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Impact of Personality Traits on Choices: The Mechanism of Openness and Conscientiousness on the Adoption of AI Travel Planning among Young Chinese Tourists

Chenxi Li

Faculty of Business, The Hong Kong Polytechnic University, Hong Kong, China
24053224G@connect.polyu.hk

Abstract. This study focuses on the actual choice behavior of young Chinese tourists (aged 18–35) in travel planning, referring specifically to their preference for Artificial Intelligence (AI)-dominant, human-generated content (HGC)-dominant, or mixed-use travel planning strategies. It investigates how these behavioral preferences are influenced by two core personality traits, Openness and Conscientiousness, through cognitive appraisal. Based on 336 valid questionnaires, this research constructs and empirically tests a mediation model of "personality trait → cognitive appraisal → behavioral choice", finding that openness positively predicts the preference of AI-dominant planning, while conscientiousness predicts the preference of HGC-dominant information sourcing. Such influences of personality traits are partially mediated by perceived usefulness of AI and perceived reliability of HGC. Meanwhile, users are divided into three groups showing systematic gradient differences in their cognitive evaluations. This work not only provides a new explanation path in view of the crucial repositioning of personality traits from mere moderators to stable antecedents within technology acceptance, but also offers empirical evidence for the tourism platform to implement personalized marketing and differentiated service design.

Keywords: AI travel planning, personality traits, young Chinese tourists, behavioral choice

1. Introduction

Artificial Intelligence (AI) is profoundly transforming the way travel planning is conducted, particularly in the stages of information retrieval and pre-trip preparation. In today's highly developed internet and social media landscape, while the human-generated content (HGC) based planning model offers a sense of authenticity, it is constrained by limitations such as outdated information, inconsistent quality, and time-consuming retrieval processes. Generative AI travel assistants, represented by ChatGPT and DeepSeek, represent a disruptive alternative capable of generating customized travel itineraries in an instant. This massively increases the efficiency of planning, without the need to laboriously retrieve, absorb, and memorize destination information. Yet, they also have their problems in areas particularly influential upon users' perceptions: information accuracy, data source transparency, and user trust. In China, young travelers from ages 18 to 35 are digital natives who frequently use HGC and actively adopt AI technology. When they

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plan a trip, they face the choice between highly efficient, tailored AI solutions on the one hand, and more experience-based HGC on the other. Understanding the decision-making mechanisms of the group carries significant theoretical and practical implications.

While existing research has explored the potential of AI in travel planning and its acceptance mechanisms, its applicability in nuanced and complex real-world decision-making scenarios remains insufficiently clear, revealing several research gaps [1,2]. First, while personality traits are often treated as moderating variables, their role as stable antecedents influencing behavioral choices through cognitive appraisal has not been systematically examined. Second, much of the research related to AI travel planning adopts a binary perspective of "use versus non-use," overlooking the realistic and increasingly common behavioral pattern of mixed use involving cross-verification between AI and HGC. Third, empirical evidence focusing on young Chinese travelers remains insufficient.

Therefore, this study focuses on the actual decision-making scenarios faced by young Chinese travelers during travel planning. Specifically, it aims to investigate how two core personality traits—Openness and Conscientiousness—systematically influence individuals' behavioral choice preferences by shaping their cognitive appraisal of AI-generated travel plans versus traditional HGC-based information retrieval. These preferences include a tendency toward AI dominance, HGC dominance, or a mixed usage pattern. By constructing and validating a mediating model of "personality traits → cognitive appraisal → behavioral choice," this study seeks to theoretically reveal the stable psychological antecedents and mechanisms underlying technology acceptance. In practice, it aims to provide empirical evidence that allows destination marketing organizations to precisely match their information presentation and communication tactics to the identified user segments.

Guided by this objective, this study proposes three questions:

RQ1: How do the traits of Openness and Conscientiousness predict the behavioral choice preferences of young Chinese travelers in travel planning?

RQ2: Does cognitive appraisal of AI-generated travel plans (perceived usefulness, perceived reliability) mediate the relationship between traits (Openness, Conscientiousness) and behavioral choice preferences?

RQ3: What significant differences exist in cognitive appraisal of AI between "mixed-use" travelers and those who are "AI dominant" or "HGC dominant"? What characterizes their cognitive patterns?

