Kareem M. Selem / Mohamed M. Khalil

Empowering Aging Travelers in Smart Tourism Destinations in Light of Digital Self-Efficacy: Unpacking GAI-Enabled App Usage Barriers

Abstract

This study examines the psychological and technological barriers that prevent aging travelers from adopting generative artificial intelligence (GAI)-enabled apps at tourism destinations. It addresses the growing need to bridge digital divides among aging travelers in GAI-enabled service contexts. Data were collected from 492 travelers aged 60 and older who used GAI-enabled travel apps during trips in Egypt. Digital self-efficacy was adversely affected by privacy anxiety, cognitive load, and limited trust. These barriers were significantly indirectly associated with self-reported app use through digital self-efficacy. The findings provide practical insights for tourism policymakers on promoting GAI inclusion for aging travelers through self-efficacy-building content.

Keywords: aging travelers, digital self-efficacy, cognitive load, GAI-enabled apps, smart tourism

1. Introduction

Generative artificial intelligence (GAI) has disrupted smart tourism, changing how travelers search for information, plan itineraries, make decisions, and interact with tourism services (Hu & Lin, 2026). Unlike traditional tourism applications (apps), GAI-enabled apps use large language models and other generative architectures to create personalized content, provide travel recommendations, communicate in natural language, and tailor responses to traveler preferences and requirements. Digital transformation in tourism ecosystems has been accelerated by these features, enabling AI-based travel assistants, conversational destination chatbots, itinerary planners, multilingual translation systems, and recommendation engines (Costa et al., 2025). Although service personalization and efficiency may be increased by such innovations, new forms of algorithmic autonomy, information opacity, privacy uncertainty, and cognitive complexity are introduced, distinguishing GAI-enabled travel apps (Bilgihan et al., 2024; Ilieva et al., 2024). Thus, research on travelers' reactions to emerging technologies is essential in smart tourism.

Although research has focused on GAI-enabled tourism services, prior technology adoption studies have focused on general audiences, with little attention to older travelers. The unique psychological, cognitive, and emotional features of older adults provide theoretical justification for this gap, as they affect technology adoption more than in younger people (Huang & Tsai, 2003; Jang & Wu, 2006). Research findings indicate that older travelers are more sensitive to risk perceptions, have lower information-processing abilities, have higher emotional security needs, and prefer familiar technologies when interacting with digital platforms (Wu & Yang, 2023; Tuomi et al., 2023). At the same time, the peculiarities of aging travelers become more apparent in GAI-enabled travel apps, as AI recommendations are adaptive, autonomous, and difficult to understand. Although conventional technology acceptance models explain technology adoption, applying them to aging

Kareem M. Selem, Corresponding Author, Hotel Management Department, Faculty of Tourism and Hotels, Suez Canal University, Ismailia, Egypt; ORCID ID: https://orcid.org/0000-0003-2987-4134; e-mail: karim.ibrahim@tourism.suez.edu.eg

Mohamed M. Khalil, Hotel Management Department, Faculty of Tourism and Hotels, Suez Canal University, Ismailia, Egypt; ORCID ID: https://orcid.org/0000-0001-8864-2750; e-mail: mohamedkhalil@tourism.suez.edu.eg

TOURISM
An International Interdisciplinary Journal
Original Research Article
Vol. 74/ No. 4/ 2026/ 662 - 678
UDC: [338.48:004.8]:316.346.32-053.9; https://doi.org/10.37741/t.74.4.8
©2026 The Author(s) | Open Access | This article is licensed
under a Creative Commons Attribution 4.0 International License (CC BY 4.0)

travelers using GAI-enabled apps may benefit from incorporating additional psychological mechanisms that capture age-related perceptions of uncertainty, trust, and digital self-efficacy (Venkatesh et al., 2003).

Although the importance of privacy concerns, cognitive load, and trust in determining technology adoption has been documented in prior research (Gefen et al., 2003; Gu et al., 2017; Paas et al., 2003), the extant literature on this topic remains theoretically disjointed. First, these barriers have been examined separately, leading to a poor understanding of their impact when they act in tandem in determining technology adoption. In addition, direct associations between technological attributes and self-reported usage outcomes have been identified in technology adoption research, leaving little room to explain the underlying psychological mechanisms that turn external barriers into internal behavioral restraints (Jia et al., 2025; Tan et al., 2025). Finally, much of the existing evidence was collected using standard digital technologies. The unique features of GAI (e.g., autonomous content creation, conversational abilities, algorithmic opacity, and decision support) introduce new uncertainties that can change travelers' attitudes toward privacy, trust, and cognitive load in ways different from those typical of traditional travel technologies (Hu & Lin, 2026; Ilieva et al., 2024). Therefore, a theoretical basis that addresses the emotional and cognitive effects of emerging technologies must be developed when applying existing technology adoption models to GAI-enabled travel apps.

These challenges matter for aging travelers, as technology adoption depends on their evaluations of technology, feelings of safety, and competence with digital tools. For instance, socioemotional selectivity theory (SST) suggests that as people age, they become more focused on emotions and avoid uncertainty and risk (Huang & Tsai, 2003; Jang & Wu, 2006). At the same time, technology self-efficacy theory (TSET) posits that travelers' perceptions of their ability to use digital tools influence behavioral processes (Bandura & Wessels, 1997; Wang et al., 2024). Although each theory has helped explain technology adoption, few studies have examined how emotional prioritization and capability beliefs interact to affect GAI adoption among aging travelers. The key theoretical issue is how psychological processes translate technology-created barriers (e.g., privacy, cognitive burden, and lack of trust) into use of GAI-enabled apps.

2. Literature review and hypothesis development

2.1. Theoretical underpinnings

Technology adoption literature has focused on trust, perceived usefulness, ease of use, and cognitive load as predictors of adopters' behavioral intention (Venkatesh et al., 2003). According to the trust model, perceptions of system reliability, transparency, and credibility shape self-reported use of GAI-enabled apps because trust reduces uncertainty and vulnerability in digital interactions (Gefen et al., 2003). Travelers have limited cognitive capacity, and complex interfaces or information processing may reduce users' ability to interact with emerging technologies (Paas et al., 2003). Although these theories have contributed to technology adoption research, they are often treated as external influences on user behavior, offering little insight into the underlying cognitive processes.

