Amara Awan / Mahwish Zafar / Kashif Hussain

# Predicting Travellers' Intentions to Adopt Generative Artificial Intelligence for Travel Planning: The Interplay of Psychosocial Factors, Perceived Attributes, and Hallucination

## Abstract

This study examines how travelers' psychosocial factors translate into the intention to adopt GAI tools for travel planning. Accordingly, the study uses an extended TPB framework that incorporates sequential pathways from users' prior experience with GAI, perceived attributes, and satisfaction, with perceived risk of GAI hallucination as a moderator. Data were collected from 310 travelers in Pakistan and analyzed using PLS-SEM in SmartPLS4. Findings revealed that travelers' attitude significantly drives prior interaction, which in turn strongly predicts GAI's perceived attributes, including anthropomorphism and personalization. These perceptions foster satisfaction and, consequently, build intentions to adopt GAI for travel planning. Crucially, this satisfaction-intention nexus is weakened in the presence of GAI hallucination. Theoretically, the study examines sequential rather than direct effects of psychosocial factors. Practically, developers and travel service providers should focus on designing advanced tools to improve customized online services, while policymakers must establish accuracy standards and verification mechanisms to mitigate hallucination-induced distrust.

***Keywords***: GAI prior experience, anthropomorphism, personalization, satisfaction, GAI hallucination

## 1. Introduction

The pervasive integration of artificial intelligence (AI) across domains is profoundly reshaping how humans interact with smart devices, offering unprecedented opportunities for efficiency and innovation. Among its most advanced applications is generative AI (GAI), which offers unique opportunities for innovation and efficiency. Producing novel content, analyzing complex information, and providing personalized information are attributes that make GAI-based tools widely attractive across sectors. The transformative potential of GAI tools is increasingly recognized in complex decision-making processes, such as travel planning (Ali et al., 2025; Dash, 2026; Duong et al., 2025). GAI-based solutions are transforming traditional travel planning, promising more efficient and responsible experiences by creating personalized itineraries and suggesting optimal routes and sustainable accommodations (Moghavvemi & Huang, 2026; Wang et al., 2026). This evolving role of GAI requires a deeper understanding of psychosocial factors, as it aligns with travelers' expectations while promoting green mobility and sustainable travel, thereby strengthening their intentions to adopt emerging technologies.

**Amara Awan**, Corresponding Author, Faculty of Economics and Commerce, The Superior University, Lahore, Pakistan;
Department of Management Sciences, Virtual University of Lahore, Lahore, Pakistan;
ORCID ID: https://orcid.org/0000-0002-1796-8427; e-mail: amaraawan84@gmail.com

**Mahwish Zafar**, Faculty of Business and Management Sciences, The Superior University, Lahore, Pakistan;
ORCID ID: https://orcid.org/0000-0003-4463-2379; e-mail: mahwish.zafar@superior.edu.pk

**Kashif Hussain**, School of Global Hospitality and Tourism, Asia Pacific University of Technology and Innovation, Kuala Lumpur, Malaysia;
Faculty of Business and Management Sciences, The Superior University, Lahore, Pakistan;
ORCID ID: https://orcid.org/0000-0002-2923-3575; e-mail: kashif.hussain@apu.edu.my

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Several studies have used the Theory of Planned Behavior (TPB) to explain individuals' readiness to adopt technology through the direct influence of psychosocial factors, including attitude, subjective norms, and perceived behavioral control (Bervell et al., 2025; Osakwe et al., 2025). However, the literature on emerging technologies shows that adoption decisions depend on more than these factors. Several contextual factors, such as users' prior general experience with technology and evaluation of its attributes, also play a crucial role in adoption decisions (Domínguez-Figaredo & Gil-Jaurena, 2025; Marghany et al., 2025). In this context, prior general experience with GAI tools, conceptualized as familiarity and prior use, represents an underexplored dimension of technology adoption. Prior experience with generative AI tools reflects users' earlier interactions and understanding of these tools (Getenet et al., 2024; Wang & Sun, 2025; Zhan et al., 2024). It builds users' confidence and provides a foundation for assessing technology's capabilities (Christensen et al., 2025; Huang et al., 2026). Its contextual relevance has increased significantly with the widespread use of GAI across domains; however, its role in linking psychosocial predictors to perceived attributes remains underexamined (Kabakus et al., 2025; Zhan et al., 2024). Furthermore, the DeLone and McLean IS Success (DMISS) Model is employed in the study to explain the influence of system attributes on users' satisfaction (DeLone & McLean, 2003). Drawing on the literature, these attributes are conceptualized as i. anthropomorphism, the extent to which GAI tools are perceived as human-like, and ii. personalization, the degree to which outputs are tailored to individuals' preferences in smart technologies (Koo et al., 2025; Rapp et al., 2025). In travel planning, where reliable, tailored recommendations are vital, including these attributes in the integrated TPB-DMISS framework addresses a significant theoretical gap. Additionally, this adoption process is gradually facing a critical challenge of hallucination, a phenomenon in the context of GAI models that produces erroneous output (Altinay et al., 2025; Lee et al., 2025). For example, an itinerary created using GAI can include inaccurate information, resulting in serious implications, eroding satisfaction, and disrupting adoption intention (Christensen et al., 2025; Lee et al., 2025). Examining GAI hallucination is crucial to understanding its role in technology adoption, especially in travel planning, where decision quality and reliability are central (Christensen et al., 2025; Wang et al., 2026).

