



The impact mechanism of Generative AI on tourists' travel decision-making: An integrated SOR-TTF-trust transfer model

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ABSTRACT

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This study aims to examine how Generative Artificial Intelligence (AIGC) influences tourists' travel decision-making by investigating the impact of AIGC's technological characteristics on behavioral intentions through psychological mediating mechanisms, while exploring the boundary role of technology readiness. Adopting long-distance and complex travel planning as a simulated decision-making scenario, this study constructs an integrated Stimulus–Organism–Response (SOR), Task–Technology Fit (TTF), and Trust Transfer theoretical framework. A scenario-based simulation survey was conducted among mainstream AIGC tool users, yielding 374 valid responses. Structural equation modeling was employed to test the hypothesized relationships among Perceived Anthropomorphism, Information Quality and Task Fit, Cognitive Trust, Value Co-creation Experience, Perceived Decision Efficiency, Technology Readiness, and Behavioral Intention. The findings reveal that Perceived Anthropomorphism and Information Quality and Task Fit are core antecedents stimulating tourists' positive psychological responses. Cognitive trust, value co-creation experience, and perceived decision efficiency significantly mediate the relationships between technological characteristics and behavioral intentions, confirming tourists' role shift from passive information receivers to active itinerary co-designers. Notably, technology readiness negatively moderates the Information Quality and Task Fit → Perceived Decision Efficiency path, confirming a technology compensation effect whereby AIGC more effectively empowers groups with lower technology readiness. These findings offer actionable guidance for online travel platforms in designing anthropomorphic, task-fitted AIGC tools and leveraging the technology compensation effect to bridge the digital divide for digitally disadvantaged tourist groups.

Contribution/Originality: This study develops an integrated SOR–TTF–Trust Transfer framework that captures both the rational and affective pathways of AIGC-empowered tourism decision-making. It reveals Value Co-creation Experience as a novel mediating mechanism and identifies a technology compensation effect favoring tourists with lower Technology Readiness, offering theoretical and practical insights for intelligent tourism development.

1. INTRODUCTION

Amid digitalization, the continuous advancement of information technology is profoundly reshaping people's modes of production and daily life. The emergence of Generative Artificial Intelligence (AIGC), exemplified by tools such as DeepSeek, Doubao, and ChatGPT, has initiated a paradigm shift from “people searching for information” to “information finding people” through natural-language interaction, significantly lowering tourists' decision-making threshold. Against the backdrop of the deep integration of China's digital transformation strategy with the cultural

tourism sector, smart tourism has become a crucial engine driving high-quality industry development (Peng & Huang, 2025). Data indicate that the cultural and tourism industry, as a representative of the experience economy, is emerging as a key application scenario for AIGC (Wang et al., 2025). Concurrently, leading platforms such as Ctrip and various cultural and tourism departments are actively deploying AIGC solutions to address the information-overload pain point of traditional models and meet tourists' demands through precision services (Wu, Shen, & Liang, 2025). The widespread application of AIGC is reshaping tourism decision-making models and becoming a key driver of new momentum in cultural and tourism consumption (Huang, 2022). The concept of smart tourism was initially proposed in academic discourse to examine the impact of information technology on the tourism industry (Zhang, 2012). International research has primarily focused on areas such as recommendation algorithm optimization, service supply chain restructuring (Azis, Amin, Chan, & Aprilia, 2020), and ethical and privacy issues in human-computer interaction (Marconi, Siegman, & Journalist, 2017). Domestic research, by contrast, has emphasized VR/AR immersive experiences (Jian & Qinghe, 2019), spatial analysis of tourism big data (Xu, Lu, & Zhao, 2020), and destination image perception (Zhang, Deng, Zhu, Shan, & Wang, 2025). Overall, existing studies have largely concentrated on traditional intelligent terminals or technological implementations, while empirical research examining the impact mechanisms of the latest generative AI on tourists' psychology and behavior remains insufficient.

Despite flourishing industrial practices, theoretical exploration has lagged. Although existing research has begun to examine AIGC's technological attributes, three specific gaps remain. First, few studies have investigated the mediating role of the Value Co-creation Experience in human-AI interaction within the AIGC tourism context. Second, there is a lack of an integrated theoretical framework that simultaneously captures the rational pathway (Information Quality and Task Fit $\rightarrow$ Perceived Decision Efficiency) and the affective pathway (Perceived Anthropomorphism $\rightarrow$ Cognitive Trust). Third, the boundary conditions concerning individual differences, particularly whether a higher level of Technology Readiness is always necessary for AIGC adoption, remain inconclusive (Qiu, Li, Shu, & Bai, 2020). To address these gaps, this study adopts long-distance and complex travel planning as a simulated decision-making context. Grounded in SOR theory, Task-Technology Fit (TTF) theory, and Trust Transfer theory, where SOR provides the macro-level Stimulus-Organism-Response causal framework, TTF explains the rational pathway from Information Quality and Task Fit to Perceived Decision Efficiency, and Trust Transfer theory explains the affective pathway from Perceived Anthropomorphism to Cognitive Trust, this study employs scenario-based simulation surveys and structural equation modeling to systematically reveal how AIGC's dual technological characteristics influence tourists' Cognitive Trust, Value Co-creation Experience, Perceived Decision Efficiency, and ultimately Behavioral Intentions, while also examining the moderating role of Technology Readiness. Accordingly, this study addresses the following research questions.

RQ1: How do AIGC's technological characteristics, namely, Perceived Anthropomorphism, Information Quality, and Task Fit, influence tourists' Cognitive Trust, Value Co-creation Experience, and Perceived Decision Efficiency?

RQ2: Through what psychological mechanisms do these technological characteristics drive tourists' behavioral intentions?

RQ3: Does Technology Readiness moderate these relationships, and, if so, does a technology compensation effect exist?

This study makes the following contributions. From a theoretical perspective, it constructs an integrated SOR-TTF-Trust Transfer model that bridges the rational (Information Quality and Task Fit $\rightarrow$ Perceived Decision Efficiency) and affective (Perceived Anthropomorphism $\rightarrow$ Cognitive Trust) pathways, addressing the limitation of single-perspective analyses in prior AIGC adoption research. It also introduces Value Co-creation Experience as a key mediating variable, elucidating the black-box mechanism through which human-AI interaction transforms tourists' roles from passive information receivers to active itinerary co-designers. Furthermore, it provides empirical evidence for a technology compensation effect on the Information Quality and Task Fit $\rightarrow$ Perceived Decision Efficiency pathway, demonstrating that AIGC's efficiency-enhancing effect is actually stronger for tourists with lower

Technology Readiness, which challenges the conventional assumption that digital literacy is a prerequisite for benefiting from AI-assisted travel planning. From a practical perspective, the findings offer actionable guidance for online travel platform developers in designing anthropomorphic, task-fitted AIGC tools and in leveraging the technology compensation effect to serve digitally disadvantaged tourist groups.

2. THEORETICAL FOUNDATION AND RESEARCH HYPOTHESES

2.1. Literature Review

2.1.1. Research Status of Artificial Intelligence in the Tourism Field

With the iterative advancement of information technology, the tourism industry has undergone a paradigm shift from e-tourism to smart tourism (Zhang, 2012). Early research on artificial intelligence in tourism primarily focused on traditional machine learning algorithms, such as collaborative filtering-based attraction recommendation systems, tourism demand forecasting models, and simple customer service chatbots (Azis et al., 2020). These studies emphasized the instrumental attributes of technology, namely, how to enhance the efficiency of information distribution through algorithm optimization. However, with the advent of large language models such as ChatGPT, generative artificial intelligence has brought disruptive changes to the tourism industry. Possessing powerful natural language processing and content generation capabilities, it can handle unstructured, complex tasks (Dogru et al., 2025). Currently, research on AIGC in tourism is in a period of rapid growth. Scholars are beginning to explore its application potential in itinerary planning (Kim et al., 2025), personalized service provision, and destination marketing. For instance, Strzelecki (2024) argues that AIGC is reshaping how tourists acquire information, shifting from passive searching to proactive conversational interaction. Although discussions at the technical level are relatively rich, empirical research from the tourist perspective examining how this emerging technology reshapes the tourism experience remains limited.

2.1.2. Research on the Impact of Technological Characteristics on Tourist Decision-Making Behavior

In the fields of human-computer interaction and tourism decision-making, technological characteristics are regarded as key external stimuli driving user behavior. The first is the anthropomorphic characteristic. Existing research generally agrees that endowing technological tools with human-like emotions and roles can significantly enhance users' sense of social presence. Qiu and Benbasat (2009) confirmed that anthropomorphic recommendation agents are more likely to gain users' trust. Fan, Wu, and Mattila (2016) found that, in service failure scenarios, anthropomorphism can effectively alleviate users' negative emotions. In the tourism context, anthropomorphism is no longer merely an optimization of interface design but serves as an emotional connection, helping to establish a parasocial relationship between tourists and intelligent agents (Deng, Benckendorff, & Wang, 2022). The second is Task-Technology Fit. The TTF theory, proposed by Goodhue and Thompson (1995), emphasizes that technological capabilities must match task requirements to achieve optimal performance. In the highly complex task of tourism planning, the accuracy and personalized matching of information are crucial. Filieri and McLeay (2014) confirmed that information quality is a core factor influencing tourists' adoption of online reviews. Oliveira, Faria, Thomas, and Popovič (2014) further pointed out that when technological functions are highly aligned with user tasks, this alignment significantly enhances users' perceived usefulness and trust. However, few studies have integrated the emotional dimension of anthropomorphism with the functional dimension of task fit within the same framework to explore the synergistic impact of AIGC's dual technological characteristics on tourist decision-making.