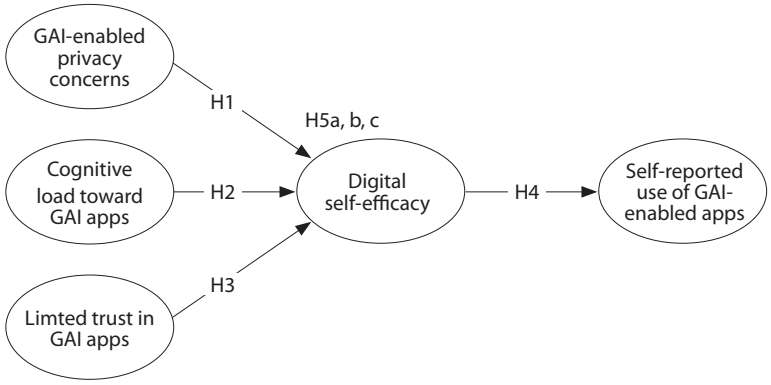
These constraints become more evident when GAI-enabled travel apps are considered by travelers (Ilieva et al., 2024; Hu & Lin, 2026). New uncertainties, privacy concerns, and cognitive complexity are introduced. In addition, many studies on the digital divide show that older travelers tend to have lower digital literacy, greater risk sensitivity, and greater fear of unfamiliar technologies than younger people (Wu & Yang, 2023; Tuomi et al., 2023). Therefore, a framework is needed that accounts for the emotions associated with uncertainty and for individuals' confidence in managing complex digital technologies.

SST posits that as people age, their motivations for action shift toward emotionally significant, psychologically safe, and risk-averse situations (Huang & Tsai, 2003; Jang & Wu, 2006). Thus, new technologies that reduce uncertainty and provide emotional protection are expected to be valued by aging travelers. At the

same time, the TSET focuses on how technology adoption depends on people's attitudes toward their ability to understand and use technology in uncertain or complex circumstances (Bandura & Wessels, 1997; Wang et al., 2024). Although previous literature has examined trust, SST, and TSET separately, no study has integrated these theoretical constructs into a single construct. In other words, a fragmented explanation of GAI-enabled app adoption is offered by the existing literature through separate examinations of external barriers, emotional evaluations, and capability beliefs.

This study's theoretical approach assumes that these three perspectives complement one another. First, external barriers that may inhibit GAI adoption are captured by limited trust and cognitive load. In contrast, aging travelers' sensitivity to uncertainty and risk is captured by SST, and the effects of these factors on digital self-efficacy are captured by TSET. By integrating SST and TSET with traditional technological barriers, technology adoption theory is extended beyond direct effects to a process-based explanation in which privacy concerns, cognitive load, and lack of trust affect technology use through digital self-efficacy. This theory can be used to explain GAI adoption among aging travelers. The conceptual framework, as illustrated in Figure 1, hypothesizes that privacy concerns, cognitive load, and trust are technological barriers that affect digital self-efficacy, leading to the use of GAI-enabled apps by aging travelers. In other words, digital self-efficacy is seen as a psychological factor that translates external technological barriers into traveler behaviors.

Figure 1
Theoretical framework



Source: Authors' own work.

2.2. Barriers to GAI-enabled app adoption

The functions and interactions in GAI-enabled travel apps differ from those on conventional digital tourism platforms. First, while predetermined functions such as search, booking, navigation, and rule-based recommendations are performed by traditional travel apps, personalized content is generated, customers are chatted with, destinations are recommended, and decision-making advice is offered based on users' context (Hu & Lin, 2026; Ilieva et al., 2024). Consequently, greater algorithmic complexity and system autonomy are exhibited by GAI-enabled apps, which may increase users' dependence on AI-generated outputs and make system responses harder to anticipate. These factors introduce new forms of uncertainty into GAI technologies that go far beyond typical digital ones. At the same time, privacy concerns, high cognitive load, and low trust are among the most significant psychological barriers to technology use (Gefen et al., 2003; Gu et al., 2017; Paas et al., 2003). However, most empirical evidence comes from traditional technology environments, where systems are more transparent and autonomous than GAI-enabled apps.

Despite extensive research on privacy concerns, cognitive load, and limited trust, the literature remains conceptually disjointed. Privacy concerns are reflected in users' sense of vulnerability stemming from a lack of control over their personal information and uncertainty about how it is managed (Gu et al., 2017).

Cognitive load is the mental effort required to navigate complex technological systems (Paas et al., 2003). Although prior research has shown that these barriers negatively affect technology adoption, they have been examined in isolation as factors influencing users' behavioral intention, offering a partial view of their impact on technology use (Jia et al., 2025; Tan et al., 2025). In addition, few studies have examined how external barriers to technology use become internal barriers for users in a GAI-enabled environment where decision-making is automated, opaque, and information-intensive (Ilieva et al., 2024). Privacy concerns, cognitive load, and limited trust are conceptualized as supplementary elements of technological resistance that affect users' digital self-efficacy.

2.3. Hypothesis development

Privacy risks from GAI-enabled apps are faced by senior travelers, including data misuse, surveillance, and identity-related concerns (Suanpang & Pothipassa, 2024). When GAI-enabled apps are perceived as intrusive or opaque, emotional incongruity and heightened risk perception may be experienced, leading to protective or avoidant responses (Hu & Lin, 2026). Low privacy signals create uncontrollable ambiguity, undermining users' sense of control and psychological safety in online interactions (Gu et al., 2017). These effects are exacerbated by an aging population, which widens the digital divide and reduces trust in navigating complex digital contexts (Wu & Yang, 2023; Shin & Baek, 2023). In turn, GAI-enabled privacy concerns affect digital self-efficacy, with increased risk perceptions reducing travelers' self-efficacy in using such technologies. Thus, it is suggested that:

H1: GAI-enabled privacy concerns are negatively associated with digital self-efficacy.

In tourism contexts, GAI-enabled apps involve complex interfaces, unfamiliar symbols, and decision-making processes that can create cognitive burdens (Hu & Lin, 2026). Emotional anxiety and avoidance reactions are created, and users' trust in and mastery of digital devices are decreased (Tuomi et al., 2023). As a result, resistance to cognitive complexity is provoked by GAI interfaces, undermining aging travelers' perceived ability to use apps (Bilgihan et al., 2024). From the TSET perspective, digital self-efficacy is shaped by prior successful technology interactions (Wang et al., 2024). High cognitive load interferes with this process by leading to adverse self-evaluation and reduced motivation to interact, learn, and adapt to emerging technologies (Bai & Yang, 2025). Users may perceive this complexity as a personal constraint in GAI-enabled travel apps, which may inhibit digital self-efficacy (Wang et al., 2024). Hence, it is hypothesized that:

H2: Cognitive load toward GAI-enabled apps is negatively associated with digital self-efficacy.

In this study, limited trust refers to aging travelers' lack of confidence in the reliability, credibility, and safety of GAI-enabled apps, which undermines their perceived ability to use these technologies. Aging travelers become more selective in their cognitive and emotional investments, focusing on familiar, predictable, and emotionally safe experiences (Suanpang & Pothipassa, 2024). Aging travelers who doubt the credibility or transparency of GAI-enabled apps, including concerns about algorithmic bias, opaque data use, or system autonomy, experience reduced emotional comfort and heightened uncertainty (Suanpang & Pothipassa, 2024). Consequently, they become less willing to use these technologies and have fewer opportunities to build trust, leading to lower digital self-efficacy (Costa et al., 2025). SST also indicates that older users who experience risky or stressful digital experiences tend to be more averse than younger users, despite these technologies' functionality (Huang & Tsai, 2003; Jang & Wu, 2006).