The study aims to examine how psychosocial factors drive travelers' intentions to adopt GAI tools for travel planning. In doing so, the study addresses a research gap by examining the sequential pathway linking prior experience, GAI attributes, and satisfaction to adoption intentions. The integrated TPB and DMISS model support this pathway. The TPB focuses on users' readiness to engage in a particular behavior through psychosocial factors, while the DMISS model explains the role of technology attributes and satisfaction. The study's extended framework uniquely proposes that travelers' psychosocial factors influence prior experience, which subsequently shapes their perception of GAI attributes. By positioning prior general experience between psychosocial factors and GAI attributes, the study explains travelers' psychosocial readiness for GAI tools through an experience-based evaluation process that fosters satisfaction and ultimately influences decisions to adopt GAI tools for trip planning. The novelty lies in extending the existing literature by theorizing prior experience and technology attributes not as direct predictors but as a bridge between psychosocial factors and intentions. Additionally, examining the moderating role of GAI hallucination offers useful insights into how reliability concerns influence the satisfaction-intention nexus.

# 2. Literature review

The following section provides a comprehensive review of the literature on predictors of technology adoption intention.

## 2.1. Psychosocial factors: attitude, subjective norms (SN), and perceived behavioral control (PBCO)

The TPB's theoretical framework for predicting human intentions is pivotal in social psychology. It states that intentions are primarily predicted by attitude, SN, and PBCO, conceptually distinct but interconnected

psychosocial factors (Ajzen, 1985). Attitude refers to an individual's assessment of performing a behavior. SN refers to the social pressure an individual perceives from those around them, while PBCO refers to the degree to which an individual perceives difficulty or ease in performing the behavior and their control over it (Ajzen, 1985; Bervell et al., 2025; Tang & Jiang, 2024). However, in the context of emerging technologies, PBCO reflects individuals' perceived comfort in giving GAI tools control to perform desired tasks (Christensen et al., 2025). Various studies show that psychosocial factors directly influence technology adoption across digital and AI contexts (Bervell et al., 2025; Osakwe et al., 2025; Paunovic et al., 2026). However, a growing body of research explores their indirect influence on technology adoption, potentially mediated by other cognitive constructs (Gil-Cordero et al., 2024; Rahman et al., 2017; Tang & Jiang, 2024). These studies provide valuable theoretical grounding for investigating the indirect role of attitudes, SN, and PBCO in shaping intentions through contextual variables, such as users' prior experience with these tools. The literature treats experience as an antecedent of technology adoption (Christensen et al., 2025; Domínguez-Figaredo & Gil-Jaurena, 2025; Nakandala et al., 2024; Oztemel & Ozel, 2019). This represents users' knowledge, skills, and competence built through prolonged exposure to technologies (Christensen et al., 2025; Hou et al., 2023). However, GAI tools are rapidly emerging and still in the early stages of diffusion. In this context, psychosocial factors are proposed to precede general experience and lead to earlier interaction with emerging tools (An et al., 2024). Travelers with positive attitudes, favorable social influence, and behavioral control are more likely to interact with these emerging tools and build initial general exposure. This led to the following hypotheses.

*H1-H3:* Attitude, SN, and PBCO significantly influence prior general experience with GAI tools.

## 2.2. Prior general experience: GAI familiarity (GAIF) and prior general use (GAIPU) of technology

In the context of advanced technologies, existing literature highlights the significance of contextual variables in predicting human intentions. Some studies highlight prior general experience as a key contextual variable, conceptualized as familiarity and GAIPU (Christensen et al., 2025; Domínguez-Figaredo & Gil-Jaurena, 2025; Nakandala et al., 2024; Oztemel & Ozel, 2019). In the context of continuously evolving GAI technology, this variable captures travelers' knowledge of and general interaction with GAI tools before they make adoption decisions for travel planning (Getenet et al., 2024; Zhan et al., 2024). It refers to users' knowledge and actual interaction with GAI tools for general activities before adopting them for travel planning (Christensen et al., 2025).

Familiarity with technology refers to perceived knowledge that helps comprehend the capabilities and limitations of technology (Christensen et al., 2025; Nakandala et al., 2024). GAIPU refers to general interaction with technology before its actual adoption, including generating ideas or content, answering questions, and taking advice on numerous topics in the context of GAI (Duong et al., 2025; Hou et al., 2023). Users' familiarity and prior engagement with emerging technologies cultivate an understanding of their innovative perceived attributes, such as anthropomorphism and personalization (Kabakus et al., 2025; Koo et al., 2025). This led to the formulation of the following hypotheses:

*H4-H5:* Familiarity and prior general use of GAI tools significantly influence the travelers' perception of personalization and anthropomorphism.