2.1.3. Research Commentary

A comprehensive review of the existing literature reveals that, although research on the impact of intelligent technology on tourism behavior has yielded fruitful results, three shortcomings remain regarding the specific context of generative AI. First, there has been insufficient exploration of the black-box mechanism through which AIGC

empowers decision-making, particularly the role of Value Co-creation Experience in human–AI interaction, which has not been fully validated. Second, there is a lack of a theoretical perspective that integrates rationality and affectivity to construct a comprehensive explanatory framework incorporating SOR, TTF, and Trust Transfer theories. Third, the boundary conditions concerning individual differences remain inconclusive; whether high Technology Readiness is still a necessary condition for adoption and whether a technology compensation effect exists require further clarification. To address these shortcomings, this study aims to construct an integrated model to systematically explore the internal mechanism through which AIGC's technological characteristics reshape tourists' psychological perceptions and subsequently drive travel decision-making.

2.2. SOR Theory, TTF Theory, and Trust Transfer Theory

The SOR (Stimulus–Organism–Response) theory was proposed by Mehrabian and Russell (1974) to explain how external environmental characteristics influence individual psychological states, thereby triggering behavioral responses. This framework consists of three core elements: Stimulus (external environmental factors), Organism (the mediating cognitive and emotional state), and Response (the final behavioral intention). Due to its clear logic and strong applicability, the SOR framework has been widely applied in information systems and tourism research. For example, Fan et al. (2016) drew on this theory to explore how the anthropomorphic characteristics of service robots influence continuous usage intention through subjective well-being. Gao, Tao, and Liu (2024) validated the pathway through which the characteristics of cultural and creative products enhance purchase intention via customer satisfaction. Li and Peng (2025) introduced social presence as a stimulus, confirming that it can enhance tourists' payment intention through pleasure and trust. These studies indicate that the SOR model possesses explanatory power in revealing the pathway from external stimuli, through psychological mechanisms, to behavioral responses. AIGC, possessing both instrumental and anthropomorphic attributes, follows this same logic through its technological characteristics. Therefore, this study adopts the SOR model as a theoretical foundation to analyze how AIGC's technological characteristics drive tourists' decision-making behavior.

The Task–Technology Fit (TTF) theory was proposed by Goodhue and Thompson (1995), emphasizing that optimal performance can only be achieved when technological capabilities match task demands. The theoretical model is shown in Figure 1. TTF posits that the degree of fit between task characteristics (i.e., user needs) and technological characteristics directly determines the ease and efficiency of users' interaction with the technology. It moves beyond a perspective focused solely on technological advancement, establishing the central role of “fit” in decision-making. In tourism research, the degree to which an intelligent conversational tool meets the need for information retrieval is a core driver of its adoption (Pillai & Sivathanu, 2020). When the capabilities of generative AI closely match the task of information acquisition, this alignment significantly enhances users' perceived usefulness (Strzelecki, 2024). Given that travel planning is highly unstructured, whether AIGC's generative capabilities can fit this complex task is key to determining tourists' evaluations. Therefore, this study introduces TTF theory to analyze AIGC's impact on Perceived Decision Efficiency and trust from a rational–functional perspective.

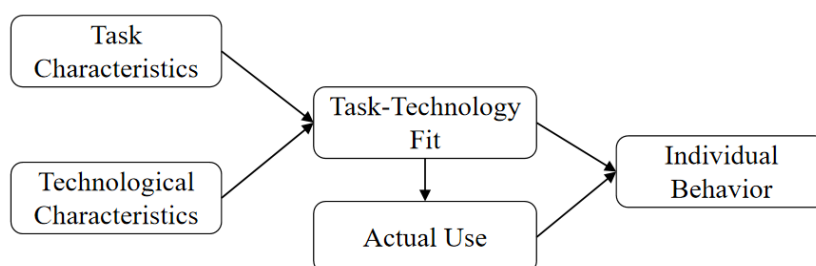


Figure 1. Task-technology fit model.

Trust Transfer theory is an important perspective for explaining the mechanism of individual trust formation. It posits that an individual's trust in a known entity can directly influence their attitude and behavioral intention toward an unknown entity (Stewart, 2003). In new environments lacking interaction experience, trust transfer typically involves a trust source, a target, and a connection path. Lee, Kang, and McKnight (2007) argue that the trustor's trust in the trust source is a significant origin for the transfer of trust to the trustee. According to the inherent mechanism of trust generation, two primary mechanisms exist, providing a framework for understanding initial trust establishment in AIGC. The first is direct transfer based on categorization, whereby trust in the source directly maps to trust in the target (Wang, Shen, & Sun, 2013). Categorization theory proposes that consumers' knowledge about products is stored in memory in a structured form (Cohen & Basu, 1987). When a new entity is perceived as belonging to a known category, existing affect transfers accordingly. For example, Lin, Lu, Wang, and Wei (2011) found that investors transfer their trust in online services to mobile services of the same category. The second is indirect transfer based on a cognitive pathway, referring to trust transfer that occurs due to the perceived close connection between the trust source and the target (Stewart, 2003). Research finds that, in high-entitativity groups, perceptions of individual characteristics easily transfer to perceptions of the group (Cohen & Basu, 1987). In other words, when users perceive a high correlation between technological capability and desired outcomes, trust flows accordingly. In the AIGC tourism context, both mechanisms operate jointly. Based on direct transfer, the anthropomorphic features of AIGC lead tourists to perceive it as a human-like agent, transferring trust from human interaction to the products recommended by the AI (Deng et al., 2022; Lu, Liu, Hu, & Zhu, 2023). Based on indirect transfer, the task fit perceived by tourists constitutes a trust source, whereby trust in technological competence logically transfers to form a perception of the reliability of the generated itinerary (Solomovich & Abraham, 2026; Wu, Yu, Zhu, & Zhang, 2020). SOR, TTF, and Trust Transfer theory exhibit complementary explanatory power regarding AIGC user behavior. SOR provides a macro-level causal framework but offers insufficient explanation of micro-level mechanisms. TTF supplements this perspective from a rational standpoint by clarifying how Information Quality and Task Fit stimulate perceived efficiency. Trust Transfer theory further supplements this analytical framework from an affective standpoint by explaining how Perceived Anthropomorphism stimulates trust. Building on this foundation, the present study constructs an integrated model, as illustrated in Figure 2. It regards AIGC's Perceived Anthropomorphism, Information Quality, and Task Fit as the stimuli. The Perceived Decision Efficiency triggered by the TTF-based rational pathway, together with the Cognitive Trust and Value Co-creation Experience triggered by Trust Transfer logic, collectively constitutes the organism's internal state. This state ultimately drives tourists' Behavioral Intention (response). Through the integration of multiple theories, this study attempts to systematically deconstruct the deeper mechanisms linking technological characteristics, psychological perceptions, and decision-making behaviors in the context of AIGC empowerment. Table 1 further summarizes each theory's core logic, its role within the model, and the corresponding pathways it explains.

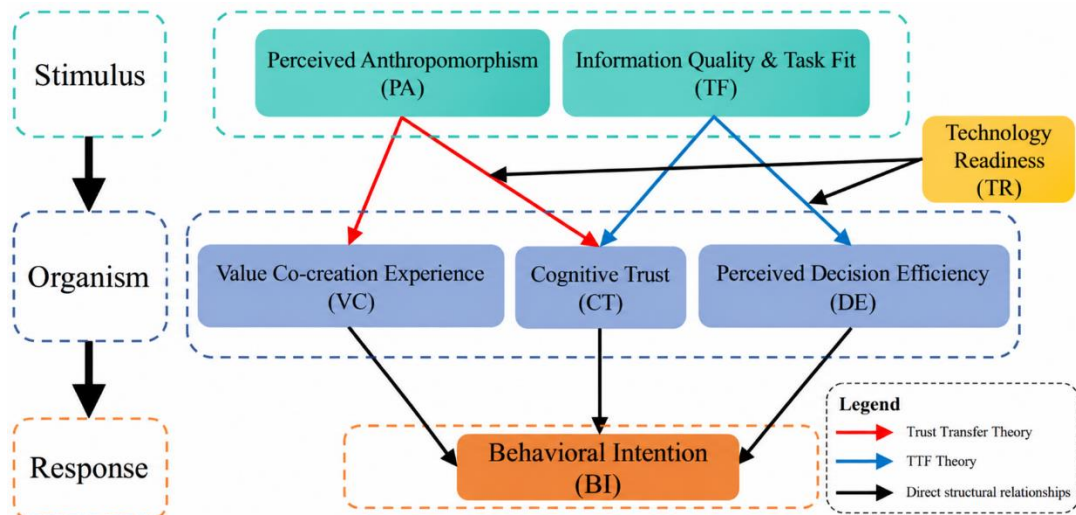


Figure 2. Research model.

Table 1. Theoretical integration of SOR, TTF, and trust transfer theory.

