Chatting vs clicking: how does AI interaction style affect travel decisions? a comparative study of generative AI and GUI-based platform

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Abstract

Purpose – The purpose of this study is to examine travelers' attitudes and intentions toward Artificial Intelligence (AI)-based travel planning assistants through an integrated task-technology fit, Technology Acceptance Model and Innovation Diffusion Theory framework, comparing generative AI and graphical user interfaces (GUI) platforms.

Design/methodology/approach – The survey data were collected from 355 generative AI and 268 GUI platform users. SEM tested relationships among constructs, and multi-group analysis compared the two groups.

Findings – The results of this study revealed that all variables except perceived ease of use and complexity positively influenced attitudes, which enhanced efficacy and intention to use. Perceived usefulness and compatibility showed consistent effects across both groups.

Originality/value – This study contributes to the literature by validating task-technology fit, Technology Acceptance Model and Innovation Diffusion Theory integration in tourism and first comparing two AI-TPA types, offering implications for design and promotion.

Keywords AI-based travel planning assistants, Task-technology fit, Technology acceptance model, Innovation diffusion theory, Generative AI, GUI platform

Paper type Research paper

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摘要

目的 – 本研究通过整合任务—技术匹配理论 (TTF)、技术接受模型 (TAM) 和创新扩散理论 (IDT) 框架, 考察旅行者对基于 AI 的旅行规划助手的态度和使用意向, 并比较生成式 AI 平台与图形用户界面 (GUI) 平台之间的差异。

研究设计/方法 – 本研究分别收集了来自 355 名生成式 AI 用户和 268 名 GUI 平台用户的调查数据。研究采用结构方程模型（SEM）检验各构念之间的关系, 并通过多群组分析比较两个用户群体之间的差异。

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研究发现 – 研究结果显示, 除感知易用性和复杂性外, 所有变量均正向影响用户态度, 而用户态度进一步提升了效能感和使用意向。感知有用性和兼容性在两个群体中均表现出一致的影响。

原创性/价值 – 本研究通过验证 TTF、TAM 和 IDT 在旅游研究中的整合应用, 为相关文献作出贡献; 同时, 本研究首次比较了两类基于 AI 的旅行规划助手（AI-TPA）, 并为其设计与推广提供了实践启示。

关键词 基于 AI 的旅行规划助手, 任务—技术匹配, 技术接受模型, 创新扩散理论, 生成式 Ai, Gui 平台

文章类型 研究型论文

1. Introduction

The impact of Artificial Intelligence (hereinafter AI) has become increasingly widespread in various industries (Han *et al.*, 2025). In particular, the tourism sector benefits from AI-based services, which offer several advantages for travelers (World Economic Forum, 2023). First, they use extensive destination information to facilitate decision-making. Second, they mitigate uncertainty by offering real-time and predictive data (Dwivedi *et al.*, 2024). Third, based on personalized recommendations, they analyze user preferences to create customized travel plans (Hlee *et al.*, 2025). Consequently, the AI travel planning assistant (hereinafter AI-TPA) is presently considered an essential tool for travel plans. According to the GuideGeek (2024) survey, more than one in five (i.e. over 22.8%) respondents had used these platforms to plan or assist with their travel.

Despite these numerous advantages, AI-based services still present certain limits for people seeking to use them (Statista, 2025). Previous studies have indicated that AI-based services exhibit weaknesses, such as providing inaccurate information and lacking human ambiance (Han *et al.*, 2025). Furthermore, Lalicic and Weismayer (2021) explained that users are less willing to use AI-based services because of the stress associated with learning to use them. Further empirical studies are necessary to enhance the understanding of how AI-based services/technologies influence user acceptance.

With the rapid advancement of AI-TPA, previous studies have explored key factors influencing tourist behavior (Gu *et al.*, 2019; Kanhed *et al.*, 2024; Li *et al.*, 2025). These recent studies have commonly identified the following factors as catalysts for AI-TPA adoption, including usefulness, convenience, personalization capabilities, information quality and efficacy. Prior studies on AI-based technology have widely applied validated frameworks such as TPB, task-technology fit (TTF), Technology Acceptance Model (TAM) and Innovation Diffusion Theory (IDT) to predict the relationship between causal and outcome variables (Foroughi *et al.*, 2024; Hwang *et al.*, 2024; Teng *et al.*, 2024; Wang and Lin, 2019). Researchers argue that more than one theoretical model is required to explain complex technology adoption behavior, particularly for innovative services (Koenig, 2025). Specifically, TTF theory, proposed by Goodhue and Thompson (1995), suggests that task performance improves when technological functionalities closely align with task requirements. However, TTF alone provided limited insight into why users initially perceived a system as user-friendly or worth adopting – questions that were central to understanding AI-TPA acceptance, particularly during its early stages (Dhiman and Jamwal, 2023). The TAM, proposed by Davis (1989), tackled this issue by emphasizing users' cognitive evaluations to explain their attitudes and behavioral intentions toward new technologies (Yen *et al.*, 2010). Likewise, Dishaw and Strong (1999) demonstrated that integrating TTF and TAM constructs provides greater explanatory power than either model alone, as they encompass complementary aspects of technology acceptance, including rational task-performance fit and attitudinal factors. Additionally, they suggested that this integration addresses the gap in which user perceptions of usefulness may be disconnected from actual performance impact. Although TAM is an effective framework for investigating how consumers adopt new technologies, it may be inadequate for explaining consumers'

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behavioral intentions across all contexts (Liu *et al.*, 2024a, 2024b). Several studies have emphasized that promoting consumer adoption of emerging technologies requires a comprehensive understanding of the diffusion of innovative products and services within society (Lu *et al.*, 2025). The IDT model effectively analyzes the adoption process and highlights the elements that contribute to one's decision to embrace or discard technological innovations (Sujood *et al.*, 2025). In this regard, the integration of TTF, TAM and IDT offers a robust framework for comprehending tourist attitudes and behavioral intentions toward AI-TPA, thereby enhancing the explanatory power of technology adoption within tourism contexts (Cai *et al.*, 2023; Gu *et al.*, 2019; Ho *et al.*, 2021). However, investigations into AI-based travel planning applications from the integrated viewpoint of these three theoretical frameworks are scarce.

Significantly, favorable attitudes toward technology enhance self-confident efficacy in using new technologies (Fakfare *et al.*, 2023). Self-confident efficacy refers to individuals' confidence in their capacity to effectively execute specific tasks using technology (Sun *et al.*, 2024). In addition, self-confident efficacy has been recognized as a primary precursor of technology adoption across several contexts (Ahmed *et al.*, 2025; Hlee *et al.*, 2025; Montag *et al.*, 2023). For instance, users with higher levels of self-confident efficacy perceive themselves as competent in their interactions with automated technology such as AI-TPA (Montag *et al.*, 2023). Moreover, users are more inclined to manage AI-recommended travel schedules more efficiently (Hlee *et al.*, 2025).