Travelers' trust in technology stems from their cognitive assessment of the external environment (e.g., prior experience and trust in apps) (Wang et al., 2024). When users perceive GAI-enabled apps as unreliable or deceptive, they feel less confident in their ability to use them (Hu & Lin, 2026). This is particularly evident among aging travelers, whose weak efficacy beliefs leave them vulnerable to risk because they have less digital

experience and are more sensitive (Wu & Yang, 2023; Shin & Baek, 2023). In turn, low trust in GAI-enabled apps creates a cognitive barrier, reducing users' confidence in their ability to perform related tasks and lowering digital self-efficacy (Tuomi et al., 2023; Sun et al., 2026). Thus, it is assumed that:

H3: Limited trust in GAI-enabled apps is negatively associated with digital self-efficacy.

TSET states that travelers tend to acquire and utilize technology more when they think they can use it (Bandura & Wessels, 1997). Digital self-efficacy is therefore a key psychological tool that negates perceived barriers (Suanpang & Pothipassa, 2024). According to Costa et al. (2025), trust in their digital skills is driven by aging travelers, which drives them to be more open to working with GAI-enabled apps. Grounded in SST, older travelers focus more on emotionally rewarding, low-risk experiences (Jia et al., 2025). Low trust in GAI-enabled apps can increase stress and discomfort, reinforcing avoidance behavior. By contrast, GAI-enabled apps are less cognitively demanding and less emotionally threatening, increasing the likelihood that travelers with high digital self-efficacy will resume use (Bilgihan et al., 2024). Thus, it is presupposed that:

H4: Digital self-efficacy is positively associated with self-reported use of GAI-enabled apps.

From a TSET perspective, travelers' attitudes toward technology adoption, as potential actors, strongly predict behavior in complex, uncertain digital settings (Wang et al., 2024). Aging travelers exposed to privacy concerns, high cognitive load, and low trust tend to experience reduced digital self-efficacy, which decreases the likelihood of using GAI-enabled apps (Tan et al., 2025). Perceived vulnerability from privacy concerns, psychological strain from cognitive load, and relational uncertainty from a lack of trust undermine users' commitment to interpersonal communication with digital apps (Jia et al., 2025). At the same time, SST supports the mediation effect by arguing that older travelers are sensitive to emotional and cognitive cues and prefer experiences that foster a sense of control and emotional safety (Suanpang & Pothipassa, 2024). GAI-enabled apps perceived as opaque, intrusive, or hard to control pose emotional and cognitive risks that aging travelers are likely to avoid when they lack confidence in their ability to handle them (Bilgihan et al., 2024). Digital self-efficacy serves as a motivational tool that helps users overcome perceived complexity and uncertainty. Self-efficacy enables aging travelers to use GAI-enabled apps despite perceived risk, whereas low self-efficacy supports avoidance. Therefore, it is assumed that:

H5: Digital self-efficacy mediates the relationships between (a) GAI-enabled privacy concerns, (b) cognitive load toward GAI-enabled apps, and (c) limited trust in GAI-enabled apps, on the one hand, and self-reported use of GAI-enabled apps, on the other.

3. Method

3.1. Research context

The study was conducted in three Egyptian destinations: Greater Cairo, Alexandria, and Luxor. As the capital, Greater Cairo is a complex urban tourism context that blends heritage resources with contemporary service ecosystems (Tuomi et al., 2023). Alexandria is represented as a semi-urban tourism setting with coastal attractions and a growing domestic senior travel market (Huang & Tsai, 2003; Jang & Wu, 2006). Luxor, a UNESCO World Heritage site and a key destination for international travelers, offers an environment where GAI-enabled apps could help travelers learn more about destinations, navigate, and stay safe (Costa et al., 2025). The empirical context is theoretically justified. Egypt is a transitional setting (Elgammal et al., 2026) where high-tech digital solutions coexist with advanced technological infrastructure and user preparedness, making it an emerging tourism destination in digital transformation (Tan et al., 2025). This heterogeneity

provides an appropriate context for studying digital self-efficacy and technology uptake among aging travelers, as it offers enabling factors and structural limitations related to smart tourism development (Shin & Baek, 2023; Sun et al., 2026). Moreover, a comprehensive assessment of user interaction with GAI-enabled apps across various service contexts is enabled by the variety of tourism formats.

3.2. Questionnaire design

The study adapted constructs from relevant studies with established psychometric properties. Each item was rated on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). GAI-enabled privacy concerns were assessed with five items from Gu et al. (2017). Cognitive load related to GAI-enabled apps was measured with five items adapted from Paas et al. (2003). Limited trust in GAI-enabled apps was measured with five items adapted from Gefen et al. (2003). Although the original items were positively worded to assess respondents' trust in GAI-enabled apps, they were reverse-coded before statistical analysis so that higher scores indicated lower trust. Thus, the construct was operationalized as limited trust, consistent with the proposed theoretical framework.

Digital self-efficacy was assessed with five items adapted from Bandura and Wessels (1997). Self-reported use of GAI-enabled travel apps was measured with five items adapted from Venkatesh et al. (2003). These items captured respondents' engagement with GAI-enabled apps across travel-related activities, including itinerary planning, translation, travel advice, destination information searches, and booking. Because usage was assessed through participants' questionnaire responses, the construct was operationalized as self-reported use. The data collection instrument was developed in English and back-translated into Arabic to ensure linguistic equivalence and cultural accuracy. Two bilingual experts translated the English version into Arabic, and three bilingual academics back-translated it into English.

Two tourism researchers were included to accommodate the needs of older travelers. To assess the survey's reliability and validity, it was pretested with 95 respondents aged 60 and older. The Google Form was distributed through community groups in Greater Cairo, Alexandria, and Luxor. Item readability and perceived relevance were evaluated by respondents. Minor amendments were made to simplify the wording of potentially sensitive items, to include the use of GAI-enabled apps (e.g., voice-based travel assistants and chatbots), and to ensure clear interpretation. Cronbach's alpha values above 0.70 were obtained for all constructs in the pretest, indicating initial reliability.

Before completing the questionnaire, respondents were given a brief definition of GAI-enabled travel apps and their travel-related functions. These apps included conversational AI chatbots and virtual travel assistants (e.g., ChatGPT and Google Gemini), AI-powered itinerary planners for generating personalized travel schedules, AI-based translation tools for multilingual communication, personalized recommendation systems for suggesting attractions, restaurants, and tourism activities, and AI-assisted booking tools for supporting travel reservations and purchase decisions. These examples clarified the scope of GAI-enabled travel apps and ensured that respondents understood the technologies addressed in the questionnaire.