Theory	Core Logic	Role in the Model
SOR Theory	External stimuli (S) trigger internal psychological states (O), which in turn drive behavioral responses (R)	Provides the overall causal framework: AIGC's technological characteristics (S) → Cognitive Trust, Value Co-creation Experience, and Perceived Decision Efficiency (O) → Behavioral Intention (R)
TTF Theory	Positive performance occurs only when technological capabilities match task requirements	Explains the rational pathway: Information Quality and Task Fit → Perceived Decision Efficiency → Behavioral Intention; also contributes to Cognitive Trust
Trust Transfer Theory	Trust in a known entity can transfer to an unknown entity through direct (Categorization) or indirect (cognitive) pathways	Explains the affective pathway: Perceived Anthropomorphism → Cognitive Trust and Value Co-creation Experience → Behavioral Intention

2.3. The Impact of AIGC's Technological Characteristics on Tourists' Psychological Perception Mechanisms

Anthropomorphism refers to the psychological process of attributing human characteristics, motivations, or emotions to non-human objects (Epley, Waytz, & Cacioppo, 2007). In the context of AI, this characteristic can enhance users' perception of the agent's competence and increase adoption intention (Wu et al., 2020). According to Task–Technology Fit (TTF) and SOR theories, Perceived Anthropomorphism, as an external stimulus, can effectively activate individuals' social schemas, eliciting emotional connections, pleasure, and trust responses (Wu, Song, Yuan, & Hu, 2023). In AIGC-based travel-planning interactions, human-like communication significantly reduces technological uncertainty. Existing research has confirmed its positive effects: Waytz, Heafner, and Epley (2014) found that anthropomorphic features increase users' trust in automation; Qiu and Benbasat (2009) demonstrated that anthropomorphic language can enhance social presence, thereby increasing trust in the service provider; Fan et al. (2016) pointed out that this characteristic can stimulate participation enthusiasm, leading users to experience value co-creation by collaboratively completing tasks with the intelligent agent. In complex tourism decision-making, an AIGC system exhibiting traits similar to those of a personal consultant is more likely to be perceived as a capable social actor, thereby establishing competence-based Cognitive Trust. Simultaneously, bidirectional interaction transforms tourists from information receivers into co-designers of the itinerary. Based on this, this study proposes the following research hypotheses.

H_{1a}: Perceived Anthropomorphism positively influences tourists' Cognitive Trust.

H_{1b}: Perceived Anthropomorphism positively influences tourists' Value Co-creation Experience.

The Task–Technology Fit (TTF) theory, proposed by Goodhue and Thompson (1995), emphasizes that the degree of match between technological capabilities and task requirements determines user performance. In travel

planning, fit manifests in whether the AIGC solution can accurately address long-term, unstructured, complex decision-making problems (Kim et al., 2025). When technological characteristics are highly aligned with task requirements, this alignment can significantly reduce users' cognitive load, thereby inducing perceptions of efficiency and trust.

For highly complex tourism tasks, AIGC leverages its generative capabilities to address the problem of information overload. Existing research widely supports the positive effect of fit on perceived performance: Filieri and McLeay (2014) found that the accuracy and relevance of information are key to enhancing decision-making efficiency; Oliveira et al. (2014) confirmed that the degree of technological fit significantly and positively influences user trust, as fit implies that the system possesses professional problem-solving capabilities; Wu et al. (2020) pointed out that effectively reducing information-screening costs can significantly enhance perceived usefulness and decision-making efficiency. In this study, we adopt a compound construct, Information Quality and Task Fit (TF), which encompasses both the information quality dimension, emphasizing the accuracy, logic, and personalization of information (Filieri & McLeay, 2014) and the task-fit dimension, capturing the alignment between AIGC's capabilities and the complex task of travel planning (Goodhue & Thompson, 1995). When the information provided by AIGC is of high quality and fits tourists' needs, it can substantially shorten the time required for itinerary planning and enhance rational trust by demonstrating professional competence. Based on this, this study proposes the following research hypotheses:

H_{1a}: Information Quality and Task Fit positively influence tourists' Perceived Decision Efficiency.

H_{1b}: Information Quality and Task Fit positively influence tourists' Cognitive Trust.

2.4. The Impact of Tourists' Psychological Perceptions on Behavioral Intention

Sun, Obrenovic, and Li (2022) define Value Co-creation Experience as the psychological satisfaction and sense of achievement consumers gain from participating in the creation process. Prahalad and Ramaswamy (2004) emphasize that, unlike passive acceptance, its core lies in the user's sense of agency and participation. According to self-extension theory, when individuals invest effort in creating something, they develop a stronger emotional attachment to and preference for it (Vlieger de Oliveira, Wache, & Raithel, 2024). In the AIGC context, the travel itinerary is a product co-crafted by tourists through multiple rounds of dialogue with AI. This human-AI co-creation process evokes a sense of psychological ownership: "this was designed by me," thereby strengthening the motivation to execute and recommend the plan. Existing research widely confirms that co-creation experience can translate into positive behaviors: Nambisan and Baron (2009) found that it significantly enhances loyalty in virtual communities; research on brand communities shows that customers participating in co-creation have higher recommendation intentions (Li & Peng, 2025; See-To & Ho, 2014) verified the enhancing effect of co-creation value on continuous usage intention in the field of intelligent services. Compared with traditional OTAs, the deep sense of participation afforded by AIGC further amplifies tourists' identification with the itinerary through the IKEA effect. Based on this, this study proposes the following research hypothesis:

H_{2a}: Value Co-creation Experience positively influences tourists' Behavioral Intention.

Cognitive Trust refers to confidence in an object's capability, reliability, and professionalism, based on rational evaluation (McAllister, 1995). In tourism decision-making characterized by high uncertainty, trust is central to reducing perceived risk and facilitating transactions (Ameen, Cheah, Ali, El-Manstrly, & Kulyciute, 2024). According to the Theory of Reasoned Action, trust beliefs are direct antecedents of adoption intention. When tourists believe that AIGC suggestions are accurate and objective, decision-making risks, such as encountering unpleasant experiences, are significantly reduced, leading to a tendency to adopt the proposed plan. In AIGC-assisted travel planning, Cognitive Trust stems from the tool's perceived competence in solving complex problems, prompting tourists to shift from psychological trial to behavioral reliance. Existing research confirms its decisive role: Gefen, Karahanna, and Straub (2003) demonstrated in e-commerce that trust significantly influences purchase intention;

McKnight, Choudhury, and Kacmar (2002) indicated that initial trust is a key predictor of continued use of new technologies; Gursoy, Chi, Lu, and Nunkoo (2019) verified that, in AI services, the level of trust directly determines acceptance intention. Therefore, this study proposes the following research hypothesis:

H_{2a}: Cognitive Trust positively influences tourists' Behavioral Intention.

Perceived Decision Efficiency reflects users' evaluations of saved time, effort, and cognitive resources (Shin, Kim, Lee, Yhee, & Koo, 2025). According to the Technology Acceptance Model (TAM), perceived usefulness is central to adoption, and Perceived Decision Efficiency is a specific manifestation of it. Tourists pursue cognitive efficiency in complex decisions; AIGC compresses fragmented information gathering to the minute level, constituting a powerful behavioral driver (Dogru et al., 2025). In complex travel planning, the value of efficiency is particularly salient. When tourists perceive that AIGC can substantially reduce time costs, their dependence on it increases accordingly. Davis (1989) confirmed that perceived usefulness predicts usage intention more strongly than perceived ease of use; Okumus, Ali, Bilgihan, and Ozturk (2018) found that the information acquisition efficiency of smartphones is key to inducing their use; Wu et al. (2020) verified that the efficiency of an AI recommendation system positively affects adoption intention. Therefore, this study proposes the following research hypothesis:

H_{2b}: Perceived Decision Efficiency positively influences tourists' Behavioral Intention.

2.5. The Mediating Role of Psychological Perception Variables

Cognitive Trust refers to an individual's psychological reliance based on rational evaluation and is considered a key mechanism for reducing uncertainty and risk perception (McKnight et al., 2002). After establishing Cognitive Trust, individuals exhibit a stronger willingness to cooperate and a greater tendency to adopt the technology. In AIGC-assisted tourism decision-making, it manifests as tourists' recognition of the tool's reliability and professionalism, serving as a psychological bridge connecting technological characteristics and decision-making behavior. As an important mediating variable in human-AI interaction, Cognitive Trust can effectively predict users' transition from trial to adoption (Gefen et al., 2003) and trigger positive Behavioral Intentions (Gursoy et al., 2019). Existing research has confirmed this transmission path: Wu et al. (2020) verified the mediating effect of perceived competence between AI recommendation features and adoption intention; Oliveira et al. (2014) confirmed the significant mediating role of initial trust between Task-Technology Fit and Behavioral Intention. Therefore, this study proposes the following research hypotheses.

H_{3a}: Cognitive Trust mediates the relationship between Perceived Anthropomorphism and Behavioral Intention.

H_{3b}: Cognitive Trust mediates the relationship between Information Quality and Task Fit and Behavioral Intention.