2. Literature review

2.1. The evolution of AI-driven travel planning research

AI has grown to be a major field of study in tourism and hospitality management, especially when it comes to the use of generative AI in travel planning. Early studies primarily focused on establishing AI's potential to enhance efficiency and provide personalized recommendations, framing it as a disruptive technological advancement [3]. In order to comprehend the factors that influence user adoption, subsequent research has extensively used well-known technology acceptance models. These studies consistently identify key beliefs such as perceived usefulness and trust as primary drivers of adoption intention rather than post-adoption choice [4-6]. This focus on the initial adoption decision leaves a gap in understanding sustained choice behavior in a multi-source information environment. For instance, within these theoretical frameworks, factors such as AI

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anthropomorphism, consumer innovativeness, and personalization have been examined to explain adoption intentions [1,7].

However, the current research paradigm exhibits a significant gap. Most studies operationalize users' decision-making as a binary choice—essentially selecting whether to use or not use AI tools [8]. This "adoption versus rejection" perspective oversimplifies the far more complex reality of users' decision-making by ignoring their comparative and selective evaluation of available information sources. In practice, travelers are not faced with a single, either-or decision regarding AI. Instead, they must navigate a complex information landscape where AI-generated content coexists and competes with HGC from sources such as travel blogs, social media platforms, and online reviews. Users actively compare, weigh, and choose among these different information sources through cognitively effortful evaluation processes [2]. Some may prefer AI-generated travel itineraries for efficiency, others may trust HGC for its authenticity and reliability, while a likely substantial portion of users may adopt a hybrid or cross-verification strategy, using AI output as a foundation and refining it with HGC. This nuanced, competitive selection behavior remains underexplored both conceptually and empirically.

Thus, the significance of the study lies in the proposed change in perspective. Not only does the study break away from the conventional adoption approach, but the research focus on "behavioral choice preference" presents an important innovation. This study attempts to explore the preferences of the online audience in favor or against certain patterns of behavior, such as favoring AI-dominant planning, following HGC-dominant information gathering, or favoring the mixed usage approach. This study attempts to present the dynamics of travel planning choice in the digital age with increased accuracy.

2.2. The role of personality traits: from moderator to systematic antecedent

Within the field of technology acceptance research, personality traits are acknowledged as influential individual difference variables. However, the predominant approach in the existing literature largely confines their role to that of moderators. Studies frequently explore how these traits strengthen or weaken the relationship between key beliefs and subsequent behavioral intentions or usage decisions [8-10]. For instance, research suggests that an individual's travel personality can moderate the impact of information sources on perceived reliability, or the influence of emotional trust on continued usage [2,5]. Similarly, personal innovativeness—a concept closely related to Openness—is also commonly positioned as a moderator, affecting how factors like effort expectancy shape behavioral intentions [9]. While this moderator-focused approach answers the question of "for whom are certain beliefs more influential?", it fails to address the underlying question of why these beliefs are formed differently at the cognitive level.

This failure to explain the formation of beliefs points to a deeper gap in the theoretical models of how stable traits shape technology-related cognition. By predominantly positioning personality as a moderator, current research has failed to conceptualize these stable, intrinsic traits as fundamental antecedents that systematically shape core cognitive appraisals within technology acceptance models. The psychological pathway from dispositional traits to the formation of specific perceptions about technology remains inadequately mapped. There is a lack of clear understanding regarding questions such as: why individuals high in Openness might inherently perceive AI tools as more useful, or why those high in Conscientiousness might naturally gravitate toward and find HGC more reliable. Although foundational studies in the information systems field suggest that personality can directly influence technology-related perceptions and usage, research examining such effects within the tourism context—where high information uncertainty elevates the stakes of source selection—

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remains scarce, particularly concerning competitive choices between AI and human-generated information sources [11,12]. The mechanisms through which core personality traits drive differentiated appraisals of competing information sources remain theoretically underdeveloped.

Accordingly, the current research suggests the need for the reconceptualization of the roles of Openness and Conscientiousness. Instead of focusing on the boundary condition roles, the current research positions both factors as key independent variables, based on the idea that individuals tend to form specific cognitive appraisals based on their predispositions by stable traits. The current research builds and tests the model "trait → cognitive appraisal → choice." The current aims to test the following hypotheses empirically: the hypothesis that Openness shapes the preference for AI by increasing perceived usefulness of AI assistants, and the hypothesis that Conscientiousness shapes the preference for HGC by increasing the perceived reliability of the human-generated information.