3.3. Sampling and data gathering

This study targeted travelers aged 60 and older who used GAI-enabled travel apps during trips to three Egyptian cities: Greater Cairo, Alexandria, and Luxor. The cities were selected for their diverse technical infrastructure, high levels of travel among senior domestic and international travelers, and local tourism authorities' digitization efforts. Purposive sampling was used to include respondents with firsthand experience using GAI-enabled travel apps, which was necessary to test the proposed relationships. Requiring prior experience with these apps aligned with the study's objectives, as the conceptual framework examines

perceptions of privacy issues, cognitive burden, trust, digital self-efficacy, and app use. The requirement for sufficient firsthand experience made purposive sampling appropriate; however, this approach may limit external validity.

Between September and October 2025, the researcher allocated 800 surveys to major attractions, senior tourism groups, and retirement tourism programs in collaboration with local tour operators. To reduce sampling bias, the researcher also distributed a Google Form through shared mechanisms managed by senior-centric online travel forums and community groups. The survey began with two screening questions: (1) "Are you aged 60 years or older?" and (2) "Have you ever used or interacted with GAI-enabled travel apps (e.g., chatbots or virtual travel assistants) during your travels?" Respondents who answered "No" to either question were excluded. The screening procedure focused on respondents who reported prior experience with GAI-enabled travel apps. These apps included conversational travel assistants, AI-generated itinerary planning tools, translation assistants, personalized tourism recommendation systems, and AI-assisted booking services. This approach ensured that participants had prior exposure to GAI-enabled app types relevant to the study's conceptual framework.

A sequential data-cleaning procedure was conducted to ensure data quality. Of the 800 questionnaires initially distributed, 107 were excluded due to incomplete responses, leaving 693 for further screening. During response-quality screening, 98 responses were excluded: 47 exhibited straight-lining patterns, and 51 failed attention checks. These exclusions were counted without duplication, leaving 595 responses for multivariate outlier assessment. Mahalanobis distance was used to identify multivariate outliers, and an additional 103 responses were excluded. After these screening procedures, the final dataset comprised 492 valid responses, representing 61.5% of the questionnaires distributed. Table 1 presents the demographic characteristics of the final sample.

Table 1
Respondent profile

Category		Sample (n = 492)	
		Frequency	%
Gender	Male	258	52.4
	Female	234	47.6
Age group	60-64	174	35.4
	65-69	156	31.7
	70-74	96	19.5
	75 and older	66	13.4
Educational level	Less than high school	84	17.1
	High school	138	28
	BSc	186	37.8
	MSc/PhD	84	17.1
Travel frequency (Yearly)	Once	192	39
	Twice	168	34.1
	More than twice	132	26.8
Technology experience	Low	168	34.1
	Moderate	204	41.5
	High	120	24.4

Source: Authors' own work.

3.4. Analysis strategy

PLS-SEM was used to estimate the measurement and structural models because it suits prediction-oriented studies and can handle complex models with mediating relationships (Vaithalingam et al., 2024). Additionally,

the method is suitable for data that may not be multivariate normal, which is typical in field-based survey research involving aging groups (Hair et al., 2019). Moreover, indirect effects can be estimated through bootstrapping (Hair et al., 2019). ADANCO-PLS v.2.4 was chosen for its easy-to-diagnose models, graphical interfaces, correspondence with latent variables and loadings, and accurate path-coefficient estimates (Elgammal et al., 2026; Tan et al., 2025). To test the model's strength, an MGA was conducted across demographic subgroups (i.e., age, gender, and technological experience). While PLS-SEM is well-suited for investigating complex relationships in cross-sectional survey data, the estimated paths should be interpreted as statistical correlations.

3.5. Common method bias (CMB)

Harman's single-factor test and collinearity diagnostics were used to assess CMB. Harman's single-factor test was conducted using Exploratory Factor Analysis (EFA), with all measurement items entered an unrotated factor solution. The first factor accounted for 29.12% of the total variance, below the 50% threshold, suggesting that a single dominant factor was unlikely to account for most of the observed variance. In addition, the variance inflation factor (VIF) values were below 3.3, indicating no substantial collinearity concerns based on this diagnostic. Taken together, concerns about potential CMB are reduced, but it is not conclusively ruled out. Procedural safeguards were also implemented during questionnaire design, including assuring respondents of anonymity and confidentiality, using unambiguous items, separating predictor and outcome measures, and emphasizing that there were no right or wrong answers. Nevertheless, given the self-reported, cross-sectional nature of the datasets, CMB cannot be ruled out.

3.6. Ethical considerations

The study was exempted from ethical review by the university's research ethics committee because it did not involve clinical trials with respondents. All aspects of respondents' interactions with this study were conducted in accordance with the ethical guidelines set by the institutional research board and the Declaration of Helsinki and its later versions. Respondents were informed of the study's purpose, the voluntary nature of participation, and their right to withdraw at any time. Verbal informed consent was obtained before data collection. No identifying information was collected, and respondents were assured that data security would be upheld. The datasets were reported with full accountability and ethical respect for respondent fairness.

4. Results

4.1. Outer model assessment

Convergent and discriminant validity were examined to assess reliability and validity. Item reliability was established because factor loadings exceeded 0.708, indicating that all indicators were related to their respective latent constructs (Hair et al., 2019). Internal reliability was verified because Cronbach's alpha and composite reliability (CR) exceeded 0.70. Convergent validity was confirmed using average variance extracted (AVE) values above 0.50 (see Table 2), indicating that each construct explained a significant amount of variance in its indicators. Second, discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) (Hair et al., 2019). Based on the Fornell-Larcker criterion, the square root of each construct's AVE exceeded its correlations with other constructs (Table 3). Moreover, HTMT values were below the conservative threshold of 0.85, confirming strong discriminant validity (Vaithalingam et al., 2024). Collinearity was assessed using inner VIFs (see Table 3), which were below 5, indicating reliable results (Hair et al., 2019).