## 2.3. GAI perceived attributes: personalization (PRN) and anthropomorphism (ANM)

The perceived attributes of GAI play a pivotal role in shaping satisfaction and, ultimately, intention to adopt them for travel planning. Rooted in the DMISS model, these refer to system, information, and service quality. System quality demonstrates perceptions about the technical performance of a system; information quality exhibits expectations about output quality, such as relevance, timeliness, accuracy, etc., while service quality

depicts the users' overall perceptions about the services and assistance provided by technology providers (Gil-Cordero et al., 2024; Rathor et al., 2025). In the context of GAI, these attributes are conceptualized as anthropomorphism and personalization, which are crucial in cultivating users' satisfaction and adoption intention (Gil-Cordero et al., 2024; Lim & Zhang, 2022).

Anthropomorphism refers to perceiving non-human objects as human and interacting with them accordingly (Liu et al., 2025; Zhang et al., 2023). Conceptually related to the DMISS model's service quality, anthropomorphism reflects perceived relational responsiveness by capturing individuals' perceptions of conversational assistance and interactive support from advanced AI tools (Bhatnagr & Rajesh, 2025; Huang, 2023; Keating et al., 2025; Manzoor et al., 2024). In GAI-based chatbots such as ChatGPT, anthropomorphism reflects empathy and cultivates strong emotional relationships with users (Manzoor et al., 2024; Marghany et al., 2025). Personalization refers to technology's ability to provide customized services that meet users' expectations (Blömker & Albrecht, 2025; Lim & Zhang, 2022), conceptually aligning with information quality in the DMISS model through the contextual appropriateness and relevance of generated content. In the context of GAI, personalization enables advanced AI-based chatbots to understand users' requirements and deliver relevant, customized information (Blömker & Albrecht, 2025; Zhang et al., 2023). Conceptualizing GAI attributes through DMISS quality dimensions helps capture users' perception of advanced AI tools. Underpinned by the DMISS model, these attributes contribute to users' satisfaction (Abou-Shouk et al., 2024; Paunovic et al., 2026). This led to the formulation of the following hypotheses:

*H6-H7:* Anthropomorphism and personalization significantly influence travelers' satisfaction.

## 2.4. Satisfaction

Satisfaction represents the extent to which humans perceive that their expectations or needs are fulfilled regarding an experience or a service (DeLone & McLean, 2003). An AI system that accurately predicts the intention of its users to perform the intended task, such as creating personalized itineraries to meet travelers' expectations, contributes significantly to satisfaction (Abou-Shouk et al., 2024; Lai et al., 2024; Rathor et al., 2025). In the context of GAI tools, satisfaction, cultivated by users' positive evaluation of smart technologies, translates into strong intentions to use these tools for task-oriented activities, such as travel planning. This led to the formulation of the following hypothesis:

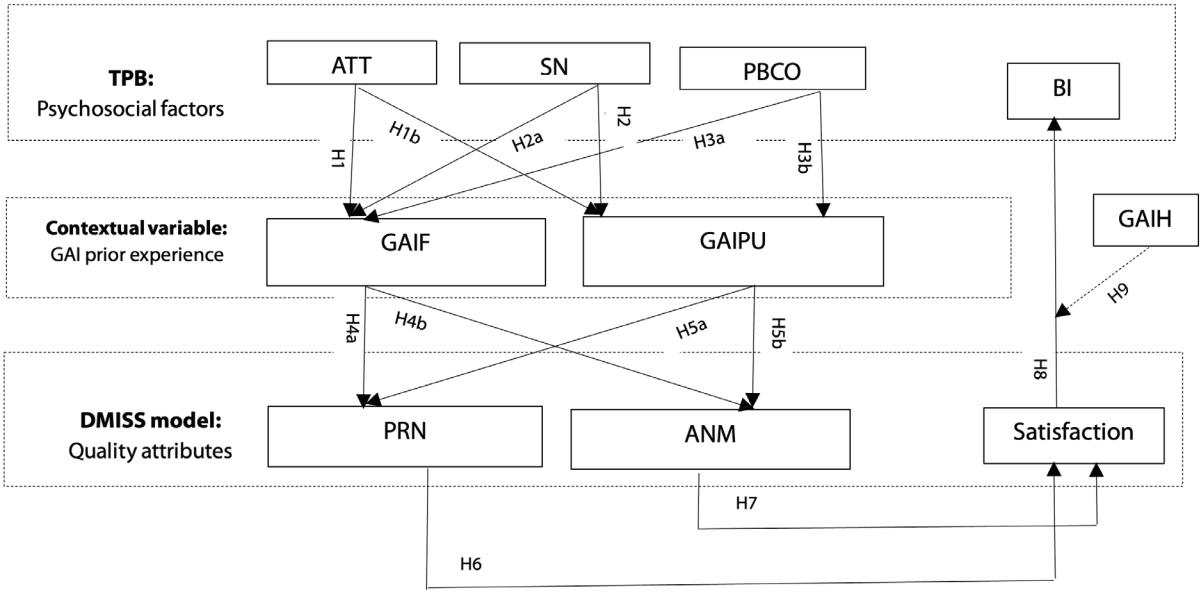
*H8:* Satisfaction significantly influences travelers' intention to adopt GAI tools for travel planning.

