers search, evaluate, and decide (e.g., conversational trip planning, itinerary curation, and property matching). This transformation is consistent with broader economic perspectives showing that long-term competitiveness depends primarily on continuous innovation and adaptive responses to rapidly evolving conditions (Vlach, 2025). In hotel selection specifically, GAI differs from earlier digital tools by producing context-aware, synthesized outputs (rather than static lists), enabling interactive refinement and preference learning during the decision process(Alsharif et al., 2024; Martin et al., 2023; Menon & Shilpa, 2023; Santos & Gonçalve, 2022; Wu et al., 2023; Strapchuk et al., 2025). Despite these advantages, the diffusion of this technology ultimately depends on consumer adoption (Lin et al., 2024). Therefore, our study focuses on a target behavior: consumers' intention to use GAI to assist hotel selection.

Hotels function as both core service providers and platformed coordinators-they aggregate demand generated by transportation and attractions, convert that demand into on-site experiences including lodging, F&B, and ancillary services (Casaló et al., 2010; Gao & Bi, 2021). Hotel selection sits at the intersection of high information complexity (prices, locations, amenities, reviews, policies) and consumers' bounded attention. Legacy channels, including OTAs, brand websites, and review platforms, excel at breadth but often burden users with fragmented, duplicative, or inconsistent information, prompting decision fatigue (Casaló et al., 2021; Fang & Pan, 2024; Gao & Bi, 2021; Milawati et al., 2023; Zeng et al., 2020; Kim et al., 2006). GAI's value proposition in this context is not merely "another technology," but a qualitatively different generative, conversational, and integrative capability: it can elicit preferences in natural language, synthesize heterogeneous signals (textual reviews, structured attributes), and iteratively co-produce tailored shortlists (Santos & Gonçalves, 2022; Laličić & Weismayer, 2021).

Understanding consumers' intention to use GAI for hotel selection merit systematic study (Huang et al., 2017; Kaushik et al., 2015) and is consequential for multiple stakeholders including hotels, OTAs, and AI vendors. Clarifying the drivers of intention informs product and channel strategy: how to design interaction flows, when to deploy social proof, and where credibility safeguards are most needed to accelerate adoption at scale (Zhang et al., 2022; García-Madurga & Grilló-Méndez, 2023).

To investigate consumers' intention to use GAI to assist hotel selection and its influential factors, the current study is deliberately grounded on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), following prior work that links technology acceptance to behavioral intentions in travel and service settings (Casaló et al., 2010; Kim et al., 2006; Roudposhti et al., 2018). TAM foregrounds perceived usefulness (PU) and perceived ease of use (PEU) as proximal cognitive appraisals driving acceptance (Davis, 1989), while TPB contributes attitude (ATT), subjective norm (SN), and perceived behavioral control (PBC) as intention (INT) determinants incorporating social influence and perceived capability (Ajzen, 1991). We adopt TAM + TPB for four reasons. (1) in GAI-assisted hotel choice, PU and PEU (TAM) capture the instrumental appraisals of generative, conversational systems, while ATT, SN, and PBC (TPB) reflect social endorsement and users' perceived ability to steer outputs (Davis, 1989; Ajzen, 1991). (2) TAM+TPB model causal routes transparently, which is diagnostic when interaction costs and verification effort may shift the balance between instrumental beliefs and perceived control. (3) compared with omnibus frameworks (e.g., UTAUT), TAM+TPB avoids construct redundancy (performance-usefulness; effort-ease), reducing collinearity and aiding SEM interpretability. (4) TAM/TPB dominate hospitality tech-adoption research, enabling cumulative comparison while testing whether generativity re-weights classic paths (Casaló et al., 2010; Kim et al., 2006).

Existing studies examine AI and recommender systems in travel (e.g., Abou-Shouk et al., 2025; Rafner et al., 2023; Yin et al., 2023), but a theory-driven account of intention to use GAI for hotel selection, centered on generative, dialogic, and synthesis properties, remains under-specified. In particular, we lack evidence on whether TAM beliefs or TPB components dominate intention in this domain, and whether PBC still matters when interaction costs are low but verification burdens are non-trivial. Therefore, the current study aims to (1) estimate the relative contributions of TAM (PU, PEU) and TPB (ATT, SN, PBC) to intention to use GAI for hotel selection; (2) probe unexpected nulls (non-significant PBC explored in quantitative study phase) through qualitative follow-up to uncover psychological mechanisms; and (3) translate findings into stakeholder-specific implications for product design, communication, and governance. We employ an explanatory sequential mixed-methods design: a quantitative phase using SEM to test the integrated model, followed by qualitative interviews to explain results emerging from the structural estimates (Creswell & Clark, 2007).

This study makes the following contributions. Theoretically, it refine the TAM-TPB account by showing that in generative, conversational hotel-choice contexts intention formation is reweighted. PEU reduces verification effort and thereby amplifies PU and elevates ATT; ATT serves as the evaluative nexus integrating functionality and credibility to drive INT; SN remains pivotal; and PBC attenuates under high ease, effective routines, and credibility-salient judgments, thus specifying a boundary condition for TPB. Methodologically, it combines SEM with qualitative explanation to unpack counter-intuitive paths (e.g., weak PBC), offering a template for emerging AI behaviors where user verification and prompt-steering complicate "ease of use". Managerially and societally, it specifies actionable levers for AI product/data owners (OTAs/AI vendors) vs. hotel managers/marketers to foster beneficial, trustworthy GAI development and usage.

2. Literature Review and Hypotheses Development

2.1 GAI in Tourism: Hotel Decision Support

GAI systems produce text and other media from prompts (Brüns & Meiner, 2024; Noy & Zhang, 2023; Yan et al., 2024), extending beyond language processing tools to interactive decision support (Rafner et al., 2023). In travel contexts, the consumer value of GAI lies in information synthesis across fragmented sources, personalized, conversational retrieval aligned to preferences, and explanations/comparisons that can lower search and verification costs (Alsaad, 2023; Chuah et al., 2021; Dwivedi et al. 2023; Nazir et al., 2023; Zeng et al., 2020). These properties map onto technology beliefs central to adoption intention-PEU (low effort to operate and verify) and PU (faster, better choices) that shapes overall evaluation.

Hotel choice entails high information load and uncertainty; travelers must reconcile amenities, policies, price dynamics, and reviews (Hu & Yang, 2020; Gao & Bi, 2021; Zhang & Yao, 2022). GAI can reduce coordination/verification effort via consolidated shortlists and side-by-side comparisons, heightening PU; its conversational interface can heighten PEU (Huang et al., 2017; Laličić & Weismayer, 2021; Kshetri, 2024). At the same time, consumers judge outputs through credibility cues (source provenance, accuracy), which feed into a global ATT toward using GAI. Furthermore, SN-signals from peers/creators/OTAs-can reduce perceived risk and nudge trial (Han, 2015; Sujood et al., 2022). These belief categories are precisely those operationalized in TAM and TPB.