Table 2
Items reliability and validity

Variables	Codes	Items	Loading	VIF	Alpha	CR	AVE
GAI-enabled privacy concerns	APC1	I worry about how GAI-enabled apps use my personal data.	0.812	2.134	0.875	0.896	0.633
	APC2	I worry that GAI-enabled apps can share my information without permission.	0.843	2.287			
	APC3	GAI-enabled apps I use do not explain how data is handled.	0.783	1.964			
	APC4	I feel uncomfortable about GAI-enabled apps that collect sensitive travel data.	0.764	1.845			
	APC5	I avoid using some GAI features due to the possibility of privacy issues.	0.772	1.902			
Cognitive load toward GAI-enabled apps	CLA1	GAI-enabled apps require significant psychological effort to use.	0.802	2.356	0.883	0.901	0.646
	CLA2	It is difficult to understand the GAI app suggestions.	0.793	2.214			
	CLA3	GAI-enabled apps are difficult for me to use.	0.784	2.178			
	CLA4	I get overwhelmed while trying to navigate GAI-enabled tasks.	0.814	2.401			
	CLA5	Learning to use the features takes a lot of time and focus.	0.826	2.489			
Limited trust in GAI-enabled apps	LTA1	I believe that GAI-enabled apps provide information about the exact journey.	0.763	1.978	0.864	0.882	0.600
	LTA2	I feel like I should rely on GAI's recommendations for my trips.	0.786	2.045			
	LTA3	I believe that GAI-enabled apps provide reliable and predictable responses.	0.742	1.876			
	LTA4	I trust the GAI-enabled apps to work safely.	0.805	2.132			
	LTA5	I feel comfortable making decisions based on GAI-enabled tips.	0.775	2.011			
Digital self-efficacy	DSE1	I am confident that I can use GAI apps while traveling.	0.833	2.421	0.903	0.914	0.679
	DSE2	I can learn how to use the new GAI features on my smartphone.	0.812	2.308			
	DSE3	I feel able to solve issues when using GAI-enabled apps.	0.844	2.512			
	DSE4	I believe that I can live with a change in GAI-enabled travel.	0.825	2.467			
	DSE5	I feel comfortable experimenting with new GAI tools on my phone.	0.806	2.276			
Self-reported use of GAI-enabled apps	SRU1	I use GAI-enabled apps to plan my travel journey program.	0.811	2.398	0.902	0.916	0.687
	SRU2	I rely on GAI-enabled translation devices while communicating abroad.	0.794	2.265			
	SRU3	I often use GAI assistants for real-time travel advice.	0.827	2.433			
	SRU4	I use GAI-enabled apps to search for attractions and restaurants.	0.846	2.521			
	SRU5	I use GAI-enabled apps for travel booking and purchase.	0.865	2.608			

Note. LTA1–LTA5 were reverse-coded before the PLS-SEM analysis. Higher scores on these items therefore represent lower levels of trust in GAI-enabled apps.
Source: Authors' own work.

Table 3
Discriminant validity

Construct		Inner-VIF	HTMT approach				
			1	2	3	4	5
1.	Self-reported use of GAI-enabled apps	1.842					
2.	GAI-enabled privacy concerns	2.134	0.451				
3.	Cognitive load toward GAI-enabled apps	2.356	0.404	0.476			
4.	Digital self-efficacy	2.421	0.392	0.331	0.493		
5.	Limited trust in GAI-enabled apps	2.045	0.365	0.356	0.326	0.439	
Construct			**Fornell-Larcker method**				
			1	**2**	**3**	**4**	**5**
1.	Self-reported use of GAI-enabled apps		**0.782**				
2.	GAI-enabled privacy concerns		0.422	**0.805**			
3.	Cognitive load toward GAI-enabled apps		0.345	0.402	**0.793**		
4.	Digital self-efficacy		0.387	0.321	0.328	**0.769**	
5.	Limited trust in GAI-enabled apps		0.253	0.487	0.201	0.309	**0.798**

Source: Authors' own work.

4.2. Inner model assessment

Table 4 and Figure 2 revealed that GAI-enabled privacy concerns adversely affected digital self-efficacy (β = –0.323, t = 4.854, p < 0.001, CI [–0.465, –0.184]), supporting H1. Similarly, cognitive load toward GAI-enabled apps reduced digital self-efficacy (β = –0.293, t = 4.107, p < 0.001, CI [–0.422, –0.162]), supporting H2. Limited trust in GAI-enabled apps also adversely affected digital self-efficacy (β = –0.255, t = 3.928, p < 0.001, CI [–0.395, –0.116]), supporting H3. Furthermore, digital self-efficacy positively affected GAI-enabled app use (β = 0.437, t = 6.328, p < 0.001, CI [0.333, 0.614]), supporting H4. In addition, digital self-efficacy explained 41.2% of the variance, indicating moderate explained variance. In contrast, the R2 value for self-reported use of GAI-enabled apps was 26.8%, also indicating moderate explained variance.

For predictive relevance, blindfolding was also used, yielding Q2 values of 0.358 and 0.241 for digital self-efficacy and self-reported use of GAI-enabled apps, respectively, indicating satisfactory predictive capacity. In addition, f2 values were analyzed as a relative measure of each predictor construct. Table 4 results suggest that GAI-enabled privacy concerns (f2 = 0.112), cognitive load (f2 = 0.096), and limited trust (f2 = 0.081) have small effects on digital self-efficacy, and digital self-efficacy has a moderate effect size on self-reported use of GAI-enabled apps (f2 = 0.214). These results emphasize that individual barriers affect digital self-efficacy and, in turn, its indirect effect on self-reported use of GAI-enabled apps. Since the collected data is cross-sectional, the indirect effects should be interpreted in line with the proposed theoretical framework, supporting H5a-H5c.

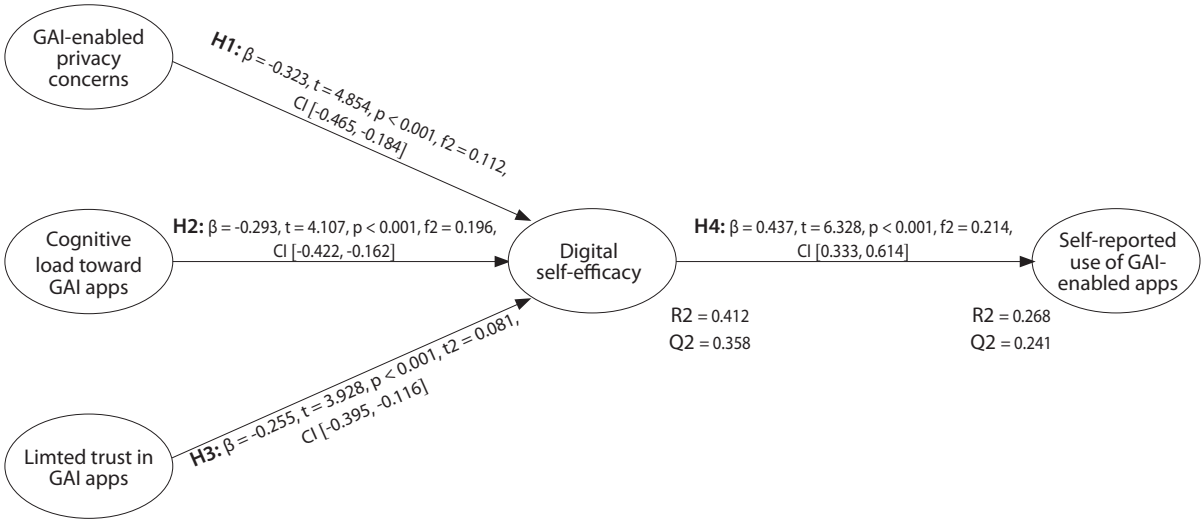
The mediation analysis revealed significant indirect associations between the three technological barriers and self-reported use of GAI-enabled apps through digital self-efficacy. Specifically, the indirect effects were significant for GAI-enabled privacy concerns (β = –0.152, t = 3.203, p = 0.001), cognitive load (β = –0.142, t = 2.886, p = 0.004), and limited trust (β = –0.125, t = 2.753, p = 0.006), supporting H5a–H5c. These findings support proposed indirect relationships. However, without comparing direct effects before and after including digital self-efficacy, the mediation cannot be classified as partial or full. Furthermore, given the cross-sectional nature of the data, these indirect relationships should not be interpreted as establishing causal mediation.