2.3. The uniqueness of the Chinese young traveler demographic

Focusing the research context on a specific demographic group—young Chinese travelers—offers a critical perspective. While existing research on AI-driven travel planning is growing, its theories and models have primarily been developed and validated within Western contexts [8]. Young Chinese travelers (typically aged 18–35) represent a distinct digital-native cohort whose formative years coincided with the parallel rise of China’s unique online social media ecosystem. Their travel planning habits are deeply rooted in a mobile-first, hyper-connected online environment. Furthermore, cultural dimensions, such as higher levels of collectivism and differing perceptions of privacy, may significantly shape trust and reliability perceptions toward AI versus human-generated information sources [13].

Currently, research specifically targeting this group’s travel planning behavior remains scarce. Although some studies have begun exploring technology acceptance among Chinese tourists, they often focus on generic mobile travel applications or social media, rather than on the choice between generative AI and HGC [14]. While research examining factors such as perceived value, risk, and trust in AI within the Chinese context exists, it has not been systematically linked to the core personality traits and resulting behavioral segmentation proposed in this study. The applicability of the "personality-cognition-choice" pathway within the unique socio-technical environment of young Chinese travelers remains an open empirical question. Their marked reliance on and trust in peer-generated HGC on domestic platforms, coupled with the rapid adoption of domestic AI tools (e.g., DeepSeek, Doubao, WenxinYiyan), together create a distinctive information landscape that has yet to be thoroughly explored.

Therefore, the present study focuses on the specific case of young Chinese tourists and seeks to offer a contextualized and fine-grained understanding of the underlying mechanisms involved in the travel planning decision-making process of these tourists. The study takes into consideration the fact that the digital behaviors and predispositions of this group of tourists might affect both the strength and the form of the connections between the different variables of intentions and final choices. The present study seeks to produce a set of highly contextualized findings by focusing on a specific and highly meaningful demographic segment, namely the one comprised of the Chinese tourists, which plays a highly important role for the economic performance of the destinations visited by these tourists.

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3. Theoretical framework and hypotheses

3.1. Theoretical framework

The framework, as shown in Figure 1, was constructed by synthesizing and expanding some strong points raised by numerous literature pieces to primarily respond to its research questions. Here, behavioral choice preference (AI-dominant, HGC-dominant, or mixed use) is treated as an end variable. For interpreting variations in that preference, it pinpoints two antecedents, namely Openness and Conscientiousness. These two constructs are conceptualized as traits that are reliable and robust enough to influence cognitive ratings of potential sources of information.

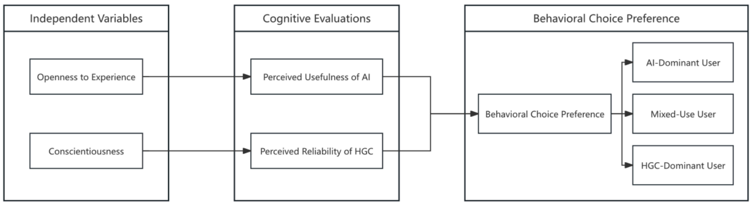

Figure 1. Theoretical framework (simplified diagram)

The framework suggests a mediator: trait → cognitive evaluations → behavior choice. The Technology Acceptance Model and the logic of personality psychology are adopted to suggest that Openness to Experience increases the perceived usefulness of AI travel assistants and boosts the adoption probability of AI-dominant planning, and that Conscientiousness increases the perceived reliability of the HGC and boosts the preference for the HGC-dominant information source. The mechanisms of hindsight bias – namely, perceived usefulness and perceived reliability – serve as the mediating nuances by which the trait and behavior constructs are connected, and the impact and workings of these pathways will be tested for the specific digital culture and quaint surroundings of the predominantly youthful Chinese travel community.

3.2. Hypotheses development

Based on the theoretical framework developed above, which posits that personality traits influence behavioral choice through specific cognitive evaluations, the following hypotheses are proposed:

H1: Direct effects of personality traits on behavioral choice preference.

H1a: Openness to experience positively predicts preference for an AI-dominant travel planning behavior.

H1b: Conscientiousness positively predicts preference for an HGC-dominant travel planning behavior.

H2: Mediating roles of cognitive evaluations.

H2a: The positive relationship between openness and preference for AI-dominant planning is mediated by the perceived usefulness of AI assistants.

H2b: The positive correlation between conscientiousness and preference for HGC-dominant planning is mediated by the perceived reliability of HGC.