2.2 Antecedents of Intention to Use GAI

TAM posits that PEU and PU are the primary cognitive antecedents of intention (Davis, 1989; Alsaad, 2023). When a system is easy to learn and operate, users allocate less effort to mechanics and more to value extraction, which increases PU and ATT (Mathew & Soliman, 2020; Abou-Shouk et al., 2021; Abou-Shouk et al., 2025; Wong et al., 2024). Evidence across domains-solar cells, EVs, healthcare-confirms PEU→ATT and PU→ATT (Fatoki, 2022; Naufal et al., 2024; Song et al., 2024 Kim et al., 2006). In hotel selection, GAI's instant, personalized responses and integration of dispersed information exemplify PU, while the chat-based interface exemplifies PEU (García-Madurga & Grilló-Méndez, 2023; Kshetri, 2023; Melián González et al., 2019).

TPB asserts that intention is shaped by ATT, SN, and PBC (Ajzen, 1991; Nimri et al., 2017; Ulker-Demirel & Ciftci, 2020). In travel technologies, favorable ATT increases willingness to use (Han,

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2015; Sujood et al., 2022); SN matters under uncertainty because endorsements from important others act as credible signals that reduce perceived risk (Rahman et al., 2023; Kamar et al., 2023; Sujood et al., 2022). PBC-confidence in one's opportunity, resources, and ability-typically predicts intention, especially when tasks are complex or unfamiliar (Nysveen et al., 2005; Hansen et al., 2018; Bošnjak et al., 2020; Nimri et al., 2020; Rozenkowska, 2023).

2.3 Integrating TAM and TPB

TAM captures the instrumental beliefs most salient in GAI (PEU & PU), while TPB adds social influence (SN) and perceived control (PBC), both relevant under uncertainty and heterogenous experience (Casaló et al., 2010; Han, 2015; Wong et al., 2024). We therefore integrate the models by retaining TAM's PEU→PU and PEU/PU→ATT routes and adding TPB's SN and PBC as parallel predictors of INT. ATT appears in both TAM and TPB, providing a theoretically coherent bridge that avoids construct proliferation while preserving each model's strengths. It is the conceptual nexus as it aggregates instrumental appraisals with credibility impressions, forming a global evaluation that most directly precedes intention in discretionary use (Davis, 1989; Dong et al., 2022). In conversational, generative systems where operability is simple and information credibility is pivotal, ATT efficiently absorbs the effect of PEU/PU (from TAM) and conditions the influence of SN/PBC (from TPB), yielding a parsimonious, internally consistent structure. Guided by this integrated framework, we next develop the hypotheses and present the study's conceptual model.

2.4 Hypotheses and Conceptual Model Development

In the context of hotel selection, GAI could retrieve a shortlist aligned with one's preferences via a single prompt. Lower operational and coordination costs allow users to focus on the tool's instrumental benefits, thereby elevating PU (Mathew & Soliman, 2020; Abou-Shouk et al., 2025). Consistent with TAM, prior work shows that when users regard a system as easy to use, they are more likely to judge it as useful (Abou-Shouk et al., 2021; Wong et al., 2024). Therefore, we propose the following hypothesis:

H1: Perceived ease of use of GAI positively influences its perceived usefulness in hotel selection decisions. (PEU → PU)

ATT is recognized a critical role in consumers' technology adoption processes (Dong et al., 2022), with PEU and PU being the primary influencing factors of ATT (Fatoki, 2022). When consumers perceive an intelligent system as easy to understand and operate, they tend to form more favorable attitudes toward using it (Sujood et al., 2022). In the hotel selection context, the usefulness of GAI manifests through instant, personalized responses that elevate satisfaction and reduce response time (García-Madurga & Grilló-Méndez, 2023; Kshetri, 2023). When consumers can accomplish tasks with GAI without extensive learning, this convenience fosters favorable impressions and strengthens ATT (Melián González et al., 2019). Moreover, PU's positive effect on ATT is well established (Abou-Shouk et al., 2025): travelers commonly view GAI as a practical decision aid that streamlines choices and saves time/effort (Şen Demir & Demir, 2023), when users believe a technology enhances their decision process, they are more inclined to hold a positive attitude toward adopting it (Naufal et al., 2024; Mariani et al., 2022). Hence, we propose:

H2: Perceived ease of use of GAI positively influences consumers' attitudes. (PEU → ATT)

H3: Perceived usefulness of GAI positively influences consumers' attitudes. (PU → ATT)

Across TAM and TPB, ATT is a central predictor of usage intention (Dong et al., 2022; Mohr & Kühl, 2021; Kamar et al., 2023). Empirically, consumers who evaluate a technology favorably are more likely to adopt it (Han, 2015). This pattern holds in travel technologies: positive attitudes toward chatbots increase vacation travelers' service-use intention (Melián González et al., 2019), and in tourism/hospitality more broadly, favorable attitudes toward intelligent technologies reliably elevate

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adoption intentions (Sujood et al., 2022). In the context of GAI for hotel selection, a positive global evaluation of GAI's usefulness and fluency should therefore translate into stronger willingness to use it. Hence, we hypothesize:

H4: Consumers' attitudes positively influence their intention to use GAI for hotel selection. (ATT → INT)

The intangibility of services and information asymmetry between consumers and hotels complicate optimal choice (Hu & Yang, 2020), making credible signals from referents especially valuable; positive feedback from significant others can mitigate this asymmetry and reduce perceived decision risk (Sujood et al., 2022). In the TPB framework, the degree to which individuals perceive that important others approve of their behavior is defined as SN (Ajzen, 1991; Rahman et al., 2023). Studies suggest that social pressure and the opinions of others significantly impact consumers' technology adoption intentions (Kamar et al., 2023). Accordingly, when friends, family, or influential social media figures endorse or encourage the use of GAI, consumers should be more inclined to adopt it (Kshetri, 2024). Therefore, we propose:

H5: Subjective norm positively influences consumers' intention to use GAI for hotel selection. (SN → INT)

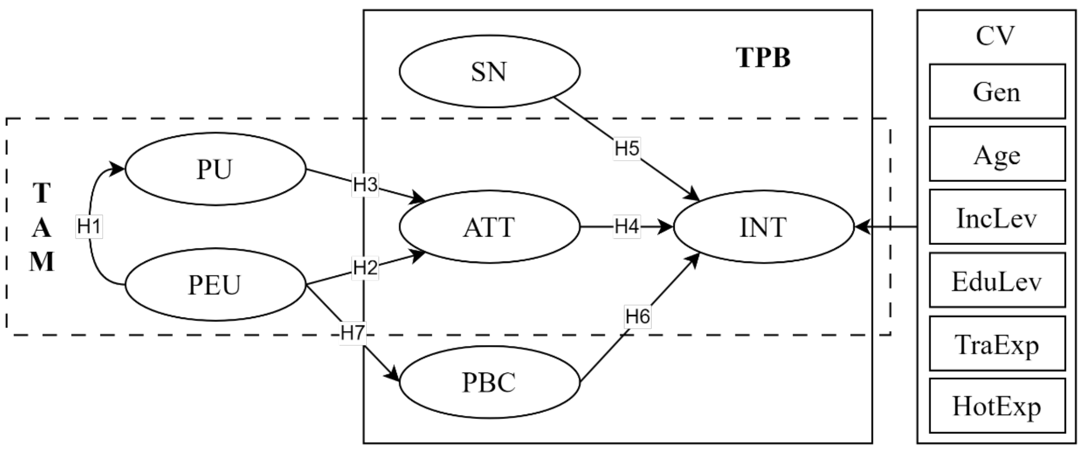
Furthermore, PBC in TPB reflects individuals' beliefs about having the opportunities, resources, and capabilities necessary to perform a behavior (Marangunić & Granić, 2015). A higher sense of control typically raises the likelihood of enactment, whereas perceived inability dampens willingness to act (Nysveen et al., 2005; Hansen et al., 2018). Consistent with this logic, prior studies found that PBC to be a robust predictor of technology adoption intention (Bošnjak et al., 2020; Nimri et al., 2020; Rozenkowska, 2023). Applied to GAI-assisted hotel selection, consumers who believe they possess sufficient ability to operate GAI, should be more inclined to use such tool (Dong et al., 2022).