According to SOR theory, environmental stimuli trigger behavioral responses by acting on the organism's psychological state (Mehrabian & Russell, 1974). The Value Co-creation Experience generated through tourists' deep interaction with AIGC serves as a bridge connecting technological stimuli to decision-making behavior. Li, Wang, Zhu, and Zhu (2026) confirmed that the anthropomorphic features of service robots influence continuous usage intention through subjective well-being (Li et al., 2026); Nambisan et al. found that co-creation experience is a key path to enhancing user loyalty in virtual communities (Nambisan & Baron, 2009; Sun et al., 2022) indicated that experience value fully mediates the relationship between the interaction process and purchase intention (Sun et al., 2022). Therefore, this paper proposes the following research hypothesis:

H_{3c}: Value Co-creation Experience mediates the relationship between Perceived Anthropomorphism and Behavioral Intention.

Perceived Decision Efficiency is the concrete manifestation of perceived usefulness in travel planning. From an integrated perspective of TAM and TTF theories, technological fit must drive behavior by enhancing perceived performance. Davis confirmed that perceived usefulness mediates the relationship between system characteristics and usage intention (Davis, 1989). By addressing the pain point of information overload, AIGC translates its technological advantages into perceived efficiency, thereby driving adoption. Wu et al. (2023) showed that AI information-

processing capability positively influences adoption by enhancing perceived efficiency (Filieri & McLeay, 2014; Wu et al., 2020) verified the mediating effect of perceived usefulness between information quality and adoption behavior (Filieri & McLeay, 2014). Based on this, this paper proposes the following research hypothesis:

H_{3a}: Perceived Decision Efficiency mediates the relationship between Information Quality and Task Fit, and Behavioral Intention.

2.6. The Moderating Role of Technology Readiness

Parasuraman (2000) defined Technology Readiness (TR) as an individual's psychological propensity to adopt new technologies, encompassing the dimensions of optimism, innovativeness, discomfort, and insecurity. As a core contextual variable, Technology Readiness moderates the strength with which technological stimuli are translated into psychological perceptions. According to the Technology Acceptance Model (TAM), tourists with different levels of Technology Readiness exhibit significant differences in their sensitivity to the same technological characteristics: tourists with high Technology Readiness tend to perceive AIGC as an assistant, readily perceive interactive value, and establish trust; conversely, tourists with low Technology Readiness often struggle to perceive decision efficiency due to technological anxiety fully and may even distrust anthropomorphism. This means that Technology Readiness can either strengthen or weaken the positive impact of technological characteristics. Existing research confirms its boundary effect: Lin, Shih, and Sher (2007) found that TR positively moderates the influence of perceived ease of use on usage intention; Pillai and Sivathanu (2020) showed that customers with high TR are better able to appreciate the usefulness of service robots; Lu, Mao, Wang, and Hu (2015) and Gursoy et al. (2019) also confirmed that an innovative spirit significantly strengthens the driving effect of perceived value on behavioral intention. In summary, this study posits that tourists with high Technology Readiness are more inclined to explore AIGC functionalities, thereby amplifying the positive influence of technological characteristics on psychological perceptions. Therefore, this study proposes the following research hypotheses.

H_{3b}: Technology Readiness positively moderates the influence of Perceived Anthropomorphism on Cognitive Trust.

H_{3c}: Technology Readiness positively moderates the influence of Information Quality and Task Fit on Perceived Decision Efficiency.

Based on the hypotheses above and integrating the Stimulus-Organism-Response (SOR), Technology Acceptance (TAM), and Task-Technology Fit (TTF) theories, the research model is constructed as illustrated in Figure 3. In this model, Perceived Anthropomorphism (PA) and the composite construct of Information Quality and Task Fit (TF) act as external stimuli; Cognitive Trust (CT), Value Co-creation Experience (VC), and Perceived Decision Efficiency (DE) represent the organism's internal psychological states; Behavioral Intention (BI) serves as the final response. Technology Readiness (TR) is simultaneously introduced as a moderating variable to systematically examine the intrinsic mechanism of AIGC-empowered tourism decision-making.

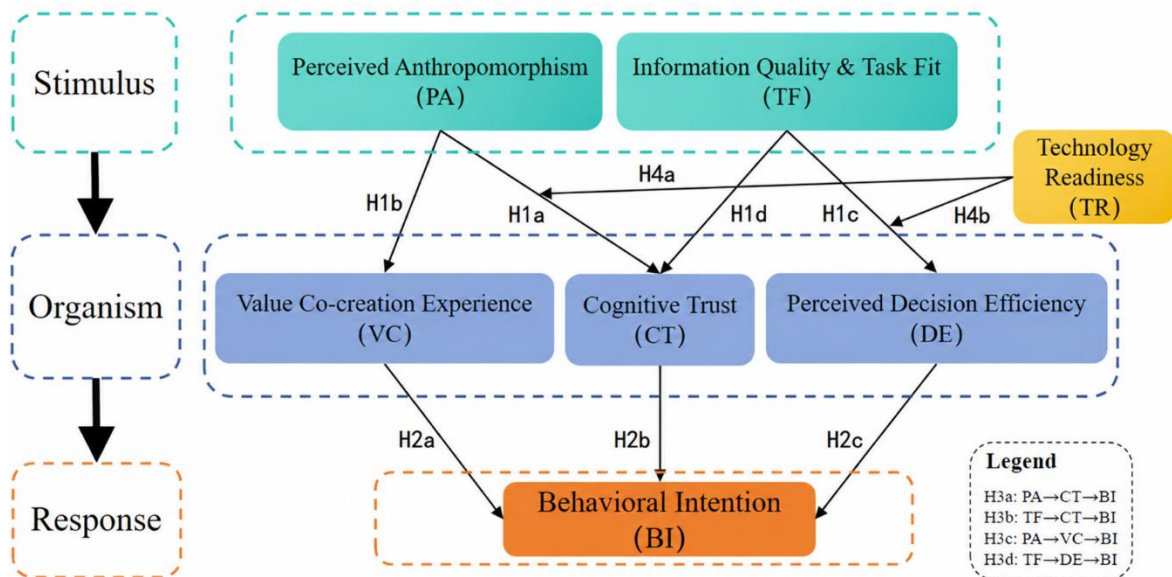


Figure 3. Structural model with hypothesized relationships.

2.7. Structural Model Specification

To enhance the transparency and replicability of the empirical model, the structural equations corresponding to the research framework are explicitly specified as follows. Based on the above hypotheses, the four structural equations are formulated as follows:

$$CT = \beta_1 \cdot PA + \beta_2 \cdot TF + \beta_3 \cdot TR + \beta_4 \cdot (PA \times TR) + \varepsilon_1 \quad (1)$$

$$VC = \beta_5 \cdot PA + \varepsilon_2 \quad (2)$$

$$DE = \beta_6 \cdot TF + \beta_7 \cdot TR + \beta_8 \cdot (TF \times TR) + \varepsilon_3 \quad (3)$$

$$BI = \beta_9 \cdot CT + \beta_{10} \cdot VC + \beta_{11} \cdot DE + \varepsilon_4 \quad (4)$$

Where CT denotes Cognitive Trust, VC denotes Value Co-creation Experience, DE denotes Perceived Decision Efficiency, BI denotes Behavioral Intention, PA denotes Perceived Anthropomorphism, TF denotes Information Quality and Task Fit, and TR denotes Technology Readiness. $PA \times TR$ and $TF \times TR$ represent the interaction terms for the moderating effects specified in H4a and H4b, respectively. β_1 through β_{11} are the estimated path coefficients, and ε_1 through ε_4 are the residual error terms. Specifically, Equation 1 estimates the effects of Perceived Anthropomorphism and Information Quality and Task Fit on Cognitive Trust, along with the moderating role of Technology Readiness (H4a). Equation 2 estimates the effect of Perceived Anthropomorphism on Value Co-creation Experience (H1b). Equation 3 estimates the effect of Information Quality and Task Fit on Perceived Decision Efficiency, along with the moderating role of Technology Readiness (H4b). Equation 4 estimates the effects of the three psychological mediators on Behavioral Intention (H2a–H2c).

3. RESEARCH DESIGN AND DATA COLLECTION

3.1. Variable Measurement

The research model encompasses seven main constructs: Perceived Anthropomorphism, Information Quality and Task Fit, Cognitive Trust, Value Co-creation Experience, Perceived Decision Efficiency, Technology Readiness, and Behavioral Intention. To ensure the reliability and validity of the measurements, this study drew upon well-established scales from leading domestic and international journals. These scales were semantically adapted and revised to fit the context of this study. To ensure data quality, attention-check items were also included in the questionnaire. The specific sources of the measurement indicators are as follows:

Perceived Anthropomorphism was primarily adapted from the scales of Qiu and Benbasat (2009) and Fan et al. (2016), focusing on the tool's human-like interaction characteristics, emotional feedback, and perceived private

consultant-like role, comprising three items. Information Quality and Task Fit was mainly adapted from the scales of Goodhue and Thompson (1995) and Filieri and McLeay (2014), covering the accuracy and logic of information, as well as its fit for the complex travel-planning task described in the scenario simulation, comprising three items. Cognitive Trust was adapted from the scales of Gefen et al. (2003) and McKnight et al. (2002), focusing on tourists' rational evaluation of the tool's professional capability, reliability, and risk-mitigation ability, comprising three items. Value Co-creation Experience was adapted from the scales of Nambisan and Baron (2009) and Yi and Gong (2013), measuring the perceived enjoyment of interaction, sense of co-participation, and inspirational stimulation during the itinerary-design process, comprising three items. Perceived Decision Efficiency was adapted from Davis (1989) and related research by Wu et al. (2020), emphasizing the evaluation of the tool's time-saving and effort-reducing capabilities in filtering vast amounts of information and generating plans, comprising three items.