H3: Cognitive differences among user segments. Based on the final behavioral choice preference, three user types are identified: AI-dominant, HGC-dominant, and Mixed-use. Their cognitive evaluations are hypothesized to differ systematically.

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H3a: Regarding the perceived usefulness of AI assistants, significant differences exist among the three user types. Specifically, the rating from Mixed-use users is significantly higher than that from HGC-dominant users but significantly lower than that from AI-dominant users.

H3b: Regarding the perceived reliability of HGC, significant differences exist among the three user types. Specifically, the rating from Mixed-use users is significantly higher than that from AI-dominant users but significantly lower than that from HGC-dominant users.

H3c: Regarding the perceived reliability of AI assistants, significant differences exist between two user types. Specifically, the rating from Mixed-use users is significantly higher than that from AI-dominant users.

4. Research method

4.1. Sample and measures

This study collected data via the online survey platform Credamo. After screening based on recent travel planning experience, a valid sample of 336 Chinese young tourists was obtained. All measurements were conducted using an online questionnaire, with core constructs measured by established scales to ensure reliability and validity.

Personality Traits: Items were drawn from the Big Five Inventory (BFI-44) to measure Openness and Conscientiousness, with 4 items for each dimension on a 7-point Likert scale [15].

Perceived Usefulness: Adapted from classic subscale in Davis's Technology Acceptance Model (TAM), 4 items were used to measure perceived usefulness of AI assistants and online travel information respectively [16].

Perceived Reliability: Based on the trust scale by McKnight et al. and focusing on the dimension of information trustworthiness, 4 items were formulated to assess the perceived reliability of both AI assistants and online travel information, using a 7-point scale [17].

Behavioral Tendency: Context-specific scales measuring "AI-use tendency" and "HGC-use tendency" were developed, each containing 4 items. The final section of the questionnaire collected demographic and travel behavior data.

4.2. Data analysis

The data analysis was conducted in SPSS, beginning with descriptive statistics and correlation tests. Regression models were then used to explore how personality traits directly shape behavioral tendencies. The Process macro examined the mediating roles of usefulness and reliability. Clustering classified respondents into AI-dominant, HGC-dominant, and mixed-use groups, followed by one-way ANOVA to compare perceptual ratings across groups.

5. Results

5.1. Descriptive statistics

This study collected a total of 336 valid questionnaires. Table 1 summarizes the demographic profile of the sample. The respondents included slightly more females (58.9%), with the majority holding a bachelor's degree (43.8%). The annual frequency of leisure trips was concentrated at 2–3 times (38.4%). Regarding the frequency of AI usage, "sometimes use" accounted for the highest proportion (35.7%), while the time spent on travel planning was mainly "a few hours" (43.5%).

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Table 1. Respondents' demographic characteristics (N=336)

Variable	Category	Frequency	Percentage (%)
Gender	Male	138	41.10%
	Female	198	58.90%
Education Level	High school or below	28	8.30%
	College	46	13.70%
	Bachelor	147	43.80%
	Master	108	32.10%
	PhD	7	2.10%
Annual Leisure Trips	1 time	74	22.00%
	2–3 times	129	38.40%
	4–5 times	81	24.10%
	6 times or more	52	15.50%
AI Chatbot Usage	Never used	52	15.50%
	Rarely use	95	28.30%
	Sometimes use	120	35.70%
	Often use	69	20.50%
Time Spent on Planning	Little, spontaneous	62	18.50%
	A few hours	146	43.50%
	1–2 days	96	28.60%
	More than 3 days	32	9.50%

Table 2 summarizes the descriptive statistics for the key variables in this study. The mean values of the variables ranged from 3.21 to 5.12, with standard deviations between 1.23 and 1.67, indicating a certain degree of variability in the data, making it suitable for subsequent inferential analysis.

Table 2. Key variable descriptive statistics (N=336)

Variable	Mean	SD	Min	Max
Openness	5.12	1.23	1	7
Conscientiousness	4.87	1.45	1	7
AI Use Tendency	4.56	1.67	1	7
HGC Use Tendency	3.21	1.52	1	7
Perceived Usefulness of AI	4.89	1.38	1	7
Perceived Usefulness of HGC	4.32	1.41	1	7
Perceived Reliability of AI	4.45	1.33	1	7
Perceived Reliability of HGC	4.78	1.29	1	7

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5.2. Model assessment

To validate the quality of the measurement scale, this study conducted tests on the measurement model. The results are as follows:

Regarding reliability testing, as shown in Table 3, the Cronbach's alpha coefficients for all constructs exceed 0.7, demonstrating satisfactory measurement reliability of the scale.