Finally, unlike previous studies, this study seeks to examine the moderating role of two distinct forms of AI-TPA. AI-TPA can be categorized into generative AI and graphical user interfaces (hereafter GUI). Generative AI enables users to directly pose inquiries or submit prompts in an input box (Kanhed *et al.*, 2024). A GUI-based platform enables users to plan travel by clicking on graphic elements (such as buttons and maps) on an app or website (Cybulski and Horbiński, 2020). Thus, differences such as interface design may significantly impact users' attitudes and intentions (Chenchu *et al.*, 2025). For example, generative AI offers flexible conversational responses via natural language processing; however, it may occasionally generate inaccurate or inconsistent information (Kim *et al.*, 2019). Conversely, GUI-based platforms offer structured navigation through predefined options, although it may exhibit limited flexibility for personalized travel plans (Liu *et al.*, 2024a, 2024b).

In summary, this study uses a comprehensive framework that integrates TTF, TAM and IDT. Specifically, it aims to:

- predict user attitudes using the integrated framework;
- examine the effects of attitudes on self-confidence efficacy and intentions to use;
- investigate attitudes' mediating role between theoretical antecedents and outcomes; and
- assess the moderating effect of AI-TPA types (generative AI vs GUI-based platforms).

2. Literature background

2.1 Role of Artificial Intelligence travel planning assistant in tourism

AI refers to "computer systems capable of executing tasks that typically require human intelligence, such as learning, reasoning, and problem-solving" (NASA, 2024). AI-based services are extensively used to assist consumers in their daily lives, enhancing convenience in the tourism industry (Lalicic and Weismayer, 2021). For example, AI is used in various applications, including virtual assistants (e.g. Siri and Alexa), recommendation engines, self-driving cars and travel planning (McKinsey, 2024). Recent studies have demonstrated that

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AI-TPA enhances user's travel experience through service optimization, including content-based filtering and personalization (Hlee *et al.*, 2025). According to the 2025 Statista report, one-third of respondents regard AI-TPA as valuable tools for discovering new information, especially for their ability to streamline the decision-making process.

2.2 Task technology fit theory (TTF)

TTF, developed by Goodhue and Thompson (1995), emphasized the interaction between task, technology and individual. A key premise of TTF is that technology and tasks enhanced performance only when matched to the task requirements (Yen *et al.*, 2010). TTF comprises three sub-variables: task characteristics, technology characteristics and task-technology fit. Task characteristics refers to "the actions conducted by individuals in transforming inputs into outputs" (Goodhue and Thompson, 1995, p. 216). Technology characteristics denote "tools utilized by individuals in performing their tasks" (Goodhue and Thompson, 1995, p. 216). Finally, task technology fit is described as "the extent to which a technology assists individuals in performing their portfolio of tasks" (Goodhue and Thompson, 1995, p. 216).

In tourism and hospitality, TTF has been effectively applied to explain technology adoption behaviors associated with hotel self-service kiosks, digital museums and service chatbots (Dhiman and Jamwal, 2023). In particular, TTF is crucial in shaping attitudes toward AI-based services, where personalization is a core feature. Prior research confirmed that task and technology characteristics significantly impact TTF and attitudes (Dhiman and Jamwal, 2023). Therefore, the following hypotheses were proposed:

H1. Task characteristics has a significant effect on task technology fit.

H2. Technology characteristics has a significant effect on task technology fit.

H3. Task-technology fit has a significant effect on attitudes.

2.3 Integrated theoretical models link to attitude

The concept of TAM, as proposed by Davis (1989), elucidates the mechanisms via which users embrace new technologies. TAM comprises two key factors such as perceived ease of use and usefulness. Perceived ease of use is defined as "the extent to which a person believes that using a particular system is possible without effort," whereas perceived usefulness refers to "the degree to which a person believes that using a particular system would improve his or her job performance" (Davis, 1989, p. 320). In travel and tourism contexts, TAM is extensively acknowledged for explaining how consumers' perceptions of new technologies influence their attitudes and intentions to use them (e.g. smart hotels, travel apps, AI chatbots and travel assistant apps) (Du *et al.*, 2025; Foroughi *et al.*, 2024; Li *et al.*, 2025; Liu *et al.*, 2024a, 2024b). Research indicates that individuals are more willing to adopt innovative technologies when they believe these technologies effectively fulfill users' needs and are user-friendly. For example, Foroughi *et al.* (2024) discovered that perceived ease of use and usefulness significantly influenced users' attitudes toward travel apps. They demonstrated that when travelers could effortlessly learn and use the app with minimal effort, they were more inclined to perceive the app as useful for travel planning action, thereby fostering favorable attitudes toward continuous use.

IDT, as proposed by Rogers (1995), is conceptualized as a framework that describes why individuals adopt novel ideas or technologies. IDT encompasses five categories: relative advantage, compatibility, complexity, trialability and observability, and examines whether an individual or an organization influences the adoption or non-adoption of those sub-factors of

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IDT (Rogers, 1995). Relative advantage is denoted as the degree to which an innovation is perceived as superior to the idea it supersedes (Rogers, 1995). Compatibility is defined as the degree to which innovation is perceived as being consistent with existing values, past experiences and needs of potential adopters (Rogers, 1995). Complexity refers to the degree to which an innovation is perceived as relatively complex to understand and to use (Rogers, 1995). For instance, consumers adopt innovations, such as new concepts, novel applications and advanced products, as they diffuse over time (Han *et al.*, 2025). This process transpired when users evaluate advantages in comparison to conventional alternatives (Sujood *et al.*, 2025). Thus, innovative technology, such as AI-TPA, is less likely to be adopted if it is perceived as overly complex or incompatible. Prior researchers have applied IDT sub-factors to examine adoption of innovative technologies in tourism contexts, including ChatGPT, VR tourism, travel apps and smart tourism platforms (Han *et al.*, 2025; Lu *et al.*, 2025; Lim *et al.*, 2022). Lim *et al.* (2022) affirmed that relative advantages, compatibility and complexity were significant determinants that influenced attitudes toward mobile travel applications.

More importantly, previous studies focused on consumers' attitudes through the integrated TAM and IDT framework in various fields associated with technology-based service (Gu *et al.*, 2019; Sujood *et al.*, 2025; Terrah *et al.*, 2024). TAM and IDT both rely on the assumption that ease of use and perceived complexity are fundamental determinants of technology acceptance (Venkatesh *et al.*, 2003). In other words, users are less inclined to adopt even innovative technology when they anticipate excessive effort or difficulty. By contrast, users are more inclined to accept technology that provides distinct performance benefits while being user-friendly (Dishaw and Strong, 1999). In this context, several empirical studies have shown that integrating TAM and IDT enhances the prediction of technology-related attitudes and behavioral intentions. For example, Gu *et al.* (2019) indicated that the integrated TAM and IDT framework demonstrated higher explanatory power than single-theory models in the context of mobile tourism shopping. Recently, Terrah *et al.* (2024) validated the effectiveness of integrating TAM and IDT in predicting hotel guests' adoption of AI-enabled technologies. Based on the above discussion, we proposed the following hypothesis:

H4. Perceived ease of use has a significant effect on perceived usefulness.

H5. Perceived ease of use has a significant effect on attitudes.

H6. Perceived usefulness has a significant effect on attitudes.

H7. Relative advantage has a significant effect on attitudes.

H8. Compatibility has a significant effect on attitudes.

H9. Complexity has a significant effect on attitudes.