In addition, self-efficacy theory suggests that when individuals perceive a behavior as easy to perform, their belief in their ability to successfully carry out the behavior is strengthened, thereby enhancing their perceived behavioral control. In other words, PEU conceptualized in TAM, has a significant positive impact on PBC within the TPB framework-a relationship that has also been supported by empirical studies (e.g., Hansen et al., 2018). The connection between TAM and TPB lies not only in their overlapping constructs of usage intention and attitude, but also in the relationship between PEU and PBC. Therefore, we propose the following hypotheses:

H6: Perceived behavioral control positively influences consumers' intention to use GAI for hotel selection. (PBC → INT)

H7: Perceived ease of use of GAI positively influences consumers' perceived behavioral control. (PEU → PBC)

Graph 1. **Conceptual framework, TAM-TPB integrated model**



Source: Authors

Prior work indicates that technology adoption varies systematically with users' socio-demographic characteristics (Devolder et al., 2012; Gefen & Straub, 1997; Ata et al., 2022; Martín-Martín et al., 2023). To rule out alternative explanations and enhance the robustness of our estimates, we therefore include gender (Gen), age group (Age), income level (IncLev), education level (EduLev) as control variable. Moreover, we control for travel experience (TraExp), and hotel decision-making experience (HotExp) because domain familiarity can shape both the perceived need for assistance and established routines in hotel. Including these variables allows us to isolate the effects of the focal TAM/TPB constructs on intention to use GAI for hotel selection.

Based on these hypotheses, we propose the theoretical model illustrated in Graph 1.

3. Quantitative Study Methods

Drawing on prior literature, measurement items were developed for each construct and incorporated into a structured survey. The questionnaire consisted of three sections: (1) an introduction to the research purpose and the application of GAI in hotel selection scenarios; (2) demographic information and respondents' prior GAI usage experience; and (3) measures of usage intention and its influencing factors, with questionnaire items and their sources presented in Table 1.

Table 1. **Measurement items and sources**

Constructs	Measurement Items	References
Perceived Usefulness	PU1: Using Generative AI to select hotels can help me find suitable hotels.	Davis (1989); Huang et al. (2017)
	PU2: Using Generative AI to select hotels can save me time.	
	PU3: Using Generative AI to select hotels can provide more choices and information.	
	PU4: Using Generative AI to select hotels can improve my decision-making quality.	
	PU5: Using Generative AI to select hotels can reduce the risk of making wrong choices.	
Perceived Ease of Use	PEU1: Learning how to use Generative AI to select hotels is easy.	Fatoki et al. (2022); Wong et al. (2024)
	PEU2: The operation of using Generative AI to select hotels is simple.	
	PEU3: Using Generative AI to select hotels does not require complex steps.	
	PEU4: I find using Generative AI to select hotels to be intuitive.	
	PEU5: The interface design of Generative AI for hotel selection is reasonable and easy to understand.	
Attitude	ATT1: I have a positive view towards using Generative AI to select hotels.	Fatoki (2022); Kamar et al. (2023)
	ATT2: I believe using Generative AI to select hotels is a wise choice.	

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	ATT3: I think Generative AI for hotel selection is better than traditional methods.	
	ATT4: Using Generative AI to select hotels aligns with my values and lifestyle.	
	ATT5: I have a high evaluation of using Generative AI to select hotels.	
Perceived Behavioral Control	PBC1: Even if the cost of using Generative AI to select hotels is slightly higher, I am confident that I will use it.	Bošnjak et al. (2020); Hansen et al. (2018); Taylor et al. (1995);
	PBC2: Even if someone suggests using traditional methods to select hotels, I will stick to using Generative AI.	
	PBC3: I believe using Generative AI to select hotels can bring a positive experience.	
	PBC4: I can decide on my own whether to use Generative AI to select hotels.	
	PBC5: I am confident that I will continue to use Generative AI to select hotels in the future.	
	PBC6: I have the resources, knowledge, and ability to use Generative AI to select hotels.	
Subjective Norm	SN1: I think most people who are important to me believe I should use Generative AI to select hotels.	Kaushik et al. (2015); Naufal et al. (2024)
	SN2: I think most people who are important to me believe using Generative AI to select hotels is a good idea.	
	SN3: The opinions of people I value tend to support my use of Generative AI to select hotels.	
Intention to Use	INT1: Because of the advantages of using Generative AI to select hotels, I am willing to try (continue using) it.	Dong et al. (2022); Wong et al. (2024)
	INT2: I plan to try (continue using) Generative AI to select hotels in the future.	
	INT3: If I have the opportunity, I would recommend friends or family to use Generative AI to select hotels.	
	INT4: Given a choice, I would prefer to use Generative AI to select hotels rather than traditional methods.	
	INT5: I am willing to try Generative AI for hotels recommendation.	

Source: Authors

We tested the theorized relationships using covariance-based SEM estimated by maximum likelihood (ML-SEM), which is appropriate for theory confirmation with reflective latent constructs and hypothesized direct/indirect paths (Hair et al., 2011; Kline, 2011; Byrne, 2010). Compared with variance-based approaches, ML-SEM is preferred when the goal is to evaluate a theory-driven model and to assess global model fit (GFI/NFI/TLI/CFI, RMSEA) alongside reliability/validity evidence (Hair et al., 2021; Bagozzi & Yi, 2012). Following rules of thumb for SEM, N ≥ 200, or ≥10 indicators per parameter block (Abdulmawla et al., 2024; Hair et al., 2011; Kline, 2011). With 28 observed items, the target sample size was set at over 280. Employing simple random sampling,

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data were gathered via an expansive online survey platforms in China "Wenjuanxing". It allowed to randomly distribute questionnaires nationwide via social media, email, and other channels. Respondents were compensated with monetary rewards upon validation of questionnaires, distributed through the platform. Prior to the study, all participants were clearly informed that the data they provided would be used solely for research purpose, and that their personal identifying information would be strictly kept confidential. Data collection officially commenced only after obtaining informed consent from participants. Data collection was carried out in two phases: the first phase took place from September 3 to 17, 2024, with 328 samples recovered in total; the second phase occurred from August 24 to 27, 2025, during which an additional 231 samples were collected. A total of 559 samples from the two phases underwent data cleaning: 13 participants were removed due to excessively rapid responding (mean item response time < 2 s), 17 participants were excluded because they repeatedly selected the same response option across items and provided contradictory answers. Ultimately, 529 valid questionnaires were retained for subsequent analysis. All participants are from China.

4. Quantitative Study Results

The 529 valid responses reflected diverse demographic backgrounds and varying experiences in travel and hotel selection, with a particular focus on users of GAI (see Table 2). According to diffusion theory, new technologies are typically adopted first by innovators and early adopters. Given that the current study was conducted during the initial stage of AI integration into the tourism and hospitality industry, this segment was intentionally targeted.