Table 4
Path analysis results

Direct effects							
H	**Paths**	**β**	**t-value**	**p-value**	**f2**	**95%CI**	**Decision?**
H1	AI-enabled privacy concerns → Digital self-efficacy	-0.323***	4.854	0.000	0.112	[-0.465, -0.184]	Supported
H2	Cognitive load toward GAI-enabled apps → Digital self-efficacy	-0.293***	4.107	0.000	0.096	[-0.422, -0.162]	Supported
H3	Limited trust in GAI-enabled apps → Digital self-efficacy	-0.255***	3.928	0.000	0.081	[-0.395, -0.116]	Supported
H4	Digital self-efficacy → Self-reported use of GAI-enabled apps	0.437***	6.328	0.000	0.214	[0.333, 0.614]	Supported
Indirect effects							
H	**Paths**	**β**	**t-value**	**p-value**	**95%CI**	**Decision?**	
H5a	AI-enabled privacy concerns → Digital self-efficacy → Self-reported use of GAI-enabled apps	-0.152**	3.203	0.001	[-0.206, -0.024]	Significant indirect effect	
H5b	Cognitive load toward GAI-enabled apps → Digital self-efficacy → Self-reported use of GAI-enabled apps	-0.142**	2.886	0.004	[-0.233, -0.053]	Significant indirect effect	
H5c	Limited trust in GAI-enabled apps → Digital self-efficacy → Self-reported use of GAI-enabled apps	-0.125**	2.753	0.006	[-0.221, -0.042]	Significant indirect effect	
R^2	Digital self-efficacy	0.412	Self-reported use of GAI-enabled apps			0.268	
Q2	Digital self-efficacy	0.358	Self-reported use of GAI-enabled apps			0.241	

Note. ***p < 0.001, **p < 0.01, CI = confidence interval
Source: Authors' own work.

Figure 2
Path coefficient results



Source: Author preparation.

A multi-group analysis (MGA) was conducted to examine potential differences in the structural relationships across age, gender, and technological experience groups (see Table 5). Measurement invariance was assessed using the MICOM procedure before subgroup comparisons. The available MGA results did not indicate significant differences in the examined structural relationships across the reported demographic comparisons ($p > 0.05$). However, equivalence between groups is not established by nonsignificant differences. Moreover, the purposive sampling approach and unequal subgroup sizes limit the extent to which these findings can be generalized to the wider population of aging travelers.

Table 5
MGA analysis of structural relationships across demographic subgroups

Hypothesis / structural path	Subgroup	β	MGAp-value
Privacy concerns → digital self-efficacy	Male	-0.341	0.538
	Female	-0.303	
	60–64	-0.288	0.412
	65–69	-0.347	
	70–74	-0.315	
	75+	-0.362	
	Low	-0.349	0.467
	Moderate	-0.307	
	High	-0.314	
Cognitive load → digital self-efficacy	Male	-0.301	0.491
	Female	-0.284	
	60–64	-0.319	0.365
	65–69	-0.278	
	70–74	-0.306	
	75+	-0.257	
	Low	-0.269	0.522
	Moderate	-0.302	
	High	-0.314	

Table 5 ***(continued)***

Limited trust → digital self-efficacy	Male	-0.235	0.576
	Female	-0.277	
	60–64	-0.237	0.448
	65–69	-0.283	
	70–74	-0.230	
	75+	-0.275	
	Low	-0.273	0.489
	Moderate	-0.237	
	High	-0.264	
Digital self-efficacy → self-reported use	Male	+0.451	0.462
	Female	+0.422	
	60–64	+0.469	0.391
	65–69	+0.425	
	70–74	+0.412	
	75+	+0.454	
	Low	+0.416	0.434
	Moderate	+0.463	
	High	+0.421	

Source: Authors' own work.

5. Discussion

This study contributes to existing research on GAI-enabled travel contexts by showing that privacy concerns, cognitive overload, and low trust are negatively associated with digital self-efficacy. In contrast, the use of GAI-enabled apps among aging travelers is positively associated with digital self-efficacy. This interpretation broadens the technology adoption literature, which has examined relationships between technology characteristics and behavior (Venkatesh et al., 2003; Gefen et al., 2003). A processual understanding of emotional evaluation and the capability factors that influence technology adoption in this context can be enabled by applying SST and TSET to GAI-enabled travel apps.

An inverse relationship between privacy concerns and digital self-efficacy has been corroborated by previous studies, showing that privacy concerns negatively affect users' intentions to use digital technologies (Gu et al., 2017). Likewise, data transparency, autonomy, and potential misuse of information have been identified as critical issues in more recent studies on GAI-enabled travel apps (Ilieva et al., 2024; Hu & Lin, 2026). While privacy concerns have been viewed in prior studies as factors that discourage users from adopting emerging technologies, the present study shows that privacy concerns also reduce users' self-perceived efficacy when using and interacting with digital devices. In this vein, the results complement SST by suggesting that older travelers may be vulnerable to the uncertainties and intrusiveness posed by emerging technologies, which undermine their emotional safety and control (Huang & Tsai, 2003; Jang & Wu, 2006).

The results further confirm that digital self-efficacy is reduced by higher cognitive load and lower trust, corroborating prior literature showing that complex, uncertain technological developments demotivate engagement with digital services (Paas et al., 2003; Gefen et al., 2003). In the tourism context, older travelers experience greater cognitive load when using advanced digital technology because they have lower information-processing ability and less digital literacy (Wu & Yang, 2023; Tuomi et al., 2023). Similarly, it is argued in the literature that GAI-enabled travel apps impose greater cognitive load because consumers must consider AI recommendations, while the decision-making process remains elusive (Bilgihan et al., 2024; Costa et al., 2025). However, the findings add to the extant literature by indicating that complexity and trust affect technology use through travelers' beliefs about their digital capabilities. This aligns with TSET, which maintains that

consumers' confidence in their abilities affects their ability to handle technological challenges (Bandura & Wessels, 1997; Wang et al., 2024).

A positive relationship between digital self-efficacy and reported use of notable GAI apps was found, along with a statistically significant indirect effect of technological barriers on reported use through digital self-efficacy. These findings align with previous research highlighting self-efficacy as a critical variable in adopting AI solutions among aging travelers (Jia et al., 2025; Costa et al., 2025). While self-efficacy has been examined independently in prior literature, the current study focuses on its potential role as an intervening variable that may mediate the impact of privacy concerns, cognitive load, and distrust in GAI technologies on reported use. However, because the direct effects of these barriers on self-reported use have not been tested before or after including digital self-efficacy as a mediator, it is not possible to determine whether the mediation is partial or full. Therefore, the results should be interpreted as significant indirect relations according to the theoretical framework. Moreover, causal mediation cannot be established by the cross-sectional design.