Table 3. Reliability test results

Construct	Cronbach's α
Openness	0.916
Conscientiousness	0.901
Intention to Use AI Assistant	0.917
Intention to Use HGC	0.895
Perceived Usefulness of AI	0.905
Perceived Usefulness of HGC	0.913
Perceived Reliability of AI	0.912
Perceived Reliability of HGC	0.922

In terms of validity testing, the overall Kaiser-Meyer-Olkin (KMO) value for the scale was 0.938, and Bartlett's test was significant ($p < 0.001$), confirming that the data were suitable for factor analysis. The KMO values for each construct were all above 0.7, and Bartlett's tests were significant for all, suggesting good structural validity of the variables.

Subsequently, exploratory factor analysis using principal component analysis was performed, extracting factors with eigenvalues greater than 1. A total of 8 factors were extracted, with a cumulative variance explanation rate of 80.316%, indicating a clear factor structure. The factor loadings for all items were above 0.6, and no instances of high cross-loadings across factors were observed, demonstrating good discriminant and convergent validity of the scale.

5.3. Overall impact test

To test the direct effects of traits on behavioral choice preferences (Hypotheses H1a and H1b), two separate regression analyses were conducted.

The first regression examined the impact of Openness on the preference for AI-dominant travel planning behavior (AI-use tendency). As shown in Table 4, Openness demonstrated a significant positive effect ($\beta = 0.444$, $p < 0.001$). The model was significant ($F = 76.506$, $p < 0.001$), explaining 18.6% of the variance in AI-use tendency. Thus, H1a is supported.

The second regression confirmed that Conscientiousness significantly predicted a preference for HGC-dominant planning, which aligns with the tendency of conscientious individuals to value and seek out information sources they perceive as highly reliable and well-structured. Results in Table 4 indicate a significant positive effect ($\beta = 0.400$, $p < 0.001$). This model was also significant ($F = 65.359$, $p < 0.001$), accounting for 16.4% of the variance in HGC-use tendency. Therefore, H1b is supported.

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Table 4. Results of regression analysis for direct effects (hypotheses H1a & H1b)

Hypothesis	Path	β	F	p	R^2
H1a	Openness → AI-use tendency	0.432	76.506***	0.000***	0.186
H1b	Conscientiousness→ HGC-use tendency	0.405	65.359***	0.000***	0.164

Note: β = Standardized regression coefficient. ***$p < 0.001$.

5.4. Mediation effect test

To examine the mediating roles of cognitive evaluations (perceived usefulness, perceived reliability) between personality traits and behavioral choice preferences (H2a, H2b), a stepwise regression approach along with the Bootstrap method was employed.

5.4.1. Mediating role of perceived usefulness of AI assistants between openness and AI-use tendency

The regression analysis results are shown in Table 5. Openness was significantly positively correlated with AI-use tendency ($\beta=0.444$, $p<0.001$); openness was also significantly positively correlated with AI usefulness ($\beta=0.449$, $p<0.001$). When both openness and AI perceived usefulness were included in the model, both exerted a significant positive influence on AI-use tendency ($\beta=0.322$, $p<0.001$; $\beta=0.273$, $p<0.001$). This pattern indicates that Openness influences AI-use tendency both directly and indirectly through perceived usefulness. The model's explanatory power improved (Adj. $R^2=0.232$). The Bootstrap test results, as shown in Table 6, indicate that the 95% confidence interval for the mediating effect was [0.071, 0.177], which does not include zero, confirming a significant mediating effect with a mediation proportion of 27.528%. Therefore, Hypothesis H2a is supported.

Table 5. Regression analysis for the mediating effect of AI usefulness

Variable	AI-Use Tendency	Perceived Usefulness of AI	AI-Use Tendency
Constant	1.935***	2.667***	1.208***
Independent Variable			
Openness	0.444***	0.449***	0.322***
Mediator			
Perceived Usefulness of AI			0.273***
F	76.506***	94.833***	51.463***
R^2	0.186	0.221	0.236
Adj. R^2	0.184	0.219	0.232

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Table 6. Bootstrap test for the mediating effect of AI usefulness

Mediation Path	Effect Type	Effect	S.E.	95% CI LLCI	ULCI
Openness → Perceived Usefulness of AI → AI-Use	Direct	0.322	0.056	0.212	0.432
	Total	0.444	0.051	0.344	0.544
	Indirect	0.122	0.028	0.071	0.177