Technology Readiness was measured using items adapted from the TRI scale developed by Parasuraman (2000). The original TRI framework comprises four dimensions, optimism, innovativeness, discomfort, and insecurity, which are conceptually categorized into two opposing groups: motivators (optimism and innovativeness) and inhibitors (discomfort and insecurity). In this study, only the two motivator dimensions were retained, yielding two items. This selection was guided by three considerations. First, this study focuses on the positive enabling effects of AIGC on tourism decision-making efficiency and trust, which are theoretically aligned with the motivational dimensions rather than the inhibitory ones. Second, including the negative dimensions (discomfort and insecurity) would introduce constructs beyond the theoretical scope of the SOR-TTF-Trust Transfer framework adopted in this study, potentially confounding the interpretation of the moderating effect. Third, selective dimension retention has been supported in prior research; for instance, Lin et al. (2007) employed a simplified TR measure focusing on motivational facets when examining technology acceptance, and Pillai and Sivathanu (2020) similarly adopted a streamlined approach in the context of AI-based service adoption. The two-item measure demonstrated acceptable reliability in this study (Cronbach's $\alpha = 0.873$), and its validity was further confirmed through confirmatory factor analysis.

Behavioral Intention was adapted from the scale developed by Gursoy et al. (2019), encompassing willingness to adopt the proposed itinerary, willingness to continue using the tool, and travel intention to the destination, and comprising three items.

The final scale used in this study is detailed in Table 2. All items were measured using a 7-point Likert scale, where "1" represents "strongly disagree" and "7" represents "strongly agree." Before the formal survey, a small-scale pilot study was conducted through online channels, and 80 questionnaires were distributed. After invalid responses were excluded, 68 valid questionnaires remained. Reliability and exploratory factor analyses were performed, and items with low factor loadings were removed. This process yielded the final formal questionnaire, containing seven latent variables and 20 measurement items.

Table 2. Variable measurement scale.

Construct	Code	Measurement Item	Source
Perceived Anthropomorphism (PA)	PA1	The AI tool gives me the feeling of interacting with a real person.	Qiu and Benbasat (2009) and Fan et al. (2016)
	PA2	The tool's responses carry a certain emotional tone (e.g., warmth, humor, thoughtfulness), rather than being just cold, factual data.	
	PA3	The tool feels not just like an assistant, but more like a knowledgeable local guide or a seasoned travel companion.	
Information Quality and Task Fit (TF)	TF1	The information provided by the tool accurately responds to my specific, personalized needs.	Goodhue and Thompson (1995) and Filieri and McLeay (2014)
	TF2	The itinerary plan generated by the tool is logical, clear, and detailed.	
	TF3	The tool can handle my complex instructions and provides personalized suggestions, rather than generic, one-size-fits-all recommendations.	

Construct	Code	Measurement Item	Source
Cognitive Trust (CT)	CT1	This AI tool is professional in planning travel itineraries.	McKnight et al. (2002) and Gefen et al. (2003)
	CT2	I believe the attractions and routes recommended by the tool are reliable.	
	CT3	Overall, this is a trustworthy assistant for travel decision-making.	
Value Co-creation Experience (VC)	VC1	The process of using this AI tool to plan the itinerary is enjoyable.	Nambisan and Baron (2009) and Yi and Gong (2013)
	VC2	I feel that I co-designed this itinerary with the AI, which gives me a great sense of accomplishment.	
	VC3	This interactive mode of "me asking and it answering" inspires my curiosity and imagination about exploring the destination.	
Perceived Decision Efficiency (DE)	DE1	Using this tool can save me a lot of time in searching for and organizing travel guides.	Davis (1989) and Wu et al. (2020)
	DE2	The tool helps me reduce the hassle of filtering and comparing vast amounts of information.	
	DE3	Using this tool to make travel plans makes the entire decision-making process feel easy and simple.	
Technology Readiness (TR)	TR1	I believe new technologies like AI can make my life freer and more efficient.	Parasuraman (2000)
	TR2	I am confident in my ability to master new tools like AI.	
Behavioral Intention (BI)	BI1	If I were to travel to this destination, I would directly adopt the itinerary plan recommended by this tool.	Gursoy et al. (2019)
	BI2	For future travel planning, I am willing to use similar AI tools again.	
	BI3	After seeing the travel guide generated by this tool, I very much want to travel to this destination.	

3.2. Data Collection and Sample Profile

This study selected users of mainstream generative AI tools, such as DeepSeek, Doubao, ChatGPT, and ERNIE Bot, as survey respondents. These tools, leveraging their powerful natural language processing capabilities, have deeply penetrated the tourism decision-making process and represent the future direction of advisory services. Considering user distribution, this study primarily targeted online groups characterized by high internet penetration and mature digital literacy. Respondents were required to possess basic operational skills for smart devices and AI-based conversation, ensuring that the sample possessed sufficient technological readiness to authentically recreate the decision-making process within human-computer interaction.

The survey was conducted from November 20, 2025, to January 15, 2026, via Wenjuanxing (a Chinese online survey platform) and social media channels. A scenario simulation method was employed to enhance ecological validity. All respondents were presented with the same decision-making context: planning a 5-day "Hulunbuir parent-child travel" itinerary using a generative AI tool. This specific scenario was chosen because long-distance parent-child travel involves a high degree of task complexity, information uncertainty, and personalization requirements, which are well suited for examining the dual mechanisms of AIGC's technological characteristics. Respondents were instructed to interact with a mainstream generative AI tool (e.g., DeepSeek, Doubao, ChatGPT, or ERNIE Bot) to generate a personalized itinerary, either through on-the-spot interaction or by recalling their prior usage experiences, and then complete the questionnaire, which included attention-check items. A total of 467 questionnaires were distributed. After strictly excluding responses with excessively short completion times, those failing attention checks, and those showing patterned answering, 374 valid questionnaires were obtained, yielding an effective response rate of 80.1%.

The sample profile is shown in Table 3. Regarding data sources, the survey encompassed both groups experiencing the tool in real time (58%) and those relying on recalled prior experience (42%). This distribution ensured both the immediacy of the data and the incorporation of long-term feedback from experienced users,

effectively enhancing the robustness of the findings. In terms of demographic characteristics, female respondents slightly outnumbered male respondents. The age distribution skewed toward younger individuals: those aged 18–24 accounted for 42%, and those aged 25–34 accounted for 40.1%, aligning with the pattern of higher penetration of emerging AIGC technology among younger generations. Educational attainment was relatively high, with bachelor's degrees and above collectively reaching 68.2%, indicating that respondents possessed adequate human–computer interaction capabilities. Regarding income, the main groups were those earning 5,001–10,000 RMB (35.3%), 10,001–15,000 RMB (25.1%), and 2,001–5,000 RMB (23.3%), demonstrating an economic foundation capable of supporting long-distance travel. In terms of behavioral preferences, travel companions were diverse. Traveling with friends or classmates (46.5%) and with partners or spouses (29.9%) were the most common arrangements, reflecting the social nature of travel. Additionally, 15.8% preferred solo or intensive ("special forces" style) travel; this group typically places high demands on efficiency and personalization. Regarding tool usage habits, respondents exhibited high technology acceptance, with the majority being frequent users (48.4%) or almost daily users (32.1%), indicating that respondents were mostly experienced users. This provides reliable data support for exploring deeper psychological perceptions.

Overall, the sample exhibited characteristics of being young, highly educated, enthusiastic about social travel, and possessing high digital literacy. It objectively reflects the profile of the early adopter group for AIGC in travel scenarios, demonstrating good representativeness and relevance at the current stage of AIGC adoption. However, this demographic skew, particularly the overrepresentation of respondents aged 18–34 (82.1%) and those with a bachelor's degree or above (68.2%), may limit the generalizability of the findings to older populations, individuals with lower educational attainment, or those with limited digital literacy. These groups may exhibit fundamentally different psychological responses to AIGC due to varying levels of technological familiarity, information-processing styles, and risk perceptions. Therefore, the results of this study should be interpreted as primarily applicable to the early-adopter segment of AIGC users in travel contexts.

Table 3. Sample profile (N=374).