Overall, the body of knowledge on GAI-enabled travel apps is advanced by applying well-established technology-adoption theories and incorporating digital self-efficacy as a psychological factor. Thus, privacy threats and insufficient trust are indirectly linked to reported usage through travelers' perceptions of their digital skills. By combining the emotions emphasized in SST with the capability beliefs discussed in TSET, an alternative view of technology adoption among aging travelers is offered by this study. In this way, the theoretical understanding of technology adoption is advanced by considering digital self-efficacy in responses to new GAI-enabled tourism technologies. However, these contributions must be understood within the limits of the study's cross-sectional design and self-reported data from aging travelers with experience using GAI-enabled travel apps.

6. Conclusion

The results suggest that GAI-enabled barriers adversely affect digital self-efficacy and that digital self-efficacy positively affects self-reported technology use. This study combines SST and TSET to explain how emotional discomfort and cognitive evaluations shape engagement with GAI-enabled travel apps. Findings indicate that travelers' reported usage is shaped more by internal capability beliefs than by external technological impediments. This underscores the need for system design and user psychology to be considered to ensure inclusive digital tourism. Context-specific insights for emerging destinations undergoing digital transformation are provided, and contributions to the broader discourse on aging, digital inclusion, and smart tourism adoption are also made. The pivotal role of digital self-efficacy in driving equitable participation in GAI-enabled travel contexts is highlighted by this study.

6.1. Theoretical implications

Technology adoption theory is advanced by applying new theoretical perspectives grounded in an analysis of digital self-efficacy as a psychological process linked to aging travelers' use of GAI-enabled apps. Expanding the research framework of prior studies on privacy concerns, cognitive load, and trust as antecedents of technology adoption (Gefen et al., 2003; Gu et al., 2017; Paas et al., 2003), the results indicate statistically significant indirect relationships between technological barriers and the use of GAI-enabled apps mediated by digital self-efficacy. An alternative explanation of how aging travelers' perceptions of technological barriers relate to their use of GAI-enabled apps is offered by combining SST's emotional factors with TSET's ability beliefs. Rather than offering an alternative to traditional technology adoption theories, this study suggests integrating digital self-efficacy into existing frameworks, especially when analyzing emerging technologies with complex algorithms (Bandura & Wessels, 1997; Wang et al., 2024; Bilgihan et al., 2024).

This study also contributes to the broader fields of smart tourism and aging studies by offering SST, with TSET as a key mechanism, to explain the complementarities between the emotional and cognitive aspects

of technology adoption. Previous tourism studies have focused on structural aspects of digital divide barriers or technology acceptance-related characteristics among travelers (Wu & Yang, 2023; Tuomi et al., 2023), offering little insight into how emotional priorities and perceptions of digital capabilities shape AI adoption among older adults. The proposed model shows that older travelers' reactions to GAI tools result from the interaction of both elements. The integrated approach adds value to the scholarly debate by extending both theories to their application areas and offering a consistent model for technology adoption in AI-enabled tourism scenarios. Moreover, further research into digital self-efficacy as an adaptive psychological construct and into its relationship with other psychological variables (e.g., AI anxiety, technology readiness, or innovation resistance) is encouraged.

6.2. Practical implications

The results provide valuable guidance for tourism policymakers, destination managers, and technology developers seeking to support older travelers' engagement with GAI-enabled travel apps. Because the research relies on self-reported perceptions and usage, the following suggestions are actions guided by statistical associations, not proven to change behavior. First, because privacy concerns are negatively related to digital self-efficacy, privacy-related issues may be addressed when helping older travelers build confidence in using GAI-enabled apps. Transparency-by-design solutions (e.g., easy-to-understand privacy policies, consent management, and traveler-controlled privacy settings) may help inform users about how their personal data is used, which may increase understanding and control. However, the effectiveness of such solutions in increasing digital self-efficacy or app usage has not yet been tested.

Second, the negative association between cognitive load and digital self-efficacy underscores the importance of age-specific interface design. One option is to design technology with simple structures, clear visuals, clear information, and multiple communication formats to minimize complexity. Another option for destination managers and tourism service providers is to implement an onboard system that includes tutorials and demonstrations for using GAI-enabled devices, as well as in-person digital assistance. However, no evidence suggests that these measures will reduce cognitive load or encourage usage behavior. Third, the negative correlation between trust and digital self-efficacy underscores the importance of trust-building features in developing GAI-enabled tourism services. Such features include transparency in AI-based recommendations, access to feedback, visibility into quality assurance, and options for human assistance.

Additionally, programs to strengthen travelers' self-perceived digital competencies can be paired with other measures to address privacy concerns, high cognitive load, and low trust, based on the indirect effects of digital self-efficacy. Digital literacy programs can be considered for implementation by national tourism organizations and digital transformation leaders. In contrast, aging travelers can be supported by local tourism authorities and service providers through guided demonstrations, digital assistance points, and intergenerational interactions. Such joint actions can lead to more inclusive digital tourism environments. Because this study did not conduct experiments or collect objective usage data, further research is needed to confirm the effectiveness of these approaches.

6.3. Limitations and future research

Despite this study's positive contributions, several limitations must be considered when analyzing the findings on digital inclusion for aging travelers. First, because purposive sampling was used, the findings may not generalize to the broader group of aging travelers. This sampling method allowed aging travelers who had used GAI-enabled travel apps before to be recruited. Thus, probability sampling techniques should be considered by future researchers to increase diversity. Second, travelers with prior experience using GAI-enhanced travel apps were included in this study, which may have excluded non-users who are likely to face greater challenges engaging in digital activities. This constraint is critical given the study's interest in digital inclusion,

since individuals who have not used these technologies may face different or even greater challenges related to privacy, cognitive load, mistrust, and digital self-efficacy. Therefore, the findings reflect users' perspectives and perceptions.

Third, GAI-enabled app usage was assessed based on traveler responses (e.g., app usage logs, login data, or digital interactions). Accordingly, the results may be affected by traveler engagement with GAI-enabled travel apps and may be subject to recall and social desirability biases. This measurement limitation reduces the extent to which the findings can be taken as evidence of actual usage behaviors. Further research should combine subjective and objective measures of technology engagement. The significant indirect effects through digital self-efficacy identified cannot be taken as confirmation of causal relationships. Moreover, because the direct effect of technology barriers on self-reported technology use was not analyzed separately before and after adding digital self-efficacy to the model, there is no basis to determine whether the mediation is partial or full.