2.4 Attitudes link to self-confident efficacy and intentions to use

Attitude is denoted as "the degree to which a person possesses a favorable or unfavorable evaluation or appraisal of the behavior" (Ajzen, 1991, p. 188). In other words, attitude is a fundamental concept in the consumer decision-making literature, as it reflects the positive or negative evaluation of a service or product. Existing studies have demonstrated the significance of attitude and its significant correlation with diverse variables and intentions in technology-based service-related tourism settings (Ahmed *et al.*, 2025; Fakfare *et al.*, 2023; Sun *et al.*, 2024). In addition, Lim *et al.* (2022) revealed that attitude significantly mediates

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the nexus between multi-dimensional factors of IDT and behavioral intentions within the context of travel apps.

Furthermore, researchers contended that the relationship between attitude and self-confident efficacy determines behavioral intentions in tourism contexts (Hlee *et al.*, 2025). Self-confident efficacy can be described as "the respondent's belief in their ability to accurately assess the attributes of a destination" (Valencia and Crouch, 2008, p. 27). Self-confident efficacy is considered an essential factor, as it significantly influences tourists' travel-related decision-making (Fakfare *et al.*, 2023). For instance, Sun *et al.* (2024) discovered that tourists' attitudes toward travel positively influence self-confident efficacy. They also explained that individuals are more likely to be favorable toward international travel when they feel confident in their ability to plan their trips. Currently, Ahmed *et al.* (2025) have shown that a positive association between attitudes and self-confident efficacy significantly affects intentions to use in the context of AI voice-based assistant services. Hence, the following hypothesis was proposed:

H10. Attitude has a significant effect on self-confident efficacy.

H11. Attitude has a significant effect on intentions to use.

H12. Self-confident efficacy has a significant effect on intentions to use.

H13(a–l). Attitudes have a significant mediating effect on the relationships between variables in the proposed model.

H14. Self-confident efficacy has a significant mediating effect on the relationships between attitudes and intentions to use.

2.5 The moderating role of two different types of Artificial Intelligence travel planning assistant

AI-TPA is subdivided into two types based on the operation method (i.e. generative AI and GUI-based platforms). Generative AI can be implemented in the form of ChatGPT or a chatbot grounded in natural language-based interaction (Dwivedi *et al.*, 2024). The effectiveness of generative AI in influencing users' positive perceptions has been verified in the hospitality and tourism field. Current studies have highlighted the practical benefits of generative AI, with Li *et al.* (2025) reporting that hotel customers appreciated the usefulness of ChatGPT in facilitating their service needs. According to the Expedia (2025) report, chatbot-based AI service agents enabled over 50% of travelers to independently fulfill their service requirements without human intervention, resulting in significantly higher customer satisfaction ratings, more than double those of users who used call centers for assistance. In contrast, a GUI-based platform enables users to navigate and book travel options via visual elements such as buttons, menus and icons, rather than relying solely on text-based commands (Cybulski and Horbiński, 2020). Recently, Chenchu *et al.* (2025) demonstrated that the interactive visual interface of the platform is essential for promoting users' engagement and facilitating more intuitive decision-making in travel planning. Liu *et al.* (2024a, 2024b) discovered that the graphical features in travel platforms enhance users' cognitive information processing, thereby positively influencing behavioral intentions in the trip planning phase.

Previous studies investigated the impact of various operational methodologies of AI technologies on user perceptions. For example, Kim *et al.* (2019) compared participant response characteristics between chatbot- and Web-based survey modes. They verified that

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chatbot users generated more varied responses but expressed diminished satisfaction with the survey experience than Web respondents. Similarly, Nguyen *et al.* (2022) compared chatbots and menu-based interfaces in the travel context, showing that users perceived autonomy and cognitive effort differently across the two platforms. In this regard, users with various interaction experiences and capabilities may respond differently to each platform type, indicating that generative AI or GUI-based platforms may be more effective depending on individual user characteristics (Nguyen *et al.*, 2022). Based on the above discussion, we proposed the following hypothesis:

H15(a–l). Different types of Artificial Intelligence travel planning assistant (Generative AI vs GUI-based platforms) significantly moderate the relationships between variables in the proposed model.

3. Methodology

3.1 Measurement

In this study, the questionnaire comprised 42 validated measurement items on a five-point Likert scale and demographic questions. Measurement items for task characteristics under the TTF model were adopted from Schrier *et al.* (2010) and Dhiman and Jamwal (2023), comprising four items. Technology characteristics were measured using five items sourced from Dhiman and Jamwal (2023). Four items for TTF were derived from Cai *et al.* (2023), as well as Dhiman and Jamwal (2023). Measurement items for user motivation factors based on the TAM were adopted from Davis (1989), Kim *et al.* (2007) for ease of use (three items) and from Kim *et al.* (2019) and Ha and Stoel (2009) for perceived usefulness (three items). As for the IDT factors, three items for relative advantage were drawn from Hosseinikhah Choshaly (2019), four items for compatibility from Lu *et al.* (2015) and three items for complexity from Min *et al.* (2021). Attitude was measured using four items from Rivera *et al.* (2015), while self-confident efficacy was assessed based on four items from Fakfare *et al.* (2023). Finally, behavioral intentions to use the technology were measured with four items adapted from Venkatesh *et al.* (2003).

3.2 Data collection and analysis

Data were collected via an online panel survey through SK Telecom, which provides access to approximately 16 million demographically diverse panel members in South Korea (SK Telecom, 2024). Screening questions ensured respondents had AI-TPA experience and classified them by usage type: generative AI (e.g. ChatGPT 3.5 or 4.0) or GUI-based platform (e.g. Myrealtrip, TRIPLE). Of 652 responses collected between June 2 and 6, 623 valid responses were retained for final analysis.

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) via SmartPLS 4.1.1. PLS-SEM is appropriate for complex integrated models with high predictive power (Hair *et al.*, 2010). A bootstrapping method with 5,000 samples assessed path coefficient significance (Hair *et al.*, 2017). The proposed research model is presented in Figure 1.

4. Results

4.1 Demographic characteristics

Table 1 presents the demographic characteristics of the respondents. Among the participants, 61.5% were females and 38.5% were males. Respondents were aged 20 years 13.0%, 27.1% were aged 30 years and 59.9% were aged 40 years. In addition, 58.4% of the participants had

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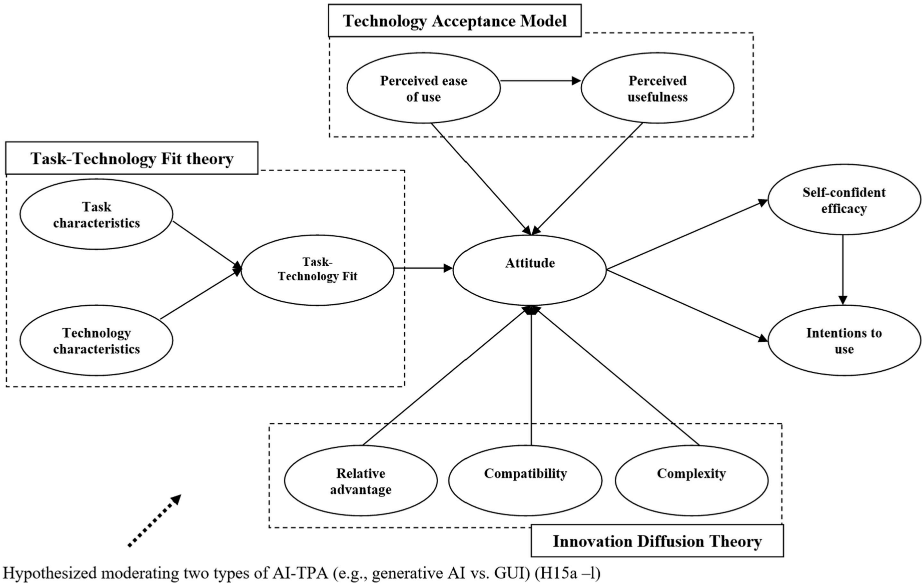