Table 2. **Descriptive results**

	Classification	Frequency	Percentage
Gender	Male	265	50.1
	Female	264	49.9
Age	18-30	238	45.0
	31-40	212	40.1
	41-50	42	7.9
	51-60	21	4.0
	Above 60	16	3.0
Education Level	Junior high school and below	5	0.9
	Secondary vocational school/technical school/vocational high school	16	3.0
	College diploma	48	9.1
	Bachelor's degree	349	66.0
	Master's degree and above	111	21.0
Income Level	Less than 1500 RMB (210.58 USD)	32	6.0
	1500-3000 RMB (210.58-421.15 USD)	42	7.9
	3000-4500 RMB (421.15-631.73 USD)	95	18.0
	4500-6000 RMB (631.73-842.31 USD)	95	18.0

	Above 6000 RMB (842.31 USD)	265	50.1
Number of Trips in the Past 5 Years	Less than 3	53	10.0
	4-5	159	30.1
	6-7	159	30.1
	More than 10	158	29.9
Number of Hotel Selection Decisions in the Past 5 Years	Less than 3	53	10.0
	4-5	156	29.5
	6-7	161	30.4
	More than 10	159	30.1
		n=529	

Note: All currency conversions use the exchange rate (1USD to 7.12RMB) on 2025-09-09. Number of Hotel Selection Decisions in the Past 5 Years: the count of occasions on which the respondent personally selected a hotel and completed a booking, for leisure or business, via any channel.

Source: Authors

The respondents covered 49.9% female and 50.1% male. The majority of respondents were aged 18-30 (45.0%), followed by those 31-40 (40.1%). Regarding educational background, 87.0% held a bachelor's degree or higher, including 66.0% undergraduates and 21.0% with postgraduate degrees. As for income level, grouped by national income quintiles (Q1-Q5) for Chinese residents (National Bureau of Statistics of China, 2024), whose quintile-specific mean incomes were 795RMB (111.6USD), 1,801RMB (252.8USD), 2,827RMB (396.9USD), 4,447RMB (624.3USD) and 8,234RMB (1,155.9USD), respectively. We operationalized five income brackets in 1,500RMB (210.58 USD) increments. 50.1% of participants reported monthly income above 6,000 RMB (842.29 USD), whereas only 6.0% reported less than 1,500 RMB (210.58 USD). The upward skew toward higher incomes relative to the general population likely reflects our online sampling frame (participants with better devices and internet access). Because the focal behavior of the current study-tourism consumption-is a luxury expenditure more prevalent at higher income levels, this income distribution is appropriate for the study context. As for travel frequency, 60.0% of respondents reported at least six trips in the past five years, with 30.1% traveling 6-10 times, and 29.9% traveling more than 10 times. 60.5% of respondents reported at least six hotel selection decisions in the past five years. Geographically, respondents were drawn from across China, which helps mitigate single-region bias and improves external validity for nationwide online hotel shoppers. That said, the sample can produce results that generalize best to digitally connected, higher-educated, mid-to-high-income travelers who have relatively early access to GAI for hotel selection among overall population.

4.1 Reliability and Validity Analysis of the Measurement Model

Variance inflation factor (VIF) was used to evaluate multicollinearity in the indicators (Fornell and Bookstein, 1982), all the values are below 5.00, indicating moderate to low correlation among predictor variables (Hair et al., 2021). Reliability was assessed using Cronbach's α and Composite Reliability (CR) (Abdulmawla et al., 2024). Items were considered for removal if their correlation with the total scale was less than 0.3, or if the α coefficient increased after their removal. Following this criterion, item PU1 was removed. After this adjustment, all latent constructs had Cronbach's α values exceeding 0.8 and CR values above 0.9, indicating good internal consistency and reliability (Hair et al., 2011). For detailed results please see Table 3.

Table 3. **Measurement items descriptive statistics, reliability and validity test results**

Latent Variable	Observed Variable	Mean	Cronbach's α if Item Deleted	VIF	Cronbach's α	AVE	CR	Standardized Loading Coefficient
Perceived Usefulness	PU2	3.91	0.897	3.261	0.927	0.760	0.927	0.877
	PU3	3.94	0.904	2.913				0.853
	PU4	3.99	0.906	3.170				0.864
	PU5	3.87	0.892	3.606				0.892
Perceived Ease of Use	PEU1	3.90	0.917	3.371	0.936	0.744	0.936	0.871
	PEU2	3.96	0.916	3.451				0.878
	PEU3	4.01	0.922	2.931				0.839
	PEU4	4.14	0.919	3.325				0.870
	PEU5	4.04	0.919	3.154				0.855
Perceived Behavioral Control	PBC1	3.94	0.933	3.378	0.945	0.741	0.945	0.877
	PBC2	3.92	0.933	3.320				0.861
	PBC3	4.00	0.930	3.895				0.848
	PBC4	4.02	0.936	2.878				0.856
	PBC5	3.97	0.933	3.217				0.843
	PBC6	4.16	0.933	3.408				0.856
Subjective Norm	SN1	4.01	0.819	2.854	0.897	0.743	0.897	0.848
	SN2	3.85	0.851	2.733				0.847
	SN3	4.11	0.847	2.619				0.861
Attitude	ATT1	3.95	0.911	2.984	0.929	0.722	0.929	0.857
	ATT2	4.06	0.913	2.852				0.889
	ATT3	3.95	0.910	3.060				0.833
	ATT4	3.89	0.911	2.977				0.857
	ATT5	4.05	0.912	2.879				0.866
Intention to Use	INT1	4.00	0.921	3.562	0.940	0.757	0.940	0.881
	INT2	4.04	0.922	3.450				0.879
	INT3	3.93	0.925	3.294				0.864
	INT4	4.22	0.927	3.105				0.853
	INT5	4.14	0.923	3.416				0.874

Source: Authors

Convergent validity was evaluated through standardized factor loadings and composite reliability (Hair et al., 2014). All item loadings exceeded 0.8, all constructs had CR values above 0.9, and AVE are above 0.7 (see Table 3). Factor loading values above 0.5, AVE values greater than 0.5, and CR values higher than 0.7 indicate that the constructs have good convergent validity (Hair et al., 2021; Fornell & Larcker,1981).

We assessed discriminant validity using the Fornell-Larcker criterion: the square root of AVE for each construct exceeded its correlations with other constructs (Fornell & Larcker, 1981; Hair et al., 2014); see Table 4.

Table 4. **Correlation analysis between variables and square root of mean extracted variance**

	PU	PEU	PBC	SN	ATT	INT
PU	0.872					
PEU	0.532	0.862				
PBC	0.266	0.359	0.861			
SN	-0.027	0.035	0.057	0.862		
ATT	0.712	0.612	0.258	-0.015	0.850	
INT	0.514	0.407	0.221	0.246	0.606	0.870

Note: The diagonal numbers represent the square root of the average variance extracted (AVE) for each factor.
Source: Authors

Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model. The model fit indices were: GFI = 0.944 (>0.9), NFI = 0.959 (>0.9), TLI = 0.995 (>0.9), CFI = 0.994 (>0.9), and RMSEA = 0.016 (<0.1), all within the acceptable threshold ranges (Hair et al., 2014), suggesting that the measurement model fits the data well.