Variables	Freq.	%	Variables	Freq.	%
Gender			5,001-10,000	132	35.3
Male	167	44.7	10,001-15,000	94	25.1
Female	207	55.3	≥15,001	39	10.4
Age			Travel Preference		
< 18	0	0	Solo Traveler (Special forces style)	59	15.8
18-24	157	42.0	With Friends/Classmates	174	46.5
25-34	150	40.1	With Partner/Spouse	112	29.9
35-44	64	17.1	With Parents/Family	29	7.8
> 45	3	0.8	Questionnaire Basis		
Education Level			Planning via live AI tool operation	217	58.0
High School/Vocational	9	2.4	Filled based on prior AI usage experience	157	42.0
College	110	29.4	AI Tool Usage Experience		
Bachelor's Degree	172	46.0	Never heard of/Never used	7	1.9
Master's Degree and above	83	22.2	Occasionally try	66	17.6
Monthly Income (RMB)			Frequently use	181	48.4
≤2,000	22	5.9	Use almost every day	120	32.1
2,001-5,000	87	23.3			

4. DATA ANALYSIS AND RESULTS

4.1. Reliability and Validity Analysis

4.1.1. Reliability and Convergent Validity

This study first conducted reliability tests using SPSS 27.0. The results showed that the Cronbach's α coefficients for the seven latent variables, including Perceived Anthropomorphism, Information Quality, and Task Fit, ranged

from 0.873 to 0.933, and the overall questionnaire reliability was 0.963, all exceeding the critical threshold of 0.7, indicating good internal consistency. Confirmatory Factor Analysis (CFA) was then performed on the measurement model using AMOS 28.0, with all latent variables allowed to covary freely. The fit indices for the measurement model were as follows: CMIN/DF = 2.065, GFI = 0.927, RFI = 0.954, IFI = 0.981, NFI = 0.964, CFI = 0.981, and RMSEA = 0.053. All indices exceeded their conventional thresholds: CMIN/DF was well below 3.0 (Kline, 2023); GFI, RFI, IFI, NFI, and CFI all exceeded 0.90 (Hu & Bentler, 1999); and RMSEA was well below 0.08 (Browne & Cudeck, 1993) indicating an excellent model fit. Regarding convergent validity, as shown in Table 4, the standardized factor loadings ranged from 0.868 to 0.928 (all $p < 0.001$), Composite Reliability (CR) values ranged from 0.874 to 0.933, and Average Variance Extracted (AVE) values ranged from 0.777 to 0.823, all well exceeding the recommended thresholds of 0.70 for CR and 0.50 for AVE (Hair, Black, Babin, & Anderson, 2019), indicating good convergent validity.

4.1.2. Common Method Bias

As all data were collected via a single self-reported questionnaire at one time point, Common Method Bias (CMB) may constitute a potential threat to the empirical results (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Two complementary techniques were adopted to examine CMB: Harman's single-factor test and the Common Latent Factor (CLF) approach.

First, Harman's single-factor test was implemented. All 20 measurement items were entered into an unrotated exploratory principal component analysis. As illustrated in Table 5, the first extracted unrotated component explained 34.489% of the total variance, which was lower than the widely used empirical cutoff value of 50%. In addition, seven factors with eigenvalues greater than 1 were extracted, consistent with the seven latent constructs proposed in the theoretical model. These results indicate that no dominant single factor accounted for most of the variance, preliminarily suggesting that no severe common method bias exists.

Table 4. Results of confirmatory factor analysis.

Construct	Mean	Std. Dev.	Loading	AVE	CR	Cronbach's α
Perceived Anthropomorphism (PA)				0.821	0.932	0.932
PA1	5.470	1.478	0.903			
PA2	5.420	1.532	0.902			
PA3	5.530	1.440	0.912			
Information Quality and Task Fit (TF)				0.805	0.925	0.924
TF1	5.540	1.510	0.928			
TF2	5.620	1.494	0.872			
TF3	5.580	1.458	0.891			
Cognitive Trust (CT)				0.787	0.917	0.917
CT1	5.020	1.404	0.868			
CT2	5.010	1.430	0.906			
CT3	5.030	1.406	0.887			
Value Co-creation Exp. (VC)				0.808	0.927	0.926
VC1	5.580	1.454	0.889			
VC2	5.510	1.507	0.910			
VC3	5.510	1.436	0.898			
Perceived Decision Eff. (DE)				0.819	0.930	0.929
DE1	5.800	1.430	0.909			
DE2	5.790	1.474	0.909			
DE3	5.810	1.404	0.891			
Technology Readiness (TR)				0.777	0.874	0.873
TR1	5.450	1.496	0.892			
TR2	5.510	1.397	0.870			
Behavioral Intention (BI)				0.823	0.933	0.933
BI1	5.370	1.503	0.895			
BI2	5.390	1.512	0.903			
BI3	5.410	1.482	0.923			

Second, the CLF method was applied for a more rigorous evaluation. Following the analytical procedure recommended by Podsakoff et al. (2003), a global Common Latent Factor (CLF) was incorporated into the baseline CFA model. All 20 observed items were allowed to load simultaneously on their corresponding substantive latent constructs and the Common Latent Factor. To achieve model identification, the unstandardized path coefficient from the CLF to item PA1 was constrained to 1, and the variance of the CLF was freely estimated. We then compared the standardized factor loadings obtained from the baseline CFA model and the CLF-augmented model (see Table 6). The maximum absolute change in standardized loadings was only 0.067 (item DE1), far below the empirical threshold of 0.2 commonly adopted in relevant studies. Meanwhile, the largest standardized loading of the observed items on the Common Latent Factor was 0.379, which was less than the empirical critical value of 0.4. Moreover, the estimated variance of the CLF was trivial (0.004, $p = 0.934$), implying that the common factor could not explain substantial additional variance beyond the seven theoretical constructs. The model fit of the CLF model (CMIN/DF = 1.884, GFI = 0.943, IFI = 0.986, CFI = 0.986, RMSEA = 0.049) was marginally better than that of the baseline CFA model (CMIN/DF = 2.065, GFI = 0.927, IFI = 0.981, CFI = 0.981, RMSEA = 0.053), further supporting the stability of the measurement model.

Collectively, consistent evidence from Harman's single-factor test and CLF analysis demonstrates that common method bias does not seriously threaten the validity of the research findings.

Table 5. Harman's single-factor test.

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	6.898	34.489	34.489
2	1.907	9.533	44.022
3	1.574	7.869	51.891
4	1.495	7.475	59.366
5	1.365	6.824	66.190
6	1.098	5.491	71.681
7	1.074	5.371	77.052

Table 6. Common latent factor (CLF) analysis results.

Item	Without CLF	With CLF	Difference	Item	Without CLF	With CLF	Difference
PA1	0.903	0.902	0.001	VC2	0.91	0.898	0.012
PA2	0.902	0.907	0.005	VC3	0.898	0.873	0.025
PA3	0.912	0.908	0.004	DE1	0.909	0.842	0.067
TF1	0.928	0.922	0.006	DE2	0.909	0.874	0.035
TF2	0.872	0.864	0.008	DE3	0.891	0.856	0.035
TF3	0.891	0.902	0.011	TR1	0.892	0.859	0.033
CT1	0.868	0.86	0.008	TR2	0.87	0.832	0.038
CT2	0.906	0.912	0.006	BI1	0.895	0.897	0.002
CT3	0.887	0.875	0.012	BI2	0.903	0.87	0.033
VC1	0.889	0.904	0.015	BI3	0.923	0.889	0.034

4.1.3. Discriminant Validity

In terms of discriminant validity, as presented in Table 7 and following the Fornell-Larcker criterion, the square root of the AVE for each latent variable was greater than its correlation coefficients with all other variables. This demonstrates that the variables maintained good independence and discriminant validity.

To further assess discriminant validity, the Heterotrait-Monotrait (HTMT) ratio was calculated using SmartPLS 4.0 (Henseler, Ringle, & Sarstedt, 2015). As shown in Table 8, all HTMT values fell below the conservative threshold of 0.85, with the highest observed value being 0.846 (between Technology Readiness and Perceived

Anthropomorphism). The HTMT value between Perceived Anthropomorphism and Value Co-creation Experience was 0.830, while the value between Information Quality and Task Fit and Perceived Decision Efficiency was 0.756; both satisfied the conservative threshold. These results, combined with the Fornell-Larcker criterion reported above, provide robust evidence of discriminant validity across all constructs.

Collectively, both the Fornell and Larcker (1981) criterion and the HTMT analysis provide converging evidence that all constructs in this study demonstrate adequate discriminant validity.

Table 7. Discriminant validity test.

Construct	TF	PA	DE	VC	CT	BI
Information Quality and Task Fit (TF)	0.897					
Perceived Anthropomorphism (PA)	0.871	0.906				
Perceived Decision Eff. (DE)	0.887	0.773	0.903			
Value Co-creation Exp. (VC)	0.756	0.868	0.671	0.899		
Cognitive Trust (CT)	0.783	0.817	0.694	0.709	0.887	
Behavioral Intention (BI)	0.790	0.799	0.780	0.791	0.745	0.907

Table 8. Heterotrait-monotrait (HTMT) ratios.

Construct Pair	HTMT	Construct Pair	HTMT	Construct Pair	HTMT
CT<->BI	0.757	TF<->CT	0.769	TR<->TF	0.813
DE<->BI	0.818	TF<->DE	0.756	VC<->BI	0.828
DE<->CT	0.749	TF<->PA	0.814	VC<->CT	0.767
PA<->BI	0.819	TR<->BI	0.827	VC<->DE	0.829
PA<->CT	0.793	TR<->CT	0.821	VC<->PA	0.830
PA<->DE	0.832	TR<->DE	0.756	VC<->TF	0.836
TF<->BI	0.800	TR<->PA	0.846	VC<->TR	0.828

4.2. Structural Equation Modeling and Path Analysis

This study employed AMOS 28.0, using the maximum likelihood estimation method to test the main-effect model, as shown in Figure 4. The model exhibited a good fit.

First, technological characteristics significantly drove psychological responses. Perceived Anthropomorphism had significant positive effects on both Cognitive Trust ($\beta = 0.559$, $p < 0.001$) and Value Co-creation Experience ($\beta = 0.868$, $p < 0.001$). This indicates that strong interactive characteristics help build trust and foster deep co-creation; thus, H1a and H1b were supported. Information Quality and Task Fit also demonstrated significant positive effects on Perceived Decision Efficiency ($\beta = 0.887$, $p < 0.001$) and Cognitive Trust ($\beta = 0.296$, $p < 0.001$). This suggests that precise matching enhances both efficiency and trust; therefore, H1c and H1d were supported.