Figure 1. Proposed conceptual model

Table 1. Profile of the survey respondents

Variable	Generative AI (n = 355)	GUI platform (n = 268)
Gender		
Male	149 (42.0%)	91 (34.0%)
Female	206 (58.0%)	177 (66.0%)
Age		
20s	45 (12.7%)	36 (13.4%)
30s	98 (27.6%)	71 (26.5%)
40s	212 (59.7%)	161 (60.0%)
Education level		
High school diploma	57 (16.1%)	32 (11.9%)
Associate’s degree	71 (20.0%)	45 (16.8%)
Bachelor’s degree	197 (55.5%)	167 (62.3%)
Graduate degree	30 (8.5%)	24 (9.0%)
Marital status		
Single	190 (53.5%)	161 (60.0%)
Married	159 (44.8%)	98 (36.6%)
Others	6 (1.7%)	9 (3.4%)
Monthly income level		
Mean (US$)	2,475 USD	2,475 USD

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an undergraduate education. Moreover, 41.3% of the respondents were married. Finally, the respondents reported an average monthly income of US$2,475.

4.2 Normality and common method bias tests

Descriptive analysis showed means between 2.61 and 3.68 with standard deviations ranging from 0.791 to 0.834. Normality assumptions were validated using Shapiro–Wilk tests ($p > 0.05$) alongside acceptable skewness (±1.0) and kurtosis (±1.5) indices, confirming appropriate data distribution for parametric procedures (George and Mallery, 1994).

Additionally, common method bias (CMB) can inflate relationships between variables because of self-report measures. Therefore, Harman's single-factor test was used to assess CMB. Results showed that a single factor accounted for 45.236% of the variance, below the 50% threshold (Podsakoff *et al.*, 2003), indicating CMB is not a significant concern.

4.3 Measurement model

Appendix 1 presents the constructions used in this study with their standardized factor loadings of the two data sets as follows:

(1) Generative AI data; and

(2) GUI platform data sets.

In addition, no factor loading values fell below 0.736. Appendix I shows that all the composite reliability (CR) values exceeded 0.700 (between 0.870 and 0.946), providing evidence for the internal consistency of the measurement models (Hair *et al.*, 2006). Moreover, all the average variance extracted (AVE) values exceeded 0.500 (between 0.655 and 0.814), which reveals a high level of convergent validity (Fornell and Larcker, 1981).

As shown in Appendix 2, discriminant validity between constructs was evaluated using two established methods: the Fornell–Larcker criterion (Fornell and Larcker, 1981) and the heterotrait-monotrait (HTMT) technique (Henseler *et al.*, 2016). The diagonal elements, shown in bold, indicate the average variance extracted (AVE), while the off-diagonal values represent the squared correlations between the latent constructions. All values of the AVE exceeded the squared correlations values between pairs of constructs, which supports a high level of discriminant validity (Bagozzi and Yi, 1988). Furthermore, Appendix 2 presents that all the Cronbach's α values exceeded 0.700 (between 0.824 and 0.902), justifying the reliability of constructs (Henseler *et al.*, 2016). The HTMT correlation ratios presented in Appendix 2 ranged from 0.091 to 0.862, all remaining below the recommended threshold of 0.900 (Henseler *et al.*, 2016), thus indicating satisfactory discriminant validity among the constructs.

4.4 Structural equation modeling

Model fit adequacy was assessed using Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) as important indicators of goodness of fit. The results demonstrated satisfactory fit, with SRMR achieving 0.050 (below the 0.08 threshold) and NFI reaching 0.817 (exceeding the 0.8 criterion) (Hu and Bentler, 1999).

The structural model was examined using R^2 and path coefficient significance (β). The model explained substantial variance: attitudes (R^2 = 76.4%), self-confident efficacy (R^2 = 59.5%) and intentions to use (R^2 = 76.9%). Based on established thresholds including strong ($R^2 \geq 0.75$), moderate ($R^2 \geq 0.50$) or weak ($R^2 \geq 0.25$) (Hair *et al.*, 2019), R^2 values demonstrated strong performance (≥0.75) for attitudes and intentions to use and moderate performance (≥0.50) for self-confident efficacy. Effect sizes were assessed using f^2 criteria:

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small ($f^2 \geq 0.02$), medium ($f^2 \geq 0.15$) or large ($f^2 \geq 0.35$) (Cohen, 1988) and exceeded zero for all endogenous constructs in Table 2, supporting predictive adequacy (Hair *et al.*, 2019).

Path coefficient significance was determined through bootstrapping with 5,000 resamples. Bootstrapping is an analytical technique showing the significance level of the paths between each construct (Henseler *et al.*, 2016). Multicollinearity was assessed using VIF values, which ranged from 1.000 to 3.602 – all below the acceptable threshold of 3–5 (Hair *et al.*, 2019), indicating no collinearity issues in the model. The hypothesis testing results showed that 10 of 12 hypotheses were supported. These results are summarized in Figure 2.

As shown in Table 3, the mediation analysis revealed that attitude serves as a significant mediating factor in the relationship between various independent variables and the dependent variables (i.e. self-confident efficacy and intention to use). Specifically, the mediating effect of attitude was strongest in the relationship between perceived usefulness and self-confident efficacy (β = 0.055), followed by compatibility (β = 0.054) and task-technology fit (β = 0.035). However, attitude did not significantly mediate the relationship between perceived ease of use and self-confident efficacy (β = 0.006) and complexity and self-confident efficacy (β = −0.002). Notably, attitude fully mediated the relationship between relative advantage and self-confident efficacy (β = 0.067). Likewise, the mediating effect of attitude was strongest in the relationship between relative advantage and intention to use (β = 0.148), followed by perceived usefulness (β = 0.123) and compatibility (β = 0.119). However, attitude did not significantly mediate the relationship between perceived ease of use and intention to use (β = 0.013) and between complexity and intention to use (β = −0.003).

4.5 Multi-group analysis

As Henseler *et al.* (2016) suggested, measurement invariance should be tested with MICOM before conducting multigroup analysis (MGA). MICOM involves three-steps:

(1) configural invariance;

(2) compositional invariance; and

(3) equal means and variances assessment.