In summary, the measurement model demonstrated acceptable reliability, convergent validity, and discriminant validity, providing a sound foundation for the subsequent structural equation modeling (SEM) analysis.

4.2 Structural Equation Model (SEM) Results

The results of the structural equation modeling indicate an acceptable model fit: GFI = 0.942, NFI = 0.957, CFI = 0.995, and RMSEA = 0.015. Among the seven proposed hypotheses, six are supported. Specifically, PEU has a significant positive effect on PU (H1, $\beta = 0.59$, $p < 0.001$), ATT (H2, $\beta = 0.297$, $p < 0.001$), and PBC (H7, $\beta = 0.379$, $p < 0.001$). PU also shows a positive influence on ATT (H3, $\beta = 0.519$, $p < 0.001$). ATT (H4, $\beta = 0.596$, $p <0.001$) and SN (H5, $\beta = 0.303$, $p < 0.001$) significantly influences INT. However, we did not confirm the influence of PBC on INT at 1% significance level (H6, $\beta = 0.047$, $p > 0.01$). Detailed results are presented in Table 5 and Graph 2.

Table 5. **Results of SEM analysis**

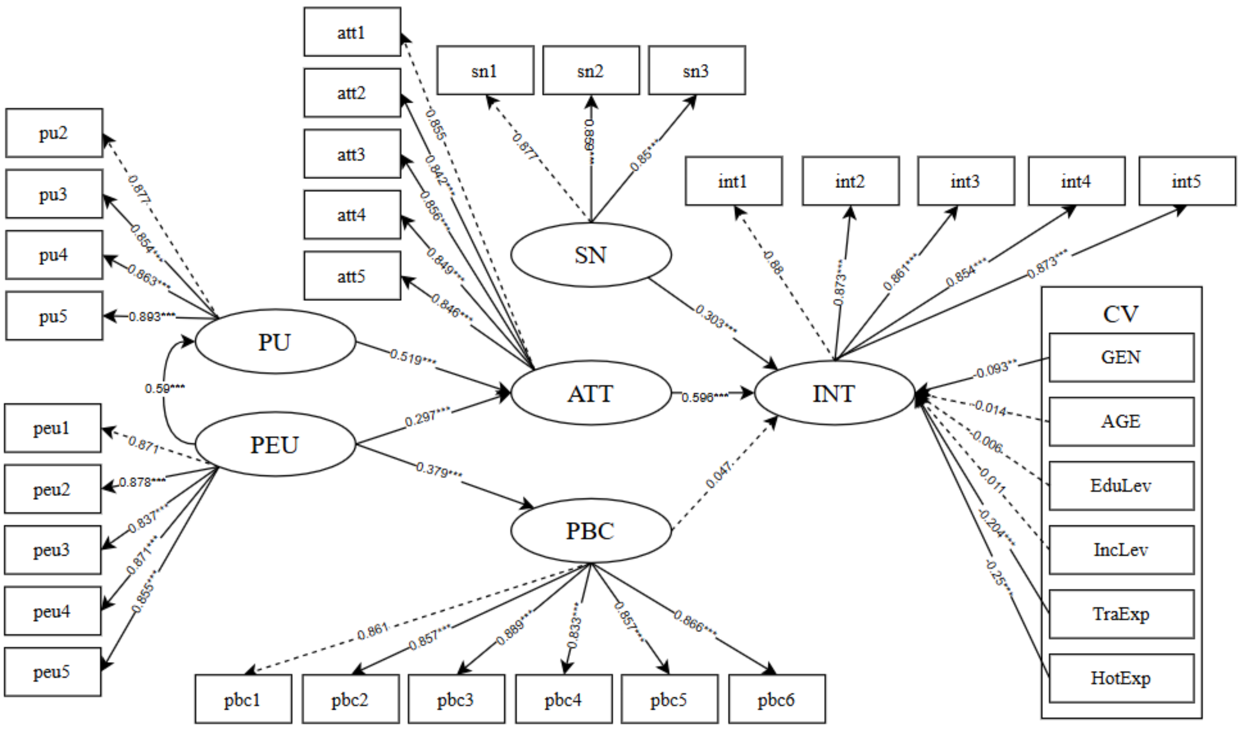
Hypothesis Number	Path	Standardized Coefficient (β)	S.E.	Z	P	Test Result
H1	PEU→PU	0.590	0.045	13.134	***	Supported
H2	PEU→ATT	0.297	0.036	8.251	***	Supported
H3	PU→ATT	0.519	0.038	13.703	***	Supported
H4	ATT→INT	0.596	0.036	16.581	***	Supported
H5	SN→INT	0.303	0.032	9.343	***	Supported
H6	PBC→INT	0.047	0.028	1.681	0.093	Not Supported
H7	PEU→PBC	0.379	0.044	8.580	***	Supported
CV	Gen → INT	0.093	0.047	1.978	*	Significant
	Age → INT	-0.014	0.024	-0.579	0.563	Insignificant
	IncLev→INT	0.011	0.019	0.596	0.551	Insignificant

	EduLev→INT	-0.006	0.033	-0.181	0.857	Insignificant
	TraExp→INT	-0.204	0.024	-8.399	***	Significant
	HotExp→INT	-0.250	0.025	-10.203	***	Significant

Notes: ***: Significant at the 0.1% level, **: Significant at the 1% level; *: Significant at the 5% level
Source: Authors

Additionally, analysis of control variables revealed that respondents' gender (Gen, $\beta = 0.093$, $p < 0.05$) is positively correlated with usage intention, male respondents show a slightly higher level of intention. Meanwhile, travel frequency (TraExp, $\beta = -0.204$, $p < 0.01$) and hotel decision-making experience (HotExp, $\beta = -0.250$, $p < 0.01$) were negatively associated with intention to use GAI. Age, income level, and education level showed no significant effects on intention.

Graph 2. **SEM path diagram**



Source: Authors

The non-significant effect of PBC on INT contrasted with theoretical expectations. While correlation analysis (Table 4) showed a significant relationship between PBC and INT at the 0.001 level, the SEM path was not statistically significant. Possible explanations include measurement error, model fit issues, or multicollinearity. However, the first two were ruled out based on the following evidence: The Cronbach's α for PBC was 0.945, indicating acceptable internal consistency. The model fit indices were all within acceptable thresholds, suggesting a well-fitting model (GFI = 0.942, NFI = 0.957, CFI = 0.995, RMSEA = 0.015).

Thus, a more plausible explanation is that INT is shaped by multiple variables, and the independent effect of PBC is diminished when other predictors (e.g., PEU, PU, ATT, SN) are controlled. The shared variance may weaken PBC's unique contribution, leading to a non-significant path coefficient in SEM.

To better understand why PBC does not significantly influence usage intention in this model, it is necessary to conduct explanatory qualitative research in the next phase.

5. Qualitative Study Methods

While the quantitative analysis revealed the statistical relationships between variables, it falls short in uncovering the underlying psychological motivations and mechanisms of influence behind consumer behavior. To address this limitation and gain a more comprehensive understanding of the applicability of the integrated TAM-TPB model in the context of hotel selection, as well as to explore the unexpected finding that PBC did not significantly impact INT, this study adopts a qualitative approach as part of an explanatory sequential research design (Creswell & Clark, 2007).