## 2.5. Generative AI hallucination (GAIH)

Literature on emerging AI technology highlights AI hallucination, a situation where the Gen AI model provides incorrect and false information that appears credible to users (Christensen et al., 2025). Hence, it reflects the perceived risk in the context of GAI tools that can influence the relationship between users' satisfaction and intention. Users' satisfaction with GAI tools is based on their perceptions of reliability, accuracy, and helpfulness. However, exposure to the perceived risk of AI hallucinations significantly erodes this satisfaction and disrupts adoption intention. In the context of the travel industry, exposure to hallucinations, such as suggesting a non-existent flight, hinders users' decisions associated with using GenAI (Christensen et al., 2025; Wang et al., 2026). Satisfaction, driven by positive perceptions of GAI attributes, does not translate into adoption intention when users perceive a risk of GAI hallucination (Lai et al., 2024; Shah & Hisashi, 2025). Accordingly, the following hypothesis is postulated:

*H9:* Perceived risk of GAIH significantly moderates the relationship between satisfaction and intention.

**Figure 1**
*Conceptual framework*




# 3. Methodology

This research examines travelers' intentions to adopt Gen AI for travel planning, a social phenomenon influenced by observable, measurable factors derived from the integrated TPB and DMISS models. The study adopted a quantitative research design to test hypotheses and analyze empirical data. It focused on travelers' intentions to adopt GAI tools for travel planning. This required respondents to be GAI users, meaning they had interacted with at least one GAI tool, such as ChatGPT or Gemini. However, because no complete list of travelers in Pakistan's travel sector is available, the study first used purposive sampling to select respondents. To identify target respondents, the survey began with two screening questions before proceeding to the main section. These questions collected information on whether respondents traveled annually and used GAI to perform any task. After applying these criteria, we recruited respondents through convenience sampling.

The survey link was distributed online through social media platforms, such as WhatsApp communities and Facebook. The survey link was also shared with respondents contacted in person at various venues, including conferences. The data were cross-sectional, collected from a sample of 344 respondents from October 1, 2024, to March 30, 2025. However, due to screening questions and conditions, respondents who had never used any GAI tool were not directed to the main survey section. Similarly, respondents with no travel history could not proceed to the main section of the survey. Thus, of the 344 responses, 34 did not meet the selection criteria and were excluded during data screening. The final sample consisted of 310 valid responses. The main section of the survey included test items for key variables, each using a 5-point Likert scale and adapted from well-established scales. For example, the variables PBCO, GAIF, GAIPU, attitude, and BI consisted of seven, five, six, four, and seven items, respectively, and were adapted from Christensen et al. (2025). The variables SN, personalization, and anthropomorphism were adapted from Bajunaied et al. (2023) and Zhang et al. (2023) and consisted of four, three, and four test items, respectively. The satisfaction scale was adapted from Chao (2019) and consisted of three test items.

# 4. Findings of the study

The current study assessed the measurement and structural models using PLS-SEM in SmartPLS4. PLS-SEM is a non-parametric technique suitable for predicting and explaining complex models based on the underpinning theory (Hair et al., 2019). . However, the demographic profile of respondents and their travel history were analyzed before assessing the measurement and structural models.

## 4.1. Demographics

The demographics show that respondents were 53.5% (166) male and 46.5% (144) female. Most respondents were young, educated adults: 45.2% (140) were 21-30 years, 26.1% (81) were 31-40 years, 15.8% (49) were under 20 years, and the remaining 42.9% (40) were over 41 years. Data were collected across Pakistan, with the most responses from Punjab, the most populous province, at 61.9% (192), followed by Sindh at 17.4% (54), KPK at 15.5% (48), and the remaining 5.1% (16) from the Capital and Balochistan. These respondents were frequent travelers: 32.9% (102) traveled 6 or more times annually, 31.3% (97) traveled 2-3 times, 10.3% (32) traveled 4-5 times, and 25.5% traveled at least once a year for recreation, business, or both.

## 4.2. Common method bias analysis

CMB was assessed using both statistical and procedural methods. Statistically, the Variance Inflation Factor (VIF) was examined to assess multicollinearity among predictors, as multicollinearity can contribute to common method bias and make coefficients unreliable. VIF values for all predictors were below 5, indicating no multicollinearity and suggesting that common method variance is likely not a serious concern. In addition, we employed procedural methods, including ensuring respondent anonymity and structuring the questionnaire to conceal the underlying model, to further minimize potential common method bias.