Table 2. Structure model assessment

Predictor	f^2 effect size	Construct	Q^2	R^2
TAC → TTF	0.095	TTF	0.673	0.675
TEC → TTF	0.658	PU	0.522	0.523
TTF → AT	0.028	AT	0.732	0.764
PE → AT	0.001	SCE	0.667	0.708
PE → PU	1.098	IU	0.670	0.785
PU → AT	0.061			
CP → AT	0.084			
CX → AT	0.000			
RA → AT	0.081			
AT → IU	0.264			
AT → SCE	0.041			
SCE → IU	0.031			

Note(s): TAC = Task characteristics; TEC = Technology characteristics; TTF = Task technology fit; PE = Perceived ease of use; PU = Perceived usefulness; CP = Compatibility; CX = Complexity; RA = Relative advantage; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use

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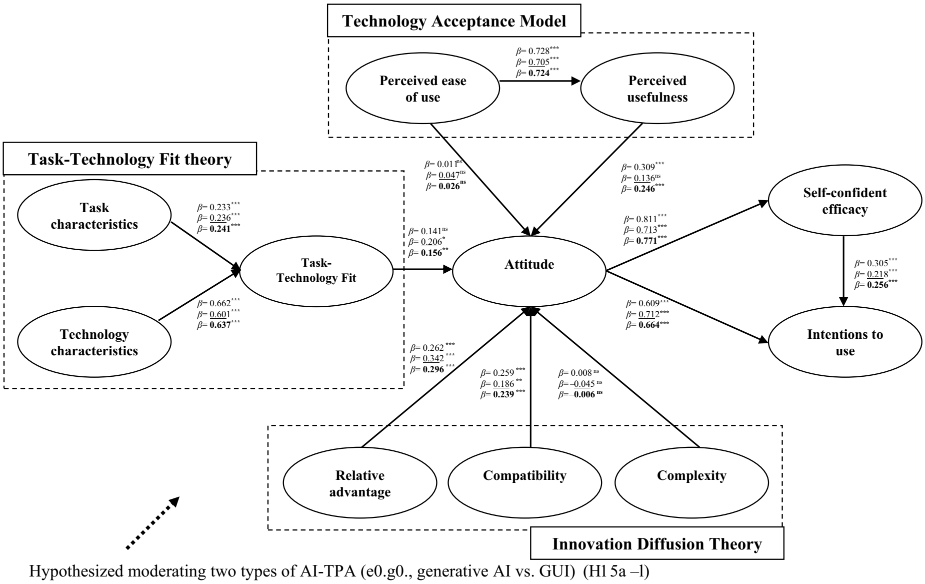

Figure 2. Measurement model

Note(s): The unmarked values are for generative AI; the underlined values are for GUI; and values in boldface type are for merging two data. *$p < 0.05$; NS = Not supported

The first step established configural invariance by maintaining identical model specifications across groups (Hair *et al.*, 2024). The second step confirmed compositional invariance when original correlation met or exceeded the 5.00% quantile (Henseler *et al.*, 2016). As presented in Table 4, adequate compositional invariance was achieved. The third step assessed whether mean and variance difference fell within permutation-based confidence intervals (Hair *et al.*, 2024; Matthews, 2017). As shown in Table 4, full measurement invariance was established as all three conditions were satisfied. According to Henseler *et al.* (2016), partial measurement invariance (Steps 1 and 2) provides sufficient grounds for MGA regardless of Step 3 results. Therefore, the analysis proceeded to test the group-specific differences.

MGA results indicated significant differences in path estimates between generative AI and GUI groups (Table 5). Perceived usefulness positively affected attitudes in both groups (generative AI: $\beta = 0.309$, $p < 0.001$ and GUI: $\beta = 0.136$, $p = 0.008$) with a significant difference between groups (Henseler's MGA p-value = 0.047). Compatibility has a positive effect on attitudes in both groups (generative AI: $\beta = 0.259$, $p < 0.001$ and GUI: $\beta = 0.186$, $p = 0.009$), showing significant group difference (Henseler's MGA p-value = 0.009). Moreover, attitudes significantly affected self-confident efficacy in both groups (generative AI: $\beta = 0.811$, $p < 0.001$ and GUI: $\beta = 0.713$ and $p < 0.001$) with a significant difference between groups (Henseler's MGA p-value = 0.028). Finally, attitudes significantly affected intention to use in both groups (generative AI: $\beta = 0.609$, $p < 0.001$ and GUI: $\beta = 0.712$, $p < 0.001$), showing a significant difference between groups (Henseler's MGA p-value = 0.014). Therefore, hypotheses *H15f*, *H15h*, *H15j* and *H15k* were supported, indicating that the generative AI and GUI groups exhibit significantly different behavioral patterns in technology adoption processes. These results are presented in Figure 3.

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Table 3. Mediating effect

Hypothesis	IV	→	M	→	DV	Association	β	LLCI	ULCI	*t*-value	*p*-value	Result
H13a	TTF	→	AT	→	SCE	Total	0.182	0.084	0.296	3.388	0.001	Partial supported
						Indirect	0.035	0.013	0.074	2.296	0.022	
H13b	PE	→	AT	→	SCE	Total	0.208	0.096	0.313	3.746	0.000	Not supported
						Indirect	0.006	−0.011	0.029	0.595	0.552	
H13c	PU	→	AT	→	SCE	Total	0.216	0.099	0.329	3.629	0.000	Partial supported
						Indirect	0.055	0.027	0.100	3.063	0.002	
H13d	CP	→	AT	→	SCE	Total	0.395	0.306	0.498	8.526	0.000	Partial supported
						Indirect	0.054	0.027	0.098	3.069	0.002	
H13e	CX	→	AT	→	SCE	Total	0.048	−0.005	0.101	1.722	0.085	Not supported
						Indirect	−0.002	−0.014	0.007	0.289	0.773	
H13f	RA	→	AT	→	SCE	Total	0.069	−0.053	0.177	1.186	0.236	Full supported
						Indirect	0.067	0.030	0.127	2.944	0.003	
H13g	TTF	→	AT	→	IU	Total	0.159	0.057	0.279	2.768	0.006	Partial supported
						Indirect	0.079	0.028	0.141	2.729	0.006	
H13h	PE	→	AT	→	IU	Total	0.273	0.165	0.377	4.850	0.000	Not supported
						Indirect	0.013	−0.025	0.059	0.596	0.551	
H13i	PU	→	AT	→	IU	Total	0.268	0.163	0.362	5.207	0.000	Partial supported
						Indirect	0.123	0.076	0.187	4.341	0.000	
H13j	CP	→	AT	→	IU	Total	0.224	0.148	0.321	5.147	0.000	Partial supported
						Indirect	0.119	0.080	0.168	5.174	0.000	
H13k	CX	→	AT	→	IU	Total	0.027	−0.021	0.071	1.142	0.254	Not supported
						Indirect	−0.003	−0.026	0.019	0.297	0.766	
H13l	RA	→	AT	→	IU	Total	0.202	0.078	0.312	3.263	0.001	Partial supported
						Indirect	0.148	0.095	0.209	4.849	0.000	
H14	AT	→	SCE	→	IU	Total	0.534	0.434	0.629	10.616	0.000	Partial supported
						Indirect	0.034	0.016	0.073	2.738	0.006	