Through in-depth interviews, the study aims to further investigate consumers' intention toward using GAI in hotel selection, their underlying concerns, and the key influencing factors in actual usage scenarios. This qualitative phase complements and helps interpret the findings of the quantitative study.

A semi-structured interview method was employed, and purposeful sampling was used to select participants for in-depth interviews. The interviews were audio-recorded, transcribed, and analyzed using content analysis, through which key qualitative themes were identified.

Based on literature review and the findings from the quantitative phase, this study developed a semi-structured interview guide. The interview content covered three main areas: (1) basic personal information of the interviewees (e.g., gender, age, education level, occupation); (2) interviewees' experience and usage of GAI; (3) interviewees' perceptions of influencing factors in using GAI for hotel selection, with a focus on the core constructs of the TAM and TPB models-PU, PEU, ATT, SN, PBC, and their interrelations.

A purposeful sampling strategy was adopted to select interview participants. The selection criteria were based on the following considerations: interviewees were limited to the 18-40 age group to enhance sample representativeness, given that early adopters of GAI are typically in this age range; participants with varying lengths of GAI usage were included to ensure data diversity; participants were required to have satisfying communication skills to articulate their opinions clearly and accurately. A total of six individuals participated in the interviews, each of whom provided informed consent prior to their involvement. Their demographic profiles are presented in Table 6.

Table 6. **Basic information of interviewees**

No.	Age	Gender	Education Level	Occupation	Duration of GAI Use
A1	27	Male	Bachelor's	Student	2 years
A2	30	Female	Bachelor's	Civil Servant	1 month
A3	28	Male	Bachelor's	High School Physics Teacher	6 months
A4	29	Male	Associate's Degree	Construction Engineering	3 months
A5	26	Female	Master's	University Lecturer	6 months
A6	27	Female	Master's	Producer	1 year

Source: Authors

Before the formal interviews, participants were provided with the interview guide to familiarize themselves with the topics and ensure a smooth interview process. The interviews were conducted in two stages. In the first stage, the researcher introduced the background and objectives of the study, and guided participants to recall recent experiences of hotel booking or using GAI for hotel selection to help contextualize the discussion. In the second stage, questions were asked based on the interview guide, with follow-up probing depending on participants' responses to explore their views on the core variables and their interrelations.

Three measures were taken to ensure the reliability and validity of the interview data.

(1) Recording and respondent validation: With participants' consent, the entire interview process was recorded. Transcriptions were generated using the Tencent Meeting AI tool and then sent to participants for confirmation to ensure the content accurately reflected their views. Any ambiguities or unclear expressions were clarified through follow-up communication.

(2) Triangulation of questions: The researcher approached each topic from multiple angles and compared participants' responses for consistency. Key responses were confirmed with participants to verify their accuracy.

(3) Creating a comfortable interview environment: Interview times were arranged based on participants' convenience. During the interviews, the researcher maintained a friendly and patient demeanor, offering timely positive feedback to reduce psychological pressure and encourage open and in-depth expression.

The qualitative data collection was conducted from January 25 to January 30, 2025, spanning six days. After the interviews, all transcripts were carefully proofread and verified word by word. The data were then coded and analyzed using content analysis to extract key themes and insights.

6. Qualitative Study Results

6.1 Intention to Use GAI in Hotel Selection

Qualitative interviews confirmed the quantitative results that consumers generally exhibited a high level of intention to use GAI in hotel selection (mean = 4.252). Most participants acknowledged that GAI improves decision-making efficiency and reduces the time required for information search. For example, respondent A5 stated:

"*I would definitely be willing* (INT: high) *to use it because using GAI to book hotels is convenient. I usually prefer to collect all relevant information before making a decision, which often takes a lot of time. In this regard, GAI helps by integrating information from multiple platforms* (PU: information integration) *and recommending hotels that match my needs. This saves me time in searching and comparing, and makes my decision-making process more efficient* (PEU: decision efficiency)." (A5, 2025-01-29)

Respondents widely recognized GAI's information integration capability, believing it streamlines hotel selection and enhances convenience. Several respondents also emphasized GAI's role in decision support, noting that its data analytics and recommendations substantively assist in their choices. These findings align with the quantitative results, suggesting that consumers hold a positive attitude toward GAI and demonstrate a strong intention to use it in hotel selection scenarios.

However, a few experienced travelers expressed lower willingness to use GAI, indicating that they were already comfortable with traditional booking methods and saw limited added value from AI tools. As respondent A6 noted:

"*I've been booking hotels for years and I know exactly what I'm looking for. Comparing options manually is already quick and reliable for me, so I don't really see the need to rely on AI* (INT: low)." (A6, 2025-01-30)

6.2 Perceived Behavioral Control: Antecedents and Explanation for Its Non-Significant Effect

Quantitative analysis showed that PBC did not significantly influence usage intention, contradicting existing theoretical assumptions. Measurement error and model fit were ruled out, and multicollinearity was proposed as a likely explanation-i.e., the effects of PEU, PU, ATT, and SN may have weakened PBC's independent contribution. The qualitative findings support this interpretation.

Most participants perceived GAI as low-barrier and easy to use, requiring little technical skill or learning cost. This aligns with the quantitative finding that 66.23% of respondents rated PBC ≥ 4, and the overall mean was 4.08. For example:

"Most smart assistants today are pretty simple-just a few clicks to get started (PEU: operational simplicity)*, no need for special training."* (A5, 2025-01-29)

"Although I can fully control the use of GAI, what matters to me is whether it's easy to use (PEU). *Whether or not I have full command* (PBC) *doesn't affect my willingness to use it. If the tool is useful and user-friendly, I'll use it."* (A4, 2025-01-28)

Others focused more on GAI's functionality than their own control capabilities. For example:

"I'm not really concerned about whether I can operate GAI (PBC). *I care more about the accuracy of the recommendations* (PU: content quality). *For instance, I might ask for highly rated hotels, but if the ratings are fake, I could be misled. I'm more concerned about the reliability of the information* (PU: information reliability)*, so whether or not I can control the decision process* (PBC) *doesn't really influence my intention* (INT) *to use it."* (A6, 2025-01-30)

Some participants' intentions were more influenced by social norms than by personal control:

"If everyone's using it (SN: social influence)*, I'd probably try it too, even though I haven't really used GAI when booking hotels yet* (PBC: lack of experience)*."* (A2, 2025-01-26)

The interviews also confirmed a positive relationship between PEU and PBC. Some participants felt that GAI's ease of use boosted their confidence:

"The simple interface (PEU: operational simplicity) *gave me confidence as I used it. Over time, I learned to ask better questions and get more comprehensive hotel information. I feel I can fully leverage it and take control of my hotel selection process* (PBC)*."* (A5, 2025-01-29)

Overall, PBC is positively affected by PEU, the role of PBC as a determinant of INT appeared to be diminished in the context of hotel selection. While PBC may have some influence when considered in isolation, its relative importance weakens when other factors are taken into account. As respondent A3 remarked, *"I know how to use it* (PBC) *and it's not complicated. Of course I'll consider it* (using GAI in hotel selection)*"*. (A3, 2025-01-27) This suggests that PBC does contribute to intention in certain cases. However, when PEU, PU, ATT, and SN are simultaneously considered, the explanatory power of PBC becomes diluted.