5.4.2. Mediating role of perceived reliability of HGC between conscientiousness and HGC-use tendency

The regression analysis results are presented in Table 7. Conscientiousness significantly and positively predicted both HGC-use tendency ($\beta = 0.400$, $p < 0.001$) and perceived reliability ($\beta = 0.401$, $p < 0.001$). When both variables were included in the model, both conscientiousness ($\beta = 0.285$, $p < 0.001$) and perceived reliability ($\beta = 0.287$, $p < 0.001$) remained significant predictors, and the model's explanatory power increased (Adj. $R^2 = 0.229$). The Bootstrap test results, shown in Table 8, indicate that the 95% confidence interval for the mediation effect was [0.068, 0.167], which does not include zero. This confirms a significant mediation effect, accounting for 28.748% of the effect. Therefore, Hypothesis H2b is supported.

Table 7. Regression analysis for the mediating role of perceived reliability of HGC

Variable	HGC-Use Tendency	Perceived Reliability of HGC	HGC-Use Tendency
Constant	2.078***	2.466***	1.371***
Independent Variable			
Conscientiousness	0.400***	0.401***	0.285***
Mediating Variable			
Perceived Reliability of HGC			0.287***
F	65.359***	64.902***	50.655***
R^2	0.164	0.163	0.233
Adjusted R^2	0.161	0.16	0.229

Note: N = 336. Standardized coefficients (β) are reported. *** p < 0.001.

Table 8. Bootstrap test for the mediating effect of perceived reliability of HGC

Mediation Path	Effect Type	Effect	S.E.	95% CI
				LLCI ULCI
Conscientiousness →Perceived Reliability of HGC →HGC-Use Tendency	Direct Effect	0.285	0.052	[0.183, 0.387]
	Total Effect	0.4	0.05	[0.303, 0.498]
	Mediating Effect	0.115	0.025	[0.068, 0.167]

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5.5. Cognitive differences test

Testing Hypothesis H3 requires defining the three user types, namely, AI-dominant, Mixed-use, and HGC-dominant. The classification is based on the scores of the respondents on the two behavioral tendency dimensions, "AI-use tendency" and "HGC-use tendency." To be specific, an AI-dominant user should have a high score on "AI-use tendency" and a low score on "HGC-use tendency," typically above and below the sample median, respectively. On the other hand, an HGC-dominant user presents a reversed situation. The Mixed-use user had to have similar and above-median scores for both dimensions. According to such classification criteria, the whole sample was segmented into three behaviorally distinct categories: 110 AI-dominant users, 91 Mixed-use users, and 135 HGC-dominant users. In this way, meaningful user segmentation was achieved, the basis of subsequent analysis.

Subsequently, a one-way analysis of variance (ANOVA) with LSD post-hoc tests was conducted to compare whether significant differences existed in cognitive appraisals of AI assistants and online travel information among the three user types. The results are presented in Table 9.

Analysis results indicate that all four cognitive appraisal variables differed significantly across user types ($p < 0.001$). Specifically:

Perceived Usefulness of AI: The ANOVA F-value was 535.679. Post-hoc tests revealed that AI-dominant users (M=6.07) scored significantly higher than Mixed-use users (M=5.08), who in turn scored significantly higher than HGC-dominant users (M=3.54). This result fully supports Hypothesis H3a.

Perceived Reliability of AI: The ANOVA F-value was 31.349. Post-hoc tests showed that AI-dominant users (M=4.81) scored significantly higher than Mixed-use users (M=4.12), and Mixed-use users scored significantly higher than HGC-dominant users (M=3.64). This result supports Hypothesis H3c.

Perceived Usefulness of HGC: The ANOVA F-value was 19.384. Post-hoc tests revealed an inverse pattern: HGC-dominant users (M=3.40) scored the highest, significantly higher than Mixed-use users (M=2.79), who in turn scored significantly higher than AI-dominant users (M=2.31). This variable was not hypothesized but reveals a clear contrast pattern.

Perceived Reliability of HGC: The ANOVA F-value was 31.118. Post-hoc tests indicated that HGC-dominant users (M=4.24) scored significantly higher than Mixed-use users (M=3.52), who in turn scored significantly higher than AI-dominant users (M=3.05). This result fully supports Hypothesis H3b.