# 5. Measurement model assessment

Confirmatory factor analysis was conducted in SmartPLS4 to assess the measurement model, focusing on reliability and validity. Table 1 shows that all factor loadings exceed the minimum threshold of 0.5 (Hair et al., 2019), indicating that all indicators load properly on their latent variables, except BI2. BI2 has a weak loading of 0.321 and was therefore excluded from the analysis. Likewise, Cronbach's alpha and composite reliability (CR), more advanced measures of internal consistency in SmartPLS4 PLS-SEM (Hair et al., 2019), are both greater than 0.7, indicating strong internal consistency. Moreover, the average variance extracted (AVE) for each variable exceeds the minimum threshold of 0.5 (Hair et al., 2019), indicating strong convergent validity. Discriminant validity was assessed using the HTMT ratio, which measures how distinct and unrelated latent variables are (Hair et al., 2019; Henseler et al., 2015). Table 2 shows sufficient discriminant validity, as all values are below 0.85, the acceptance criterion for the HTMT ratio (Henseler et al., 2015).

**Table 1**
***Reliability and convergent validity***

| Variable | Code | F. L. | C. Alpha | CR 'Rho-a' | CR Rho-c | 'AVE' |
|---|---|---|---|---|---|---|
| ATT | ATT1 | 0.718 | 0.74 | 0.74 | 0.837 | 0.563 |
| | ATT2 | 0.733 | | | | |
| | ATT3 | 0.771 | | | | |
| | ATT4 | 0.778 | | | | |
| SN | SN1 | 0.746 | 0.821 | 0.824 | 0.882 | 0.652 |
| | SN2 | 0.857 | | | | |
| | SN3 | 0.831 | | | | |
| | SN4 | 0.792 | | | | |

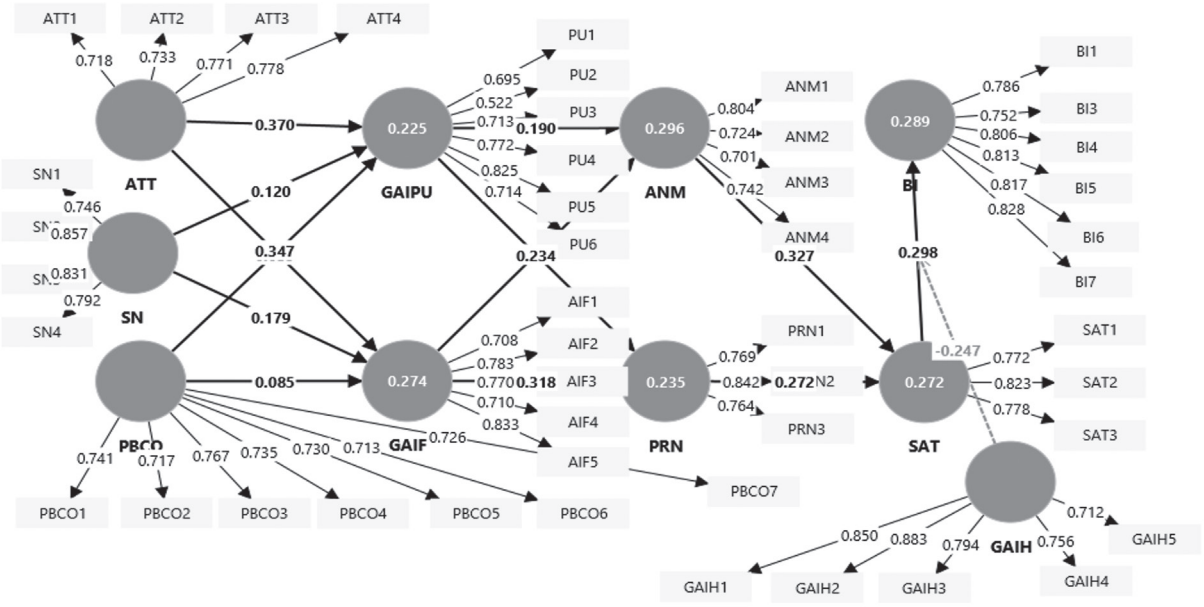
**Table 1** ***(continued)***

| | | | | | | |
|---|---|---|---|---|---|---|
| PBCO | PBCO1 | 0.741 | 0.857 | 0.862 | 0.89 | 0.537 |
| | PBCO2 | 0.717 | | | | |
| | PBCO3 | 0.767 | | | | |
| | PBCO4 | 0.735 | | | | |
| | PBCO5 | 0.73 | | | | |
| | PBCO6 | 0.713 | | | | |
| | PBCO7 | 0.726 | | | | |
| GAIF | GAIF1 | 0.708 | 0.82 | 0.829 | 0.874 | 0.581 |
| | GAIF2 | 0.783 | | | | |
| | GAIF3 | 0.77 | | | | |
| | GAIF4 | 0.71 | | | | |
| | GAIF5 | 0.833 | | | | |
| GAIPU | GAIPU1 | 0.695 | 0.805 | 0.821 | 0.859 | 0.508 |
| | GAIPU2 | 0.522 | | | | |
| | GAIPU3 | 0.713 | | | | |
| | GAIPU4 | 0.772 | | | | |
| | GAIPU5 | 0.825 | | | | |
| | GAIPU6 | 0.714 | | | | |
| ANM | ANM1 | 0.804 | 0.732 | 0.748 | 0.832 | 0.553 |
| | ANM2 | 0.724 | | | | |
| | ANM3 | 0.701 | | | | |
| | ANM4 | 0.742 | | | | |
| PRN | PRN1 | 0.769 | 0.703 | 0.706 | 0.835 | 0.628 |
| | PRN2 | 0.842 | | | | |
| | PRN3 | 0.764 | | | | |
| SAT | SAT1 | 0.772 | 0.702 | 0.701 | 0.834 | 0.627 |
| | SAT2 | 0.823 | | | | |
| | SAT3 | 0.778 | | | | |
| BI | BI1 | 0.786 | 0.889 | 0.906 | 0.915 | 0.641 |
| | BI3 | 0.752 | | | | |
| | BI4 | 0.806 | | | | |
| | BI5 | 0.813 | | | | |
| | BI6 | 0.817 | | | | |
| | BI7 | 0.828 | | | | |
| GAIH | GAIH1 | 0.85 | 0.861 | 0.885 | 0.899 | 0.642 |
| | GAIH2 | 0.883 | | | | |
| | GAIH3 | 0.794 | | | | |
| | GAIH4 | 0.756 | | | | |
| | GAIH5 | 0.712 | | | | |