Second, psychological responses significantly drove Behavioral Intention. Value Co-creation Experience ($\beta = 0.395$, $p < 0.001$), Cognitive Trust ($\beta = 0.208$, $p < 0.001$), and Perceived Decision Efficiency ($\beta = 0.371$, $p < 0.001$) all had significant positive effects on Behavioral Intention. This confirms that the organism's internal responses are key antecedents driving decision-making, thus supporting H2a, H2b, and H2c.

In summary, all direct-path hypotheses in the main-effect model were statistically significant.

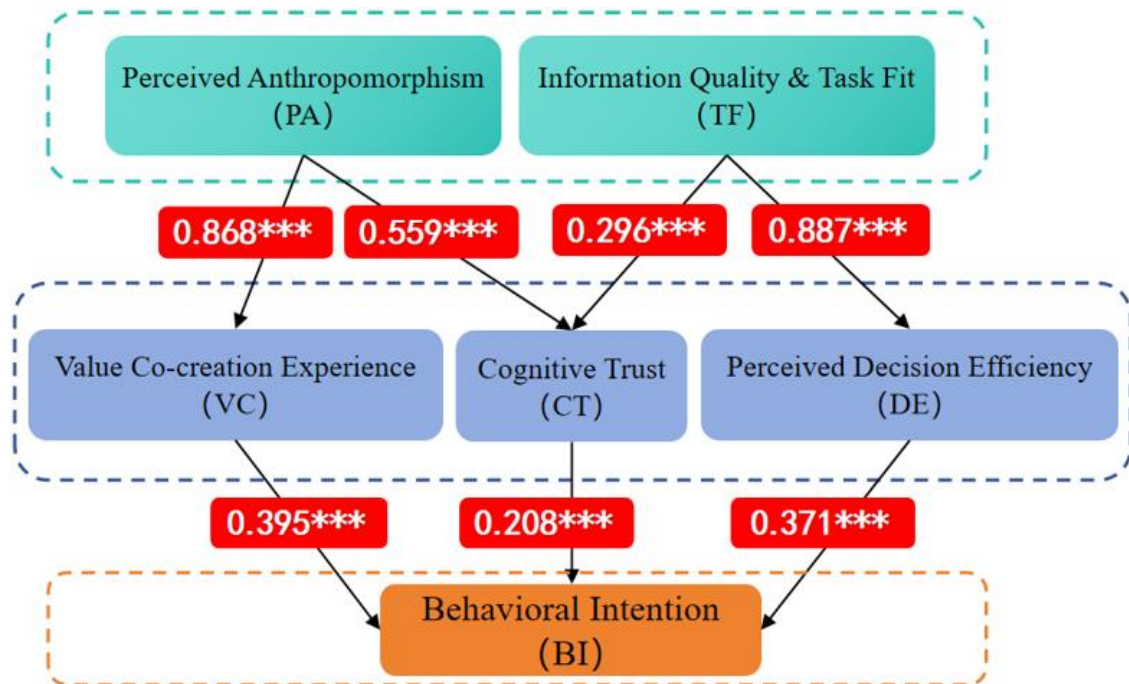


Figure 4. Model path testing results.

Note: *** $p < 0.001$.

4.3. Mediation Effect Analysis

This study employed the bootstrap method (2,000 resamples and 95% confidence intervals) to test mediation effects. The results, as shown in Table 9, indicate that the psychological variables played significant mediating roles between technological characteristics and Behavioral Intention. Specifically, Perceived Anthropomorphism produced a significant mediating effect through Value Co-creation Experience and Cognitive Trust ($\beta = 0.459$), with a confidence interval of $[0.335, 0.610]$ that did not include zero, thus supporting H3a and H3c. Information Quality and Task Fit produced a significant mediating effect through Perceived Decision Efficiency and Cognitive Trust ($\beta = 0.390$), with a confidence interval of $[0.268, 0.537]$ that did not include zero, thus supporting H3b and H3d.

Table 9. Results of mediation effect tests.

Path	Effect Value	Bias-corrected 95%CI			Conclusion
		Lower	Upper	P-value	
H3a and H3c: Perceived Anthropomorphism→ Mediating Variables→ Behavioral Intention	0.459	0.335	0.610	0.001	Support
H3b and H3d: Info Quality and Task Fit→ Mediating Variables→ Behavioral Intention	0.390	0.268	0.537	0.001	Support

4.4. Moderating Effect Analysis

This study introduced Technology Readiness as a moderating variable and examined its effect using the product indicator method with mean-centered variables. The results are presented in Table 10. Interaction Term A (Perceived Anthropomorphism $\times$ Technology Readiness) did not have a significant effect on Cognitive Trust ($\beta = 0.083$, $p = 0.054$), indicating that Technology Readiness did not significantly alter the strength of the relationship between Perceived Anthropomorphism and trust establishment; thus, H4a was not supported. Interaction Term B (Information Quality and Task Fit $\times$ Technology Readiness) showed a significant negative effect on Perceived Decision Efficiency ($\beta = -0.107$, $p = 0.005$), contrary to the expected positive moderating effect. This suggests that Technology Readiness actually weakens the positive impact of Information Quality and Task Fit on Perceived Decision Efficiency; therefore, H4b was not supported.

Table 10. Results of moderating effect tests.

Hypothesis	Path Relationship	Estimate	S.E.	C.R.	P	β	Conclusion
H4a	Dependent Variable: Cognitive Trust						Reject
	Perceived Anthropomorphism → Cognitive Trust	0.354	0.098	3.619	***	0.370	
	Technology Readiness → Cognitive Trust	0.460	0.127	3.629	***	0.445	
	Interaction Term A (PA×TR) → Cognitive Trust	0.043	0.022	1.927	0.054	0.083	
H4b	Dependent Variable: Perceived Decision Efficiency						Reject
	Info Quality and Task Fit → Perceived Decision Efficiency	0.443	0.09	4.942	***	0.429	
	Technology Readiness → Perceived Decision Efficiency	0.476	0.091	5.216	***	0.441	
	Interaction Term B (TF×TR) → Perceived Decision Efficiency	-0.063	0.022	-2.828	0.005	-0.107	

Note: ***p<0.001.

4.5. Supplementary Multi-Group Analysis by Technology Readiness

To further probe the technology compensation effect identified in the moderating analysis, a supplementary multi-group analysis was conducted. Respondents were classified into two groups based on their composite mean scores for the Technology Readiness construct ($M = 5.48$): a low-TR group ($n = 151$, $TR \leq 5.48$) and a high-TR group ($n = 223$, $TR > 5.48$). The structural model was then estimated separately for each group using AMOS 28.0, and the overall model demonstrated an acceptable fit ($CMIN/DF = 2.583$, $CFI = 0.910$, $RMSEA = 0.055$).

As shown in Table 11, the path coefficient from Information Quality and Task Fit to Perceived Decision Efficiency was substantially stronger in the low TR group ($\beta = 0.722$, $p < 0.001$) than in the high TR group ($\beta = 0.433$, $p < 0.001$), a difference of 0.289. This pattern provides direct empirical evidence for the technology compensation effect: AIGC's task-fit capabilities yield greater efficiency gains for tourists with lower Technology Readiness than for their higher-readiness counterparts.

Table 11. Multi-group analysis results for TF → DE path.

Path	Low TR (n = 151)		High TR (n = 223)	
	β	P	β	P
TF → DE	0.722	***	0.433	***

Note: ***p<0.001.

5. CONCLUSIONS AND IMPLICATIONS

5.1. Conclusions

Based on 374 valid data points, this study constructed a structural equation model to empirically examine the impact of AIGC's technological characteristics on tourists' travel behavioral intentions and explored the moderating effect of technology readiness. The main research findings are as follows:

First, the two technological stimuli, Perceived Anthropomorphism (PA) and Information Quality and Task Fit (TF), are important antecedents stimulating tourists' positive psychological responses. Data analysis validated that AIGC's technological characteristics can drive tourists' internal psychological reactions. Perceived Anthropomorphism had a significant positive influence on Cognitive Trust and Value Co-creation Experience. This result supports the "computers as social actors" perspective, indicating that human-like interactive features help tourists perceive AI as a social actor with social attributes (Deng et al., 2022; Qiu & Benbasat, 2009). Information Quality and Task Fit were confirmed to effectively enhance Perceived Decision Efficiency and Cognitive Trust, suggesting that, in complex decision-making contexts, the functional fit of the tool is foundational for establishing tourists' rational reliance and perceptions of efficiency (Oliveira et al., 2014).

Second, Cognitive Trust, Value Co-creation Experience, and Perceived Decision Efficiency are intrinsic drivers of Behavioral Intention, with the influence coefficient of Value Co-creation Experience being relatively significant. Unlike the passive reception associated with traditional OTAs, AIGC assigns tourists the role of co-designers. The psychological ownership generated through this human–AI collaboration helps enhance subsequent travel intentions. The significant positive effects of Perceived Decision Efficiency and Cognitive Trust further corroborate the fundamental roles of efficiency improvement and trust building in technology-empowered tourism decision-making (Davis, 1989; Gefen et al., 2003).