Note(s): CI = confidence interval; LL = lower limit; UL = upper limit; Estimates are based on 5,000 bootstrap samples with bias-corrected 95% confidence intervals. IV: independent variable; M = mediator; DV = dependent variable; TAC = Task characteristics; TEC = Technology characteristics; TTF = Task technology fit; PE = Perceived ease of use; PU = Perceived usefulness; CP: Compatibility; CX = Complexity; RA: Relative advantage; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use

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Table 4. Measurement invariance testing results using MICOM (generative AI vs GUI platform)

Construct	Configural invariance (same algorithms for both groups)	Compositional invariance		Differences	Equal mean 95% confidence interval		*p*-value differences	Differences	Equal variance 95% confidence interval		*p*-value differences	Full measurement invariance
		C = 1	Partial									
TAC	Yes	1	Yes	−0.417	−0.158	0.158	0.000	0.452	−0.283	0.312	0.002	×
TEC	Yes	0.999	No	−0.215	−0.166	0.154	0.004	0.447	−0.314	0.356	0.007	×
TTF	Yes	1	Yes	−0.193	−0.166	0.153	0.014	0.443	−0.290	0.329	0.007	×
PE	Yes	1	Yes	−0.247	−0.156	0.154	0.002	0.400	−0.251	0.272	0.001	×
PU	Yes	1	Yes	−0.268	−0.161	0.162	0.000	0.609	−0.309	0.326	0.000	×
RA	Yes	0.999	No	−0.224	−0.167	0.151	0.008	0.446	−0.283	0.309	0.003	×
CP	Yes	1	Yes	0.019	−0.162	0.155	0.826	0.216	−0.286	0.313	0.161	✓
CX	Yes	0.922	Yes	0.104	−0.153	0.162	0.218	0.024	−0.243	0.273	0.791	✓
AT	Yes	1	Yes	−0.166	−0.164	0.150	0.042	0.208	−0.279	0.316	0.189	×
SCE	Yes	1	Yes	−0.058	−0.16	0.153	0.476	0.083	−0.319	0.347	0.594	✓
IU	Yes	1	Yes	−0.161	−0.163	0.156	0.048	0.070	−0.295	0.325	0.667	×

Note(s): TAC = Task characteristics; TEC = Technology characteristics; TTF = Task technology fit; PE = Perceived ease of use; PU = Perceived usefulness; CP = Compatibility; CX = Complexity; RA = Relative advantage; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use

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Table 5. Multi-group analysis results

Hypothesis	Construct	Path coefficient Generative AI	GUI platform	difference	*t*-value Generative AI	GUI platform	difference	*p*-value difference Permutation	Henseler's MGA	Supported
H15a	TAC → TTF	0.233	0.236	−0.003	4.598	4.175	0.423	0.279	0.280	Not supported
H15b	TEC → TTF	0.662	0.601	0.061	13.732	12.633	1.099	0.328	0.325	Not supported
H15c	TTF → AT	0.141	0.206	−0.065	1.942	2.515	−0.573	0.507	0.473	Not supported
H15d	PE → PU	0.728	0.705	0.023	18.503	19.692	−1.189	0.370	0.336	Not supported
H15e	PE → AT	0.011	0.047	−0.036	0.220	0.694	−0.474	0.312	0.335	Not supported
H15f	PU → AT	0.309	0.136	0.173	4.946	1.654	3.292	0.049	0.047	Supported
H15g	RA → AT	0.262	0.342	−0.080	3.310	4.661	−1.351	0.253	0.234	Not supported
H15h	CA → AT	0.259	0.186	0.073	5.748	2.636	3.112	0.015	0.009	Supported
H15i	CX → AT	0.008	−0.045	0.053	0.368	0.923	−0.555	0.104	0.155	Not supported
H15j	AT → SCE	0.811	0.713	0.098	32.045	16.734	15.311	0.048	0.028	Supported
H15k	AT → IU	0.609	0.712	−0.103	10.196	17.753	−7.557	0.013	0.014	Supported
H15l	SCE → IU	0.305	0.218	0.087	4.792	4.459	0.333	0.494	0.489	Not supported

Note(s): TAC = Task characteristics; TEC = Technology characteristics; TTF = Task technology fit; PE = Perceived ease of use; PU = Perceived usefulness; CP = Compatibility; CX = Complexity; RA = Relative advantage; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use

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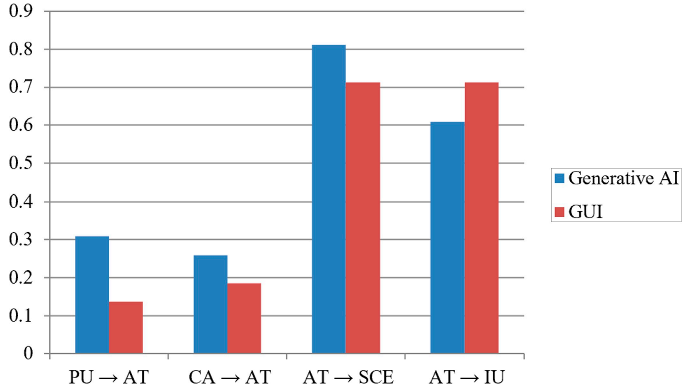

Figure 3. Visual presentation (multigroup analysis result)

Note(s): PU = Perceived usefulness; CP = Compatibility; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use

4.6 Robustness check

To assess model robustness, quadratic effects analysis was conducted (Hair *et al.*, 2024). The analysis revealed curvilinear relationships in two paths: compatibility demonstrated a U-shaped relationship with attitude ($\beta = 0.044$ and $p < 0.05$) and attitude exhibited an inverted U-shaped effect on self-confident efficacy ($\beta = -0.043$ and $p < 0.05$). When quadratic terms were included, corresponding linear effects became non-significant, confirming the curvilinear specification. Despite the limited incremental variance explained ($\Delta R^2 \leq 0.008$), which falls below Cohen's (1988) threshold for small effect sizes, the statistical significance of these quadratic terms supports their theoretical relevance. Following established robustness check protocols, we incorporated these quadratic terms in our final model to provide a more accurate representation of the underlying relationships while maintaining theoretical parsimony for the remaining linear paths.

5. Discussions and implications

5.1 Academic implications

First, this study advanced AI-based technology research by developing a comprehensive framework that incorporated TTF, TAM and IDT to enable an enhanced comprehension of the complex antecedents that underpin users' attitudes and intentions in the context of AI-TPA. However, prior combined frameworks provided partial explanations TTF and IDT models neglected cognitive evaluations (Wang and Lin, 2019), while TAM and IDT approaches overlooked task-specific fit (Terrah *et al.*, 2024). In this regard, this comprehensive framework addresses these theoretical gaps by incorporating complementary perspectives that collectively explain technology acceptance more effectively than previous dual-theory models, thereby establishing a more robust foundation for future AI tourism research.