In conclusion, all three hypotheses H3a, H3b, and H3c received support from the data. The results demonstrate a very consistent inverse spectrum of cognitive appraisals for each of the three types of users: those preferring use of AI are most positive towards AI and least positive towards HGC; those preferring HGC have the inverse opinion; while Mixed-use users always rank in-between in all respects. This substantiates the existence of meaningful cognitive discrepancies underlying decision-making.

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Table 9. Differences in cognitive appraisals across user types (one-way ANOVA)

Factor	User Type	N	Mean	SD	F	LSD Post-hoc
Perceived Usefulness of AI	1 (AI-dominant)	110	6.07	0.41	535.68***	1 > 2 > 3
	2 (Mixed-use)	91	5.08	0.25		
	3 (HGC-dominant)	135	3.54	0.87		
Perceived Usefulness of HGC	1 (AI-dominant)	110	2.31	1.18	19.38***	3 > 2 > 1
	2 (Mixed-use)	91	2.79	1.35		
	3 (HGC-dominant)	135	3.4	1.51		
Perceived Reliability of AI	1 (AI-dominant)	110	4.81	1.15	31.35***	1 > 2 > 3
	2 (Mixed-use)	91	4.12	1.13		
	3 (HGC-dominant)	135	3.64	1.19		
Perceived Reliability of HGC	1 (AI-dominant)	110	3.05	1.28	31.12***	3 > 2 > 1
	2 (Mixed-use)	91	3.52	1.08		
	3 (HGC-dominant)	135	4.24	1.19		

6. Discussion

6.1. Theoretical contributions

This study attempts to combine the field of psychology and acceptance theory to build a “trait → cognitive appraisal → behavior choice” mediated model to provide a systematic theoretical perspective upon which the underlying choice mechanisms of young travelers in selecting AI technology and traditional sources can be based. There are three theoretical contributions made in this study.

First, this study enhances theoretical developments on personality traits in studies on technology adoption. More specifically, while it has been found in existing research that personality traits function either as positive or negative moderators of the relationships between key beliefs and intentions to adopt technology, this study will test with regression and mediation analysis that personality traits like Openness and Conscientiousness can directly operate as antecedents. They significantly predict AI-dominant or HGC-dominant behavioral choice preferences rather than merely usage intentions, by enhancing the perceived usefulness of AI ($\beta=0.449$, $p<0.001$) and the reliability of HGC ($\beta=0.530$, $p<0.001$), respectively. The validation of this “trait → cognition → behavior” pathway provides a more direct and mechanistic theoretical explanation for how intrinsic psychological dispositions drive technology acceptance.

Second, recognizing the limitations of the binary adoption perspective in information-rich travel planning, this study introduces “behavioral choice preference” as a more reflective dependent variable. Using K-means clustering and ANOVA (H3a, H3b, H3c), the study not only identifies three distinct user types—AI-dominant (n=110), HGC-dominant (n=135), and Mixed-use (n=91)—but also reveals a significant and consistent spectrum of cognitive differences among them (e.g., perceived usefulness of AI: AI-dominant M=6.07 > Mixed-use M=5.08 > HGC-dominant M=3.54, $p<0.001$). By capturing systematic cognitive variation across behaviorally distinct user groups, this study provides both a nuanced theoretical lens and a concrete classification framework for future inquiry into behavioral trajectories within intricate informational settings.

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Finally, the model will be applied in the context of the digital-native and young Chinese tourist group, thus increasing the context-specific explanatory power of the model. Theoretical constructs around the accepting roles that personality has on technology acceptance that have been developed in the West will find vindication in the Chinese context, and through the lens of the Chinese digital-native tourist group's excessive usage patterns and their specific trust dynamics around Chinese-developed and Chinese-used AI applications and social media, this work will provide insight into the interplay that results in the expression of the "personality — cognition — behavior" framework.

6.2. Practical implications

The study provides clear implications for core actors within the tourism ecosystem. The revealed systematic links between personality traits, cognitive evaluations, and behavioral choices provide a scientific basis for psychologically informed user segmentation and personalized communication.