On the other hand, participants with rich travel and hotel decision-making experience expressed a preference for traditional booking methods and questioned the necessity of adopting GAI tools. Their resistance stemmed more from habit than from perceived difficulty. In this sense, PBC's role is weakened not by lack of ability, but by the limited perceived need to exert control over a process they already manage effectively through conventional means.

6.3 Subjective Norm and Their Influence on Usage Intention

Interview data revealed that family and friends' attitudes toward GAI significantly influenced participants' willingness to use it. Positive recommendations strengthened intention:

"My friends' recommendations and their descriptions of AI make me want to try it. For example, they told me it can generate content, recommend hotels, and offer other helpful features. Out of trust in my friends (SN: peer influence)*, I'm definitely willing to give it a try* (INT: high)*."* (A6, 2025-01-30)

Such users showed a strong tendency to value the opinions of significant others. When trusted people endorsed GAI and its usefulness, participants were more inclined to adopt it. This finding aligns with the quantitative result that subjective norm positively influenced consumers' intention to use GAI for hotel selection ($\beta = 0.89$, $p = 0.024$).

6.4 Attitude Toward GAI and Its Impact on Usage Intention

The interviews showed divided attitudes toward GAI, which directly affected participants' usage intentions. Supportive users believed GAI could enhance decision efficiency and reduce information search costs:

"I have a positive attitude (ATT: positive). *AI provides a more convenient search and filtering experience, integrating data from multiple platforms* (PU: information integration). *Though it has limitations in terms of subjective experiences, it saves me a lot of time* (PU: time-saving)*, so I'm quite supportive of using it for hotel selection."* (A1, 2025-01-25)

In contrast, skeptical users lacked trust in GAI and preferred traditional methods:

"I'm used to traditional platforms like Meituan and trust the information there more. GAI may look easy to use, but I worry about information accuracy and online safety (PU: low information quality). *I don't know if the recommended hotels are actually as good as described. Also, there's no room for price negotiation or access to authentic reviews. I'm not comfortable using it* (ATT: negative)*."* (A6, 2025-01-30)

These findings confirm the significant positive relationship between attitude and usage intention-participants with a positive attitude were more willing to use GAI, while those with trust concerns showed lower intention, supporting the quantitative findings.

6.5 Antecedents of Attitude and Their Interrelations

Interview results further verified the positive influence of PEU on PU and ATT. Most users found GAI easy to operate and requiring minimal learning effort, which enhanced their perceived usefulness. For instance:

"GAI is intuitive to use (PEU). *I've tried several AI tools before. For me, being able to use it instantly saves a lot of time and effort-it definitely improves efficiency* (PU: efficiency)*."* (A5, 2025-01-29)

Participants also noted that ease of use strengthened their positive attitude toward GAI:

"The interface is very simple-just a text box. I just type in what I want using everyday language and get answers. No skills needed (PEU: user-friendly). *I'd definitely be willing to use tools like this* (ATT: positive)*."* (A1, 2025-01-25)

Participants' attitudes were also shaped by their perception of usefulness. As one respondent explained:

"I have a positive attitude (ATT) *toward using GAI for hotel selection. First, it integrates data from multiple platforms* (PU: information integration)*, so I don't have to compare hotel options myself. Second, it sometimes helps me discover lesser-known hotels* (PU: alternative discovery). *Third, it's more comfortable for introverts-I don't like phone calls, and AI removes that social pressure* (PU: reduced social anxiety)*."* (A4, 2025-01-28)

In summary, perceived ease of use not only positively influences perceived usefulness, but also directly affects attitude, which in turn enhances usage intention. These findings offer strong qualitative support for the quantitative results.

7. Discussion

Drawing on TAM and TPB, following an explanatory sequential design, quantitative and qualitative studies provide triangulated findings that indicate a coherent pathway for intention to use GAI for hotel selection. Perceived ease of use (PEU) reduces coordination/verification effort, thereby raising perceived usefulness (PU) and directly uplifting attitude (ATT) (H1-H3). It aligns with domain evidence showing that when systems are easier, users judge them more useful (Abou-Shouk et al., 2021; Abou-Shouk et al., 2025; Mathew & Soliman, 2020; Wong et al., 2024). Operational simplicity translates into perceived efficiency/benefit ("intuitive ... saves a lot of time→improves efficiency," A5), ease ("no skills needed," A1) and usefulness ("alternative discovery," "reduced social anxiety," A4) then jointly improve

ATT, consistent with multi-domain findings for solar cells, EVs, and healthcare (Fatoki, 2022; Naufal et al., 2024; Kim et al., 2006) and with tourism contexts where quick, personalized responses boost evaluations (García-Madurga & Grilló-Méndez, 2023; Kshetri, 2023). In turn, ATT increase intention (INT) (H4) (e.g., A1), mirroring established TAM/TPB evidence on the centrality of attitude (Dong et al., 2022; Han, 2015; Kamar et al., 2023; Mohr & Kühl, 2021) and specific travel findings for chatbots (Melián González et al., 2019). H5 (SN→INT) is reflected in peer influence ("trust in my friends,"A6), in line with TPB and hospitality studies highlighting social influence under uncertainty (Ajzen, 1991; Rahman et al., 2023; Kamar et al., 2023; Sujood et al., 2022). The pattern is consistent with TAM's effort→utility and fluency→attitude mechanisms (Davis, 1989) and with TPB's evaluative and social-influence routes (Ajzen, 1991).

H6 (PBC→INT) is not supported, although prior studies have frequently confirmed the positive effect of perceived behavioral control on usage intention (e.g., Bošnjak et al., 2020; Hansen et al., 2018; Taylor et al., 1995), the results for H6 indicated that PBC did not significantly predict consumers' willingness to use GAI in the hotel selection context. This unexpected finding prompted further investigation through qualitative interviews. We interpret the non-significant relation as context-specific attenuation rather than lack of ability: First, low perceived task difficulty-as per self-efficacy theory (Bandura, 1978), when users perceive a task as easy, perceived behavioral control becomes high (supported by the findings of H7) (Ajzen, 1991; Bandura, 1978; Hansen et al., 2018), and at the same time, controllability becomes less diagnostic for intention formation. In GAI usage-a perceived low-complexity contexts with high level of perceived ease of use-perceived behavioral control is overshadowed by perceived usefulness, attitude, and subjective norm. Second, trust in content quality-participants weighted information accuracy/credibility over operating ability (A6: "I'm more concerned about the reliability of the information"). This aligns with information quality theory (Wong et al., 2024) that in content-centric decisions, variance loads onto PU/ATT more than PBC, which matches our structural pattern and prior work emphasizing information quality in attitude formation (e.g., El-Said & Aziz, 2021; Kim et al., 2006). Third, routine efficacy-travelers described effective conventional workflows ("I know exactly what I'm looking for," A6), implying low incremental need to exert additional control via GAI despite high ability. This is consistent with habit/routine accounts that dampen the weight of TPB predictors when established action scripts perform well (e.g., Huang et al., 2017; Ouellette & Wood, 1998; Limayem et al., 2007). Crucially, this means PBC is not low; rather, its marginal utility is low given effective routines.