Second, the analysis results confirmed a significant impact of the integrated variables TTF, TAM and IDT on attitude. From TTF perspective, task and technology characteristics emerged as crucial indicators of TTF, which significantly influenced attitudes toward AI-TPA. This result aligns with prior research (Dhiman and Jamwal, 2023), which emphasizes that TTF is crucial in shaping attitudes in the context of service chatbots. In the TAM scope, perceived ease of use positively influenced perceived usefulness, which subsequently

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significantly influenced attitudes, aligning with Foroughi *et al.*'s (2024) studies on travel apps. However, perceived ease of use insignificantly impacted attitudes, contradicting prior studies by Du *et al.* (2025). This may be because of users prioritizing functional value over ease when planning their travel itinerary (Ozturk *et al.*, 2016). From an innovation perspective, relative advantages and compatibility were validating as positively influencing attitudes, supporting findings that technology acceptance is contingent upon performance benefits and aligns with user needs (Lim *et al.*, 2022). Notably, complexity insignificantly impacted attitudes, suggesting that as AI-based technology becomes mainstream, researchers should reconsider complexity as a diminishing barrier to adoption in technology acceptance models.

Third, this study identified attitude as a crucial factor in influencing both self-confident efficacy and intentions to use AI-TPA. Importantly, self-confident efficacy demonstrated a stronger positive association with intentions to use AI-TPA than attitude alone, revealing that favorable technology evaluations are insufficient without users' confidence in their ability to use the technology. These findings underscore the essential role of self-confident efficacy in shaping intentions to use AI-TPA. This result indicates that a positive evaluation of AI-TPA must be accompanied by confidence in its use to enhance the intention to use it.

Fourth, this study examined the mediating role of attitude within the integrated TTF, TAM and IDT model, linking antecedent variables to self-confident efficacy and intentions to use in the context of AI-TPA. The findings demonstrated that attitude is essential in converting users' technology-related perceptions into intentions to use AI-TPA, aligning with Lim *et al.* (2022), who demonstrated that attitude significantly mediates among tourists using travel apps. Notably, the complete mediation effect of attitude in the correlation between relative advantage and self-confident efficacy was confirmed. This finding indicated that the objective superiority of technology alone cannot directly enhance users' confidence. Moreover, self-confident efficacy functions as a mediating variable that transforms attitudes into intentions to use, supporting the findings of Sun *et al.* (2024). The current finding demonstrated that favorable attitudes require users' confidence in their AI-TPA capabilities to generate intentions to use. This result reveals that enhancing self-confident efficacy can promote the adoption of AI-TPA more effectively in users' decision-making. This finding enhances the existing AI technology literature by bridging the gap between the perception of technology and the actual intention to use it.

Finally, this study investigated the moderating effect of AI-TPA interaction types in influencing users' attitudes and intentions. Existing studies focused on factors that can positively affect consumer attitudes toward AI-TPA; however, researchers have typically targeted users of only one type of AI-TPA, either generative AI or GUI-based platforms (Cybulski and Horbiński, 2020; Kanhed *et al.*, 2024). That is, examining the impact on attitude across two different types of AI-TPA has been overlooked. To the best of our knowledge, this is the first empirical evidence comparing generative AI and GUI interaction regarding a moderating effect within an integrated model in the context of AI-TPA. This study advances theoretical understanding by corroborating the findings of Nguyen *et al.* (2022), who identified differing consumer responses to chatbot versus menu-based interface interactions.

The analysis revealed that the relationships between perceived usefulness and attitude and compatibility and attitude differ between interaction types. The moderating effect on perceived usefulness and attitude was significant only in the generative AI group, indicating that users recognize customization through natural language, resulting in more favorable attitudes. These results align with Dwivedi *et al.* (2024), who indicated that generative AI users may express nuanced preferences via conversational input. In contrast, GUI-based

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users are constrained by pre-structured menu choices (Cybulski and Horbiński, 2020), which may not foster favorable attitudes. This finding aligns with Kim *et al.* (2019), who emphasized the differential impact of AI interaction types. Compatibility significantly affected attitude formation in both groups, with a more pronounced effect among generative AI users. This suggests users exhibit positive attitudes when the system matches their preferences via conversational interaction. This finding supported Nass and Moon (2000), who proposed social response theory, positing that people instinctively regard human-like technologies as social partners. For GUI-based platforms, compatibility holds less significance as users are already familiar with point-and-click interfaces. These findings indicate that conversational AI aligns more closely with user preferences than conventional click-based systems. This study offers a framework for systematically comparing various AI-TPA types, addressing the heterogeneity that single-platform studies cannot capture.

5.2 Practical implications

First, this study suggests that perceived usefulness significantly affects attitudes toward AI-TPA and intentions to use. Marketers can create advertisements highlighting how AI-TPA enables faster access to travel information compared to manual searches. Additionally, software developers should incorporate features demonstrating time savings and user ratings (e.g. “1,000 travelers rated this 4.1 out of 5 stars”). This social proof approach is effective because individuals tend to follow others’ attitudes in uncertain situations (Amblee and Bui, 2011). Successful platforms such as Booking.com and TripAdvisor effectively use social proof by displaying real-time booking activities and user ratings.

Second, perceived compatibility significantly affects attitudes and intentions to use AI-TPA, with differential effects across AI-TPA types. Generative AI companies should emphasize how conversational interaction aligns with natural communication styles, as real-time engagement positively influences user satisfaction (Dwivedi *et al.*, 2024). GUI-based platforms benefit from reduced compatibility barriers because of user familiarity with conventional interfaces; however, they should highlight visual clarity and intuitive navigation to compete against generative AI alternatives. Various consumer segments perceive compatibility differently, requiring tailored approaches. Providers should initially target consumers with strong digital literacy and innovativeness as early adopters (Teng *et al.*, 2024). To broaden the user base, simple tutorials and hands-on demonstrations can assist less tech-savvy consumers in becoming comfortable with AI-TPA. Moreover, customized strategies based on age, education and lifestyle characteristics will further enhance adoption across various market segments.

Finally, the findings reveal that self-confident efficacy functions as a crucial mediating factor between attitudes toward AI-TPA and the intention to use it. As more travelers adopt AI-based travel planning tools and traditional travel agent roles diminish (Ho *et al.*, 2021), this finding offers a strategic pathway for the tourism industry to navigate this transition. This presents both challenges and opportunities for the tourism industry. Travel companies should invest in upskilling their workforce to work alongside AI technology rather than competing with it. Specialized training programs can enable employees to become AI-TPA consultants that assist customers in optimizing the technology’s benefits. By repositioning staff as expert facilitators rather than traditional agents, companies can preserve human touchpoints while embracing technological advancement. This hybrid approach mitigates employment concerns while enhancing consumers’ self-confident efficacy and intentions about AI-TPA through the synergy of human expertise and AI technology.

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5.3 Study limitations and future research

Despite the significant theoretical and practical contributions of this research, certain limitations require thorough consideration. First, focusing solely on Korea may limit generalizability; future research should compare markets with varying digital adoption rates and literacy levels. Second, the cross-sectional design captured attitudes at one point; longitudinal studies are needed to examine how initial skeptical attitudes evolve, shifts in preference between generative AI and GUI and generational differences as users gain familiarity with AI technology. Third, while user preferences were quantitatively measured, mixed-methods research is essential to explore how users' demand for control and travel styles influence AI tool selection and platform preferences. Fourth, future studies should address ethical and sustainability dimensions, including data privacy, algorithmic bias, employment displacement, digital equity and environmental impacts of AI recommendations on sustainable tourism practices.