First, service providers can conduct refined market segmentation based on users' personality inclinations and cognitive characteristics, implementing differentiated marketing and service design, for example, through adaptive content recommendation and interface personalization. For young tourists high in Openness who prefer AI-dominant planning (32.7% of the sample), platforms should emphasize the efficiency, personalization, and innovativeness of AI itinerary tools—a strategy which aligns with their preference for novelty and flexible decision-making—while also ensuring the timeliness and accuracy of AI outputs to reinforce perceived usefulness. For users high in Conscientiousness who rely on HGC (40.2% of the sample), efforts should strengthen the systematic organization, authenticity verification, and timeliness labeling of user-generated content to enhance its perceived reliability. For the "Mixed-use" segment (27.1% of the sample), who hold moderately positive views of both AI and HGC, platforms can design integrated planning tools that facilitate "AI-generated drafts + HGC deep verification," catering to their need for cross-checking and efficiency balance.

Second, communication messages and interface design should be tailored to the cognitive preferences of different user groups. For AI-preferring users, promotional language can highlight "smart," "efficient," and "tailor-made"; for HGC-preferring users, emphasis should be placed on "authentic experiences," "real traveler photos," and "trusted reviews." In interface layout, the former group could be presented with prioritized AI assistant access and structured itineraries, while the latter could be shown prominent community content entry points and curated travel blogs, a strategy aimed at reducing cognitive load by aligning the interface with users' dominant information preferences.

Finally, the findings advise AI developers and travel platforms that, while improving technical performance, they should consciously shape users' trust perceptions toward information sources. For instance, transparency features, incorporating human verification mechanisms, or enhancing outputs with selected high-quality HGC can effectively increase AI's credibility among users higher in Conscientiousness, thereby broadening its user base.

6.3. Limitations

The shortcomings of the current research provide opportunities and starting points for further scholarly investigation. First, data collection relied on an online survey platform (Credamo). Although the sample size (N=336) meets analytical requirements, participants were likely limited to specific internet-active groups, and diversity in age, geography, and travel experience remains

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insufficient, potentially affecting the external validity of these results. Future studies could employ broader sampling to test the model's robustness across populations.

Methodological limitations also warrant mention, notably the collection of data at a single time point and its foundation in subjective participant responses. Though yielding substantial relationships, furnish poor bases for drawing strong causal inferences. Future research might consider using experimental designs in which specific factors are manipulated-information source presentation format, or cognitive priming-to observe real-time choice behavior, thus directly considering the dynamic impact of personality traits on cognition and choice.

Finally, this model chose to investigate two key dimensions — Openness and Conscientiousness — that although found to be significantly explanatory, do not define other variables that might be a part of the consideration either. Future studies might investigate additional complex forms of personality, as well as variables to develop a far more complete model of a decision tree. Moreover, the addition of objective behavioral variables will give a much more authentic representation of human choices instead of being dependent solely on self-reporting.

7. Conclusion

This research centered on the selection dilemmas that young Chinese tourists encounter when planning their journey and endeavored to explain how the two basic dimensions of a Chinese citizen's personality — Openness and Conscientiousness — influenced the preferences of the tourists' behavioral choices (AI-dominant group, HGC-dominant group, or Mixed-use group) in cognitively appraising the differences between the use of artificial intelligence and human-generated content. Through the development of a "personality trait → cognitive appraisal → behavioral choice" mediation model, a number of important findings emerged.

First, the analysis proved the direct predictive function of personality traits, acting as stable psychological antecedents, in decision-making. Openness had a positive predictive impact on a preference for an AI-dominant planning style, and Conscientiousness had a positive predictive impact on a preference for an HGC-dominant information sources style, which directly responds to RQ1.

Second, the current study revealed the important cognitive mediation mechanism of cognitive appraisal. Openness works primarily as a promoter of AI-use tendency by elevating the perceived usefulness of AI assistants; Conscientiousness works primarily as a promoter of HGC-use tendency by elevating the perceived reliability of HGC. This is an important articulation of the subjective psychological process intervening between the trait and the behavior to answer RQ2.

Finally, by cluster and variance analyses, the study has identified the different and systematic cognitive profiles underlying the three user types. These three groups were significantly different from one another in perceived usefulness and reliability related to both AI and HGC and presented a completely opposite spectrum of cognitive tendency. Mixed-use users always remained in the middle positions along all dimensions, reflecting their compromising and balancing characteristics. This is precisely a response to Research Question RQ3.

In summary, by deeply integrating the perspective of personality psychology into technology acceptance research and moving beyond the traditional binary adoption view, this study not only provides a novel and robust explanatory framework for the digital travel planning behavior of the important demographic of young Chinese tourists but also offers empirical evidence for related businesses to conduct precise user insight and implement differentiated service and communication strategies. Future research can further extend and deepen these findings within broader samples, dynamic research designs, and richer contextual variables.

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