In our structural model, Gender shows a small but positive association with intention to use GAI, aligning with evidence that males often show greater interest in novel tech, higher digital self-efficacy, and higher risk tolerance (Gefen & Straub, 1997; Devolder et al., 2012; Ata et al., 2022). Importantly, controlling for Gender does not alter the core TAM/TPB paths (PEU→PU/ATT; ATT/SN→INT), so it does not confound our focal mechanisms.

Our findings replicate and extend established evidence (e.g., Abou-Shouk et al., 2021; Abou-Shouk et al., 2025; Davis, 1989; Wong et al., 2024). The strong role of PEU (affecting both PU and ATT) generalizes TAM's fluency and effort-reduction mechanisms to generative, conversational systems (Davis, 1989; El-Said & Aziz, 2021). The positive effect of SN on INT aligns with hospitality studies where peer/OTA endorsements matter under uncertainty (Han, 2015; Zhang et al., 2022). Departing from prior work, we observed an attenuated PBC→INT link, which specifies a TPB boundary condition: when tasks are easy and routines are effective, control beliefs contribute less to intention (Ajzen, 1991; Hansen et al., 2018), especially when content quality dominates evaluation.

7.1 Theoretical Implications

The findings of this study contribute to the tourism literature by extending current research on hotel consumer decision-making.

First, the study re-weighted intention formation mechanism in generative contexts. Our triangulated evidence shows that PEU operates not only as interaction fluency but as a verification-effort reducer in content-synthesis tasks, which lifts PU by lowering search/coordination costs and directly raises ATT via fluency-affect (Davis, 1989). ATT functions as the evaluative nexus integrating functionality and credibility, which explains the strong ATT→INT route in our setting. The strong influence of subjective norm confirms the critical role of peer recommendations and social influence in shaping consumer behavior (Fatoki, 2022). As for PBC, we clarify that in generative decision support, usefulness and attitude absorb variance that would otherwise be attributed to control beliefs.

Second, the study formalized a boundary condition for TPB. Contrary to the generic TPB expectation (Ajzen, 1991), PBC did not predict intention once PEU, PU, ATT, and SN were considered. Interviews indicate three conjunctive conditions-(a) high PEU (simple, guidance-rich interfaces), (b) effective existing routines for hotel choice (experienced users report little additional need for control), and (c) diagnostic primacy of information quality (credibility outweighs ability)-under which PBC's marginal utility declines. This reframes TPB for generative systems: control beliefs matter less when ability is sufficient and the bottleneck is content quality rather than operability.

Methodologically, the explanatory sequential design allowed us to disambiguate ability from necessity of additional control: qualitative themes showed high ability yet low marginal value of control, thereby explaining the PBC null and offering a valuable reference for future research on complex technology acceptance processes.

7.2 Practical Implications

The findings offer managerial guidance for stakeholders in the tourism and hospitality industry regarding GAI product development, marketing strategies, and user experience optimization. Recognizing differences in GAI product/data ownership, we present practical implications separately for OTAs/AI vendors and hotel managers and marketers.

For OTAs and AI vendors (product/data owners), the priority is to design for verification-effort reduction so that perceived ease of use translates into perceived usefulness and more favorable attitudes (PEU→PU/ATT). This entails intuitive, error-tolerant prompts; scaffolded follow-ups that help travelers refine needs; and side-by-side hotel comparisons with transparent trade-offs plus explainable rationales with source provenance, freshness indicators, and quick cross-checks to harden content credibility (thereby lifting PU and ATT). Because users weight information quality over "ability to operate," data pipelines should emphasize deduped/verified reviews, fraud screening, and feedback-to-fix loops that re-rank or correct outputs (Zeng et al., 2020; Casaló et al., 2010). For experienced travelers whose existing workflows already perform well, position GAI to complement rather than replace: offer an "expert" mode that validates user shortlists (e.g., fee/policy audits, overlooked alternatives) so that control remains available without being intrusive and the marginal need for additional control is respected (Hansen et al., 2018; Huang et al., 2017).

For hotel managers and marketers-who do not own the model but can shape the informational environment-the most effective levers are data readiness, authentic social proof, and service integration. Hotels should synchronize accurate, structured content to OTAs/knowledge graphs (amenities, room types, fees, policies, accessibility) to reduce misinformation risk and improve how models represent the hotel, indirectly raising usefulness and attitudes toward AI-mediated recommendations (Gao & Bi, 2021; Casaló et al., 2010). Marketing should leverage subjective norm by amplifying credible guest narratives and creator/OTA showcases that demonstrate how GAI helped real travelers resolve trade-offs; such task-centric stories move intention without implying control over the GAI itself. In owned channels (website/app/CRM), frame GAI tools as time-saving validators-"compare my top three," "spot hidden fees," "check policy edge cases"-to reduce resistance among high-experience guests and align with their routines. Finally, frontline teams should be enabled to co-pilot with guests' GAI outputs (quickly verifying a suggested room type or policy nuance), preserving favorable attitudes even when recommendations originate outside the hotel. Taken together, these actions target the constructs our model identified as decisive-ease, usefulness, attitude, and social influence-while acknowledging that perceived behavioral control is contextually attenuated when interfaces are simple and conventional booking routines already work well.

7.3 Limitations, and Directions for Future Research

This study explains intention to use GAI for hotel selection with a TAM+TPB lens, but several limits suggest concrete next steps. First, our measures captured perceptions of "current GAI" rather than specific decision UIs. To improve construct-to-interface realism, future work could incorporate visual mockups (e.g., comparison views, provenance cues, endorsement badges) to assess how interface patterns shift PEU/PU/ATT/SN. Second, the PBC→INT null appears context-dependent (easy tasks, effective routines, credibility salience). Subsequent studies should examine higher-complexity use cases (multi-city trips, strict constraints) and routine efficacy (novice vs. experienced travelers) to identify when PBC regains explanatory power. Third, our outcome is attitudinal; to improve behavioral validity, future study could collaborate with platforms to enable behavioral indicators (e.g., time-to-decision, shortlist/booking actions, use of verification features) to validate the mechanisms observed. Additionally, gender showed a small but significant effect (men reported higher intention), to improve explanatory depth, potential mechanisms including digital confidence, risk perception, norm strength etc. can be unpacked in future works with purposive stratification. Finally, the data were primarily collected through online surveys, with a sample dominated by younger, highly educated users focused on the Chinese market; cross-cultural research with more diverse demographic profile could further improve generalizability of the findings.

8. Conclusion

This study advances understanding of GAI-assisted hotel selection by articulating a mechanism-based account of adoption within a TAM+TPB framework and validating it through an explanatory sequential design. Rather than introducing new constructs, we clarify how classic beliefs operate in a generative, conversational setting-where information synthesis, credibility cues, and social signals shape evaluations-and identify a scope condition under which perceived behavioral control contributes little to intention.

Practically, the findings translate into stakeholder-specific guidance: for product/data owners (OTAs, AI vendors), prioritize verification-effort reduction, provenance/credibility engineering, and privacy-aware personalization; for hotels, improve data readiness, activate authentic social proof, and position GAI as a complement to established routines.

Finally, the work provides portable propositions-about when ease amplifies usefulness and attitude, when credibility eclipses control, and when social proof becomes pivotal-that can be tested across travel tasks and markets. As GAI capabilities and interfaces evolve, these propositions offer a clear roadmap for cumulative research and for designing systems that help travelers decide better, faster, and with warranted confidence.

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Conflict of interest

The authors declare no conflict of interest.

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