Third, psychological response variables play a mediating role between technological characteristics and Behavioral Intention. The results validate the "technological characteristics → psychological response → Behavioral Intention" pathway. This, to some extent, elucidates the internal mechanism through which AIGC operates: technological characteristics often need to be transformed into tourists' internal emotional connections and rational evaluations to more effectively influence decision-making behavior (Li & Peng, 2025).

Fourth, the analysis of the moderating effect of Technology Readiness revealed a nuanced boundary mechanism. For H4a, Technology Readiness does not significantly moderate the relationship between Perceived Anthropomorphism and Cognitive Trust ($\beta = 0.083$, $p = 0.054$). This finding suggests that the trust-building effect of anthropomorphic interaction features possesses a degree of universality, operating similarly across tourists with varying levels of Technology Readiness. A possible explanation is that anthropomorphism triggers social-relational responses deeply rooted in human communication schemas (Qiu & Benbasat, 2009), which are largely independent of individuals' technological literacy or readiness. In other words, regardless of how comfortable an individual is with technology, perceiving an AI as a warm, human-like agent activates a similar level of cognitive trust.

For H4b, Technology Readiness significantly and negatively moderates the relationship between Information Quality and Task Fit and Perceived Decision Efficiency ($\beta = -0.107$, $p = 0.005$), contrary to the expected positive moderating effect. The supplementary multi-group analysis further confirmed this pattern (see Section 4.6). This counterintuitive finding warrants deeper theoretical discussion. Four complementary interpretations are proposed.

First, from a digital routine perspective, tourists with higher Technology Readiness may already possess well-established information-searching strategies, meaning that AIGC's task-fit capabilities offer them diminishing marginal returns in perceived efficiency, a form of ceiling effect. Second, from a critical evaluation standpoint, higher-readiness individuals may subject AI-generated outputs to more rigorous scrutiny and verification, which, while potentially enhancing decision quality, could paradoxically attenuate the perceived efficiency benefit. Third, from a psychological ownership perspective (Vlieger de Oliveira et al., 2024), tourists with lower Technology Readiness may be more willing to delegate decision-making authority to the AI tool, resulting in a more pronounced perception of efficiency enhancement. Fourth, from a digital inequality perspective, tourists with lower Technology Readiness typically face a greater cognitive burden in information processing; when AIGC provides high-quality, task-fitted outputs, this burden is disproportionately relieved, producing a larger marginal efficiency gain than that experienced by their digitally proficient counterparts.

Collectively, these interpretations challenge the conventional assumption, rooted in early Technology Acceptance Model research, that higher technological literacy uniformly facilitates technology adoption. Rather, they suggest that the relationship between Technology Readiness and AIGC empowerment is non-linear: for complex, unstructured tasks such as travel planning, AIGC may function as an equalizer that disproportionately benefits digitally disadvantaged users. This finding resonates with the broader discourse on inclusive technology design and has important implications for how online travel platforms position AIGC tools for diverse user segments.

5.2. Theoretical Contributions and Practical Implications

Integrating theoretical deduction with empirical data, this study conducted a preliminary exploration from the following three aspects, aiming to provide references for academic research and industrial practice.

First, it constructed a dual-path model encompassing functional fit and emotional interaction, suggesting that developers should focus on creating an empathetic intelligent companion. This study attempted to integrate SOR, TTF, and Trust Transfer Theory, expanding the understanding of AIGC's generative and interactive characteristics. To some extent, this addresses the shortcomings of prior research, which often examined technology adoption from a single perspective (Davis, 1989; Okumus et al., 2018) and was confined to contexts such as traditional mobile apps (Lu et al., 2023) or social media (Leung, Law, van Hoof, & Buhalis, 2013). Based on this, it is recommended that developers, while optimizing functionalities, also strengthen the AI's anthropomorphic persona and natural language processing style. The empirical findings of this study directly support this recommendation: Perceived Anthropomorphism serves as a significant driver of both Cognitive Trust (H1a) and Value Co-creation Experience (H1b), while Information Quality and Task Fit significantly enhance both Perceived Decision Efficiency (H1c) and Cognitive Trust (H1d). By providing emotional value to reduce users' unfamiliarity with the technology, developers can establish deeper, affect-based trust with users.

Second, it elucidated the mediating mechanism of Value Co-creation Experience in the decision-making process, suggesting that platforms should foster immersive co-creation scenarios. The findings revealed that the tourist's role shifts from an information receiver to a co-designer of itineraries. The significant mediating effect of Value Co-creation Experience in the pathway from Perceived Anthropomorphism to Behavioral Intention (H3c) supplements the discussion on tourists' proactive psychology in AI contexts, thereby moving beyond the previous focus primarily on perceived usefulness (Filieri & McLeay, 2014). Accordingly, it is recommended that online travel platforms transform into co-creation platforms by designing interaction mechanisms that facilitate multi-round, iterative dialogue between tourists and AI. For example, providing visual, drag-and-drop itinerary-editing tools enables tourists to actively modify, rearrange, and personalize the AI-generated itinerary through direct manipulation, rather than passively accepting a one-click output. This form of interactive co-creation operationalizes the Value Co-creation Experience mechanism identified in this study, granting tourists a sense of control and psychological ownership over the planning process, thereby strengthening their intention to adopt the final itinerary.

Third, the discovery of a technology compensation effect carries significant practical implications for inclusive platform design. As demonstrated in this study, AIGC's task-fit capabilities yield disproportionately greater efficiency gains for tourists with lower Technology Readiness, suggesting that generative AI can serve as an inclusive tool for bridging the digital divide in tourism decision-making. Based on this finding, three specific recommendations are offered. First, platform developers should prioritize intuitive, low-barrier interaction interfaces, such as guided conversation flows and preset task templates, that enable technologically inexperienced users to fully benefit from AIGC's task-fit capabilities without requiring advanced digital skills. Second, marketing teams could design targeted outreach campaigns aimed at middle-aged and elderly segments, positioning AIGC not as a cutting-edge technology requiring mastery, but as an effortless planning assistant that reduces cognitive burden. Third, given that the technology compensation effect was particularly pronounced for the complex, long-distance travel scenario examined in this study, platforms should consider deploying AIGC tools most prominently in high-complexity planning contexts (e.g., multi-destination itineraries and family travel with diverse needs), where the efficiency gains for lower-readiness users are maximized. By implementing these strategies, platforms can simultaneously expand their user base into underserved demographic segments and fulfill the broader social mission of reducing digital inequality.

5.3. Research Limitations and Future Prospects

This study conducted a preliminary exploration of the mechanisms through which AIGC empowers tourism decision-making. Nevertheless, due to practical constraints, it has the following limitations, which future research can address.

First, the representativeness of the sample and the scope of data collection warrant further expansion. The sample in this study was predominantly young and highly educated, which, while aligning with the current mainstream user

profile of AIGC, resulted in relatively insufficient coverage of elderly populations and groups with low digital literacy. Additionally, the use of a specific scenario, "Hulunbuir parent-child travel", may limit the generalizability of the findings to other destination types, travel purposes, or cultural contexts. Reliance on voluntary self-selection in respondent recruitment may also introduce self-selection bias, as individuals who chose to participate may differ systematically from nonparticipants in their attitudes toward technology. Future research could employ a combination of online and offline methods to broaden the sample scope, replicate the model across diverse scenarios, or conduct longitudinal tracking studies to verify the stability of the findings.

Second, the selection of variables and the construction of the model could be more comprehensive. This study primarily focused on positive drivers such as Perceived Anthropomorphism, Information Quality, and Task Fit. However, negative factors potentially associated with AIGC, such as privacy concerns, algorithmic bias, or information inaccuracies, may also hinder its adoption. Future research could attempt to incorporate perceived risk as a mediating variable, examining how concerns about data privacy or algorithmic errors attenuate the positive effects of AIGC's technological characteristics on Behavioral Intention. Similarly, flow experience could be explored as an additional mediating mechanism, capturing the immersive and enjoyable state tourists experience during human-AI interaction, which may further explain the link between Perceived Anthropomorphism and Behavioral Intention beyond the Value Co-creation Experience. In terms of boundary conditions, future studies could explore destination type as a moderating variable, as decision-making complexity and information demands may differ substantially between, for example, international long-haul trips and short domestic excursions. Travel party composition is another promising moderator, given that solo travelers, family groups, and friend groups may exhibit different levels of reliance on AIGC tools and varying sensitivity to anthropomorphic features. These extensions would contribute to a more multidimensional explanatory framework for understanding AIGC-empowered tourism decision-making.

Third, the segmentation of research subjects and methodological diversification merit further investigation. This study examined various AIGC tools as a whole, without making differentiated comparisons between industry-specific tourism AI tools or across different interaction modalities. Moreover, although Harman's single-factor test indicated that common method bias was not a serious concern, the reliance on self-reported data collected through a single cross-sectional survey inherently limits the ability to establish causal relationships, as it captured associations at a single point in time rather than dynamic processes. Future research could adopt longitudinal designs, integrate neuroscientific methods (e.g., eye-tracking or EEG experiments), or employ field experiments to obtain more objective behavioral data, thereby strengthening causal inference. Such approaches would also enable deeper exploration of the micro-level psychological mechanisms underlying human-computer interaction.

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