Future research should use longitudinal or experimental designs and report total, direct, and indirect effects. The MGA analysis also requires careful interpretation. Although the MGA results show no significant differences across age, gender, and technological experience, the equivalence or generalizability of the examined relationships across demographic subgroups is not supported by these findings. The lack of recoverable estimates of path coefficients at the subgroup level further complicates the interpretation of possible differences in the structural associations. Although procedural safeguards and statistical diagnostics (e.g., Harman's single-factor test and VIF analysis) show no significant common method bias, shared-method variance is not eliminated by these tests. In this vein, because this study uses self-reported data from a single survey, common method bias remains a methodological limitation for future research in the field. Another limitation is the heterogeneity of GAI-enabled travel apps. Although different application categories (e.g., conversational assistants, itinerary planners, translation, recommendation, and booking assistants) are considered, travelers' use of these categories is not analyzed separately. In this context, how these constructs relate across app categories should be explored.

Lastly, this study's recommendations are based on statistical relationships between perceptions and technology use, not on an evaluation of specific interventions. It remains to be seen whether transparency-by-design, privacy dashboards, age-appropriate interfaces, guided onboarding, and digital literacy interventions improve digital self-efficacy and GAI-enabled app usage. Future studies can investigate how these interventions relate to measured GAI-enabled app usage. This would provide better insights for designing a digital tourism strategy that supports both existing and digitally excluded aging travelers.

Declaration of Competing Interests

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

Funding: No financial support was provided for this paper.

Ethical Approval Statement: The university's Research Ethics Committee exempted this paper from ethical review because it did not involve clinical trials with respondents. All interactions with respondents were conducted in accordance with the ethical guidelines set by the institutional research board and the Helsinki Declaration and its later versions. Respondents were informed of the purpose of this paper, the voluntary nature of participation, and the right to withdraw at any time. Verbal informed consent was obtained before data collection. No identifying information was collected, and respondents were assured that confidentiality and data security would be upheld. The paper was designed by the authors, and datasets were collected and reported with full accountability and ethical respect for respondent fairness, without maleficence or harm.

References

Bai, X., & Yang, L. (2025). Digital literacy's impact on digital village participation in rural left-behind women through serial mediation of political trust and self-efficacy. *Scientific Reports, 15*(1), Article 34226. https://doi.org/10.1038/s41598-025-16093-3

Bandura, A., & Wessels, S. (1997). *Self-efficacy* (pp. 4–6). Cambridge University Press.

Bilgihan, A., Dogru, T., Hanks, L., Line, N., & Mody, M. (2024). The GAI marketing model: A conceptual framework and future research directions. *International Journal of Hospitality Management, 123*, Article 103929. https://doi.org/10.1016/j.ijhm.2024.103929

Costa, R., Coelho, J., Lima, D., Duarte, C., & Moita, P. (2025). ElderWander: An accessible digital tourism platform for older adults. *Information Technology & Tourism, 27*(3), 833–863. https://doi.org/10.1007/s40558-025-00321-7

Elgammal, I., Islam, M. S., Tan, C. C., Selim, S. M., & Selem, K. M. (2026). Sharpening the edge: Big data analytics as game-changers for decision-making in health tourism education. *Journal of Hospitality & Tourism Education*, 1–16. https://doi.org/10.1080/10963758.2026.2619600

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 112*, 51–90. https://doi.org/10.2307/30036519

Gu, J., Xu, Y. C., Xu, H., Zhang, C., & Ling, H. (2017). Privacy concerns for mobile app download: An elaboration likelihood model perspective. *Decision Support Systems, 94*, 19-28. https://doi.org/10.1016/j.dss.2016.10.002

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hu, J., & Lin, B. (2026). What is next for travel innovation? Generative artificial intelligence (GAI) in tourism product development from multi-perspectives. *Asia Pacific Journal of Tourism Research, 31*(1), 130-149. https://doi.org/10.1080/10941665.2025.2568617

Huang, L., & Tsai, H.-T. (2003). The study of senior traveler behavior in Taiwan. *Tourism Management, 24*(5), 561–574. https://doi.org/10.1016/S0261-5177(03)00008-6

Ilieva, G., Yankova, T., & Klisarova-Belcheva, S. (2024). Effects of generative AI in tourism industry. *Information, 15*(11), Article 671. https://doi.org/10.3390/info15110671

Jang, S. S., & Wu, C.-M. E. (2006). Seniors' travel motivation and the influential factors: An examination of Taiwanese seniors. *Tourism Management, 27*(2), 306–316. https://doi.org/10.1016/j.tourman.2004.11.006

Jia, G., Wan, L. C., Liu, X., & Wen, J. (2025). Exploring uncharted digital horizons: Role of internet self-efficacy in shaping the destination preferences of senior tourists. *Tourism Management, 107*, Article 105056. https://doi.org/10.1016/j.tourman.2024.105056

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist, 38*(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1

Shin, H., & Baek, S. (2023). Unequal diffusion of innovation: Focusing on the digital divide in using smartphones for travel. *Journal of Hospitality and Tourism Management, 55*, 277-281. https://doi.org/10.1016/j.jhtm.2023.04.012

Suanpang, P., & Pothipassa, P. (2024). Integrating generative AI and IoT for sustainable smart tourism destinations. *Sustainability, 16*(17), Article 7435. https://doi.org/10.3390/su16177435

Sun, H., Jing, P., Fu, X., & Xu, J. (2026). How to bridge the older adults' digital divide in using digital travel services? A comparative analysis between ride-hailing and train E-ticket services in China. *Cities, 169*, Article 106536. https://doi.org/10.1016/j.cities.2025.106536

Tan, C. C., Atef El-Akhras, H., Abd El-Wahab, M. A., Saghier, E. G., & Selem, K. M. (2025). Multilevel investigation of higher tourism education service quality in the digital era: Integrating SAMR framework and technology affordance theory. *Tourism: An International Interdisciplinary Journal, 7*3(3), 465-486. https://doi.org/10.37741/t.73.3.5

Tuomi, A., Moreira Kares, E., & Zainal Abidin, H. (2023). Digital cultural tourism: Older adults' acceptance and use of digital cultural tourism services. *Scandinavian Journal of Hospitality and Tourism, 23*(2-3), 226-247. https://doi.org/10.1080/15022250.2023.2256698

Vaithilingam, S., Ong, C. S., Moisescu, O. I., & Nair, M. S. (2024). Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research. *Journal of Business Research, 173*, Article 114465. https://doi.org/10.1016/j.jbusres.2023.114465

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 7*(3),425-478. https://doi.org/10.2307/30036540

Wang, K., Ruan, Q., Zhang, X., Fu, C., & Duan, B. (2024). Pre-service teachers' GenAI anxiety, technology self-efficacy, and TPACK: Their structural relations with behavioral intention to design GenAI-assisted teaching. *Behavioral Sciences, 14*(5), Article 373. https://doi.org/10.3390/bs14050373

Wu, X., & Yang, Y. (2023). Digital divide and senior travel consumption: An empirical study from China. *Asia Pacific Journal of Tourism Research, 28*(4), 306-322. https://doi.org/10.1080/10941665.2023.2228938

Submitted: January 02, 2026
Revised: October 08, 2026
Accepted: October 14, 2026