**Table 2**
***HTMT-matrix***

| | ATT | SN | PBCO | GAIF | GAIPU | ANM | PRN | SAT | BI |
|---|---|---|---|---|---|---|---|---|---|
| **ATT** | | | | | | | | | |
| **SN** | 0.826 | | | | | | | | |
| **PBCO** | 0.477 | 0.454 | | | | | | | |
| **GAIF** | 0.636 | 0.521 | 0.340 | | | | | | |
| **GAIPU** | 0.572 | 0.430 | 0.254 | 0.641 | | | | | |
| **ANM** | 0.705 | 0.583 | 0.367 | 0.649 | 0.506 | | | | |
| **PRN** | 0.665 | 0.624 | 0.442 | 0.575 | 0.506 | 0.710 | | | |
| **SAT** | 0.601 | 0.446 | 0.285 | 0.383 | 0.350 | 0.642 | 0.627 | | |
| **BI** | 0.791 | 0.635 | 0.532 | 0.507 | 0.448 | 0.512 | 0.566 | 0.534 | |

**Figure 2**
***Measurement model***



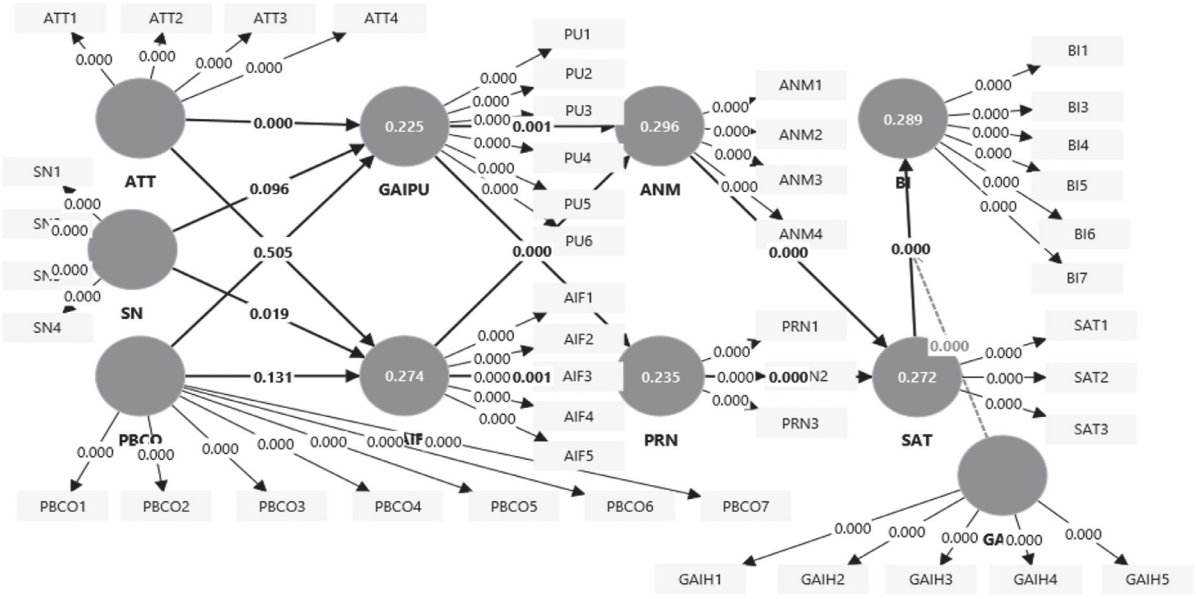

# 6. Assessment of structural model

The structural model is assessed using structural equation modeling to test the significance of hypothesized paths. SmartPLS4 uses default bootstrapping settings: 5,000 bootstrap resamples, percentile bootstrap confidence intervals, and a two-tailed significance level of 0.05. Table 3 presents the results. Among the psychosocial factors, attitude significantly and positively influences both measures of prior experience, GAIF and GAIPU. SN significantly influences GAIF, but not GAIPU. Likewise, PBCO does not significantly influence either measure. GAI familiarity and prior use, which are strongly predicted by attitude, further influence anthropomorphism and personalization, and these relationships are significant at the 5% level. The significant positive evaluation of perceived GAI attributes also significantly and positively affects users' satisfaction. Overall, this enhanced satisfaction positively and significantly influences intention to adopt GAI tools for travel planning. Additionally, GAIH significantly and negatively moderates the relationship between satisfaction and intention.