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Appendix 1

Table A1. Confirmatory factor analysis: Items and loadings

Construct and scale item	Loadings		CR		AVE	
	Generative AI	GUI platform	Generative AI	GUI platform	Generative AI	GUI platform
Task characteristics (0.838, 0.791)						
When I use AI-TPA, I am able to complete my travel plan without assistance from the travel agent	0.825	0.817	0.902	0.877	0.755	0.704
AI-TPA that I have used are flexible to be able to respond to my needs	0.888	0.864				
It is easy to travel effectively planning through AI-TPA	0.892	0.836				
Technology characteristics (0.820, 0.792)						
AI-TPA helps me to answer several enquiries regarding my travel plans	0.859	0.758	0.925	0.905	0.712	0.655
AI-TPA serve as a virtual travel agent and helps me plan my trips/bookings in an effective way	0.865	0.839				
AI-TPA helps me to connects to real travel agents in case of any complex enquiry	0.769	0.752				
AI-TPA can recommend me attractions/hotels/flights based on availability and preferences	0.857	0.847				
AI-TPA keeps me updated about the journey details/flights ticket/ check-in and many more	0.863	0.846				
Task technology fit (0.872, 0.872)						
Using AI-TPA fits well with my travel goal and needs	0.832	0.867	0.912	0.913	0.722	0.723
Using AI-TPA fits well with the way I like to enhance the efficiency of my travel	0.866	0.875				
Using AI-TPA fits well with the way I like to strengthen the security of my travel	0.845	0.812				
Using AI-TPA fits well with all aspects of my travel demand	0.855	0.845				
Perceived ease of use (0.873, 0.885)						
It is easy to use AI-TPA	0.910	0.879	0.922	0.929	0.797	0.814
It is easy to get AI-TPA to do what I want it to do	0.863	0.902				
It is convenient to access AI-TPA	0.905	0.924				
Perceived usefulness (0.858, 0.827)						
Using AI-TPA is useful	0.873	0.852	0.914	0.897	0.779	0.743
If I use AI-TPA, I can get a faster information what I want	0.865	0.847				
Using AI-TPA increases efficiency in receiving information I find	0.909	0.887				
Relative advantage (0.839, 0.823)						
I am able to derive satisfaction from using AI-TPA	0.896	0.895	0.903	0.894	0.757	0.739
Using AI-TPA is useful	0.853	0.888				
I am able to reduce the cost of information gathering	0.861	0.791				

(continued)

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Table A1. Continued

Construct and scale item	Loadings Generative AI	Loadings GUI platform	CR Generative AI	CR GUI platform	AVE Generative AI	AVE GUI platform
Compatibility (0.880, <u>0.915</u>)						
AI-TPA fits well with the way I like to plan a trip	0.858	0.881	0.918	0.94	0.736	0.797
AI-TPA is compatible with my lifestyle	0.863	0.868				
AI-TPA does not fit with my preferences. (r)	0.866	0.910				
AI-TPA fits with my travel needs	0.844	0.911				
Complexity (0.814, <u>0.838</u>)						
AI-TPA requires technical skills	0.880	0.736	0.887	0.870	0.723	0.693
AI-TPA requires a lot of mental effort	0.851	0.767				
AI-TPA can be frustrating	0.818	0.975				
Attitude (0.881, <u>0.897</u>)						
Using AI-TPA on my trip is a good idea	0.866	0.825	0.918	0.928	0.737	0.764
I intend to use AI-TPA for my next vacation	0.863	0.878				
AI-TPA make my travel more interesting	0.820	0.888				
I like traveling with AI-TPA	0.883	0.904				
Self-confident efficacy (0.887, <u>0.912</u>)						
I am confident in my choice of travel plan	0.873	0.888	0.922	0.938	0.747	0.791
I am certain of my choice of travel plan	0.870	0.889				
I believe that my choice of travel plan is the right One	0.855	0.892				
I am convinced of my decision to purchase the travel	0.859	0.889				
Intentions to use (0.886, <u>0.923</u>)						
I will use AI-TPA when planned travel	0.868	0.914	0.922	0.946	0.746	0.813
I intend to use AI-TPA frequently	0.887	0.913				
I intend to use AI-TPA in the future	0.853	0.902				
I intend to recommend that other people use AI-TPA	0.846	0.876				

Note(s): AVE = Average Variance Extracted; CR = Composite Reliability; Cronbach's α = In parentheses ().The unmarked values are for generative AI; the underlined values are for GUI

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Appendix 2

Table A2. Discriminant validity – Fornell and Larcker criterion

Construct	AT	PE	PU	RA	CP	CX	TAC	TEC	TTF	SCE	IU
(1) AT	*0.864*										
(2) PE	0.690 (0.763)	*0.897*									
(3) PU	0.803 (0.168)	0.724 (0.138)	*0.878*								
(4) RA	0.823 (0.743)	0.719 (0.629)	0.849 (0.125)	*0.867*							
(5) CP	0.770 (0.780)	0.662 (0.746)	0.701 (0.091)	0.752 (0.735)	*0.870*						
(6) CX	0.167 (0.823)	0.017 (0.799)	0.188 (0.191)	0.198 (0.795)	0.136 (0.833)	*0.846*					
(7) TAC	0.644 (0.778)	0.633 (0.762)	0.674 (0.237)	0.652 (0.789)	0.551 (0.836)	0.127 (0.785)	*0.864*				
(8) TEC	0.753 (0.764)	0.673 (0.768)	0.772 (0.208)	0.759 (0.670)	0.678 (0.733)	0.236 (0.840)	0.687 (0.746)	*0.833*			
(9) TTF	0.773 (0.862)	0.734 (0.823)	0.765 (0.177)	0.768 (0.742)	0.762 (0.764)	0.222 (0.788)	0.679 (0.748)	0.803 (0.752)	*0.850*		
(10) SCE	0.771 (0.850)	0.653 (0.774)	0.736 (0.252)	0.735 (0.779)	0.777 (0.775)	0.195 (0.781)	0.583 (0.812)	0.724 (0.734)	0.749 (0.792)	*0.874*	
(11) IU	0.861 (0.856)	0.683 (0.867)	0.779 (0.202)	0.781 (0.778)	0.741 (0.836)	0.183 (0.805)	0.647 (0.798)	0.720 (0.848)	0.753 (0.799)	0.768 (0.776)	*0.879*
Cronbach's α	0.887	0.878	0.851	0.835	0.893	0.824	0.830	0.889	0.872	0.897	0.902
Mean	3.458	3.446	3.357	3.324	3.592	3.497	3.324	3.073	3.521	3.308	3.534
Standard deviation	0.760	0.687	0.692	0.783	0.713	0.733	0.690	0.741	0.718	0.701	0.727

Note(s): 1: TAC = Task characteristics; TEC = Technology characteristics; TTF = Task technology fit; PE = Perceived ease of use; PU = Perceived usefulness; CP = Compatibility; CX = Complexity; RA = Relative advantage; AT = Attitude; SCE = Self-confident efficacy; and IU = Intentions to use; the diagonal element of boldface is the square root of AVEs and the corresponding below-diagonal element is the correlation of 11 constructs; Heterotrait–monotrait (HTMT) = In parentheses (); HTMT < 0.90 (Kline, 2023)

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