**Table 3**
***Analysis of path coefficients***

| | Hypothesis | Beta | S.D. | LL | UL | t-Stat | P-Value | Decision |
|---|---|---|---|---|---|---|---|---|
| H1a | **ATT → GAIF** | 0.347 | 0.081 | 0.178 | 0.453 | 4.299 | 0.000 | Supported |
| H1b | **ATT → GAIPU** | 0.370 | 0.066 | 0.174 | 0.488 | 5.608 | 0.000 | Supported |
| H2a | **SN → GAIF** | 0.179 | 0.077 | 0.243 | 0.503 | 2.341 | 0.019 | Supported |
| H2b | **SN → GAIPU** | 0.120 | 0.072 | 0.234 | 0.561 | 1.666 | 0.096 | Not supported |
| H3a | **PBCO → GAIF** | 0.085 | 0.056 | 0.114 | 0.475 | 1.510 | 0.131 | Not supported |
| H3b | **PBCO → GAIPU** | 0.039 | 0.059 | -0.336 | -0.037 | 0.667 | 0.505 | Not supported |
| H4a | **GAIF →ANM** | 0.419 | 0.085 | 0.084 | 0.308 | 4.950 | 0.000 | Supported |
| H4b | **GAIF → PRN** | 0.318 | 0.092 | 0.116 | 0.366 | 3.445 | 0.001 | Supported |
| H5a | **GAIPU → ANM** | 0.190 | 0.057 | -0.022 | 0.201 | 3.306 | 0.001 | Supported |
| H5b | **GAIPU →PRN** | 0.234 | 0.063 | -0.065 | 0.166 | 3.693 | 0.000 | Supported |
| H6 | **ANM → SAT** | 0.327 | 0.071 | 0.146 | 0.386 | 4.607 | 0.000 | Supported |
| H7 | **PRN → SAT** | 0.272 | 0.061 | 0.158 | 0.425 | 4.455 | 0.000 | Supported |
| H8 | **SAT → BI** | 0.298 | 0.069 | 0.024 | 0.325 | 4.310 | 0.000 | Supported |
| H9 | **GAIH x SAT → BI** | -0.247 | 0.065 | -0.347 | -0.101 | 3.817 | 0.000 | Supported |

**Figure 3**
***Structural model***




# 7. Discussion and conclusions

The findings revealed that among the three psychosocial factors, only individuals' attitude significantly influences both familiarity and prior use. In contrast, SN affects only familiarity, while PBCO is not significantly related to either. This highlights attitude's pivotal role in shaping users' engagement with GAI tools and aligns with the TPB's core stance that favorable evaluations of a behavioral outcome encourage preliminary actions (Bervell et al., 2025; Huang, 2023; Rahman et al., 2017; Sujood et al., 2024). In Pakistan, where the digital landscape is rapidly expanding amid smartphone penetration and e-commerce growth, individuals with positive attitudes are more likely to adopt advanced technologies.

On the other hand, the significance of SN with familiarity but not with use suggests that social influence may increase awareness of GAI technology but not necessarily drive its use. This relatively weak influence of SN reflects GAI tools' niche status. This aligns with studies supporting SN's indirect influence on individuals' technology adoption (Bervell et al., 2025; Osakwe et al., 2025; Tang & Jiang, 2024). Likewise, the insignificant relationship of PBCO suggests that perceived control's indirect influence is irrelevant. This finding aligns with the TPB, which supports the direct influence of perceived control on users' behavioral intention (Ajzen, 1985; Bervell et al., 2025; Tang & Jiang, 2024). Furthermore, structural barriers, including inconsistent internet access and digital literacy gaps between urban and rural areas, undermine individuals' perceptions of control in developing economies such as Pakistan. In such contexts, a positive attitude becomes the decisive predictor, driving attitude-led experimentation despite external barriers (Bervell et al., 2025; Christensen et al., 2025; Huang, 2023).

Furthermore, a significant positive relationship between GAI prior general experience and perceived attributes shows that users' familiarity and prior engagement with these tools contribute to building an understanding of their capabilities (Christensen et al., 2025; Oztemel & Ozel, 2019; Wu et al., 2024). Users with prior experience are more likely to perceive the conversational fluency, responsiveness, or tone of GAI-based tools, such as ChatGPT, as more empathetic and human-like. Similarly, prior experience enhances perceptions of personalization, as hands-on interaction and familiarity show the technology's ability to adapt to preferences, fostering satisfaction. These findings align with the DMISS model and existing literature (Abou-Shouk et al.,

2024; Lim & Zhang, 2022; Wang et al., 2026). In Pakistan's emerging digital landscape, these perceptions matter because early adopters who find these tools empathetic and adaptive become more satisfied and act as informal advocates, accelerating wider technology diffusion.

The study also found that positive perceptions of GAI attributes significantly increase satisfaction. This aligns with the DMISS Model, which posits that when users perceive a system as empathetic and responsive to their preferences, their satisfaction is significantly enhanced. In contexts like travel planning, where decisions are inherently personal and emotionally embedded, these positive perceptions are pivotal to fostering satisfaction in the adoption process (Chao, 2019; Prassida et al., 2024; Rathor et al., 2025). These findings suggest that even with Pakistan's digital infrastructure barriers, users who perceive GAI tools as both anthropomorphic and personalized show greater satisfaction and stronger adoption intentions. However, negative moderation of perceived risk of GAI hallucination underscores the sensitivity of the satisfaction-intention relationship. Despite exhibiting high satisfaction and strong intention, exposure to inaccurate or fabricated information significantly weakens the adoption process (Altinay et al., 2025; Christensen et al., 2025; Lai et al., 2024).

## 7.1. Implications of the study

The study provides the following insightful implications:

### *7.1.1. Theoretical implications*

i. The study moves beyond examining direct pathways as suggested in the TPB, introducing the sequential mediating pathways to understand the indirect influence of psychosocial factors on adoption intention when engaging with emerging technologies.

ii. The integration of the DMISS model with TPB provides a useful lens for investigating the role of perceived attributes of GAI and users' satisfaction in technology adoption decisions.

### *7.1.2. Practical implications*

i. The positive influence of attitude on prior experience underscores the need for targeted attitudinal interventions rather than normative or control-oriented strategies. This suggests collaboration between tech developers and travel service providers to integrate GAI technologies into their services, focusing on sustainable solutions such as eco-friendly itineraries that resonate with travelers' values.

ii. A positive relationship between GAI prior experience and perceived attributes suggests that developers, in collaboration with travel firms, should design applications that incorporate gamification, provide human-like interaction, and offer customized services. Features such as virtual tours let travelers simulate itineraries in advance, boosting perceived empathy and personalization while reinforcing satisfaction and adoption.

iii. Negative moderation of the perceived risk of GAI hallucinations between satisfaction and intention suggests that developers should invest in accuracy, verification mechanisms, and transparent communication to minimize hallucinations. For online travel platforms, embedding cross-checking functions, such as verified accommodation links or real-time transportation updates, can protect users from misinformation that undermines the decision-making process.

### *7.1.3. Policy implications*

i. Negative moderation of hallucination shows that satisfaction translates into adoption intention when technology output is perceived as reliable. This suggests that policymakers should prioritize standards and guidelines that encourage developers to focus on accuracy, verification mechanisms, and transparent communication in GAI applications to minimize hallucinations.

ii. Policymakers should design a comprehensive national AI policy to prioritize integrating smart technologies into Pakistan's travel industry by allocating dedicated funds. Beyond funding, policies should support innovation centers that connect academia, technology developers, and tourism firms, accelerating cross-sector knowledge transfer.

# 8. Limitations of the study and future prospects

Although the current study advances a novel TPB-DMISS integration to investigate GAI adoption intentions in Pakistan's nascent travel context, it has limitations.

i. The cross-sectional design of the study captures only behavioral intentions.
ii. The sample's focus on tech-savvy respondents to investigate prior experience may limit generalisability to diverse demographics.
iii. Furthermore, the study could not provide insights into actual usage behavior, as it is a common constraint in early-stage technology adoption research where tools remain experimental in emerging markets like Pakistan.

These limitations provide avenues for future research:

i. Future studies can incorporate longitudinal designs to investigate the intention-actual use gap, tracking how initial attitude translates into intention and then sustainable use of GAI-based tools for travel planning.
ii. Future studies can extend the model to a diverse group of respondents, such as tech-savvy and non-tech-savvy, minimizing the challenges of generalisability.
iii. Future studies can explore agentic AI, autonomous systems designed for travel and tourism, such as proactive itinerary agents, to investigate actual behaviours.

# 9. Conclusion

This study examined travelers' intentions to adopt GAI tools for travel planning, helping explain the nuanced psychosocial mechanisms of technology adoption in an emerging market context. By integrating the TPB with the DMISS model, this research extends the existing framework by focusing on sequential mediating paths that reveal how psychosocial factors, including attitude, SN, and PBCO, translate through prior experience and perceived GAI attributes into technology adoption intention. The findings highlight attitude toward technology as the dominant psychosocial predictor, translating into experiential engagement with GAI tools. Prior experience shapes perceptions of GAI attributes, which foster satisfaction and a strong intention to adopt GAI tools for travel planning. These findings address the objectives of identifying how psychosocial factors shape early engagement with GAI tools and subsequently analyzing how experiential evaluations of GAI attributes translate into adoption intention. Theoretically, this study advances the technology adoption discourse by integrating psychosocial predictors with system-based perspectives, providing a more holistic understanding of user cognition in AI-based contexts. Practically, the results show that a better user experience and perceived quality build satisfaction and strengthen intentions to use AI technologies for travel planning.

**Declaration of Competing Interests**

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

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