



# Fading skills, rising doubts – what fuels tourists’ skepticism toward AI?

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## Abstract

Artificial intelligence [AI] has a rising influence in the tourism sector. This study explores factors influencing Gen Z tourists’ acceptance of AI-based tourism services. Building on the Technology Acceptance Model [TAM], we introduce the SEAM model [Skill-Erosion Awareness Model], incorporating Self-Destructive Effects [SDE] as a novel predictor and moderator of AI Skepticism. Based on a survey among university students ( $n=420$ ), we tested the model using PLS-SEM. Perceived Usefulness emerged as the strongest positive predictor of Intention to Use AI, while Skepticism and SDE had significant negative effects. Findings highlight the importance of addressing psychological resistance, particularly concerns about autonomy and skill erosion. SEAM extends AI-acceptance theories and offers practical insights for designing user-sensitive AI applications, especially in tourism.

**Keywords** Artificial intelligence [AI] · Technology-acceptance · Generation Z [GenZ] · Self-destructive effects [SDE] of AI · AI skepticism in tourism

## 1 Introduction

The growing presence of artificial intelligence [AI] in everyday life and its increasing role in service industries, including tourism, has sparked research on what makes people accept or reject AI. The rapid spread of generative AI [genAI] tools, particularly large language models [LLMs] such as ChatGPT, has brought AI into the main-

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stream, reshaping not only how people interact with technology but also how they evaluate its role in everyday decision-making.

In *tourism*, AI now powers virtual assistants, personalized recommendations, dynamic pricing, and automated check-in systems, touchpoints that increasingly shape tourist's experience (Pillai and Sivathanu 2020). As AI becomes more embedded in tourism infrastructure and guest-facing applications, understanding the emotional and cognitive factors that influence acceptance becomes essential. In tourism, where service experiences are co-created through affective and sensory interactions, the balance between human presence and automation is especially critical. AI-based technologies may improve operational efficiency, but their integration must also consider how they reshape the emotional and interpersonal dimensions of the travel experience. Gen Z, as a digitally fluent yet critically engaged generation (Seyfi et al. 2023), is particularly exposed to the paradox of digital convenience and the potential loss of human touch. Furthermore, the excessive use of AI-based solutions might decrease some traditional skills on the long run that have been essential for tourists (e.g., rapid information gathering, critical decision-making, navigation in unusual environments). Despite extensive research on AI adoption, there is a research gap in understanding how these psychological concerns, particularly fears of *skill erosion and autonomy loss* shape young tourists' acceptance of AI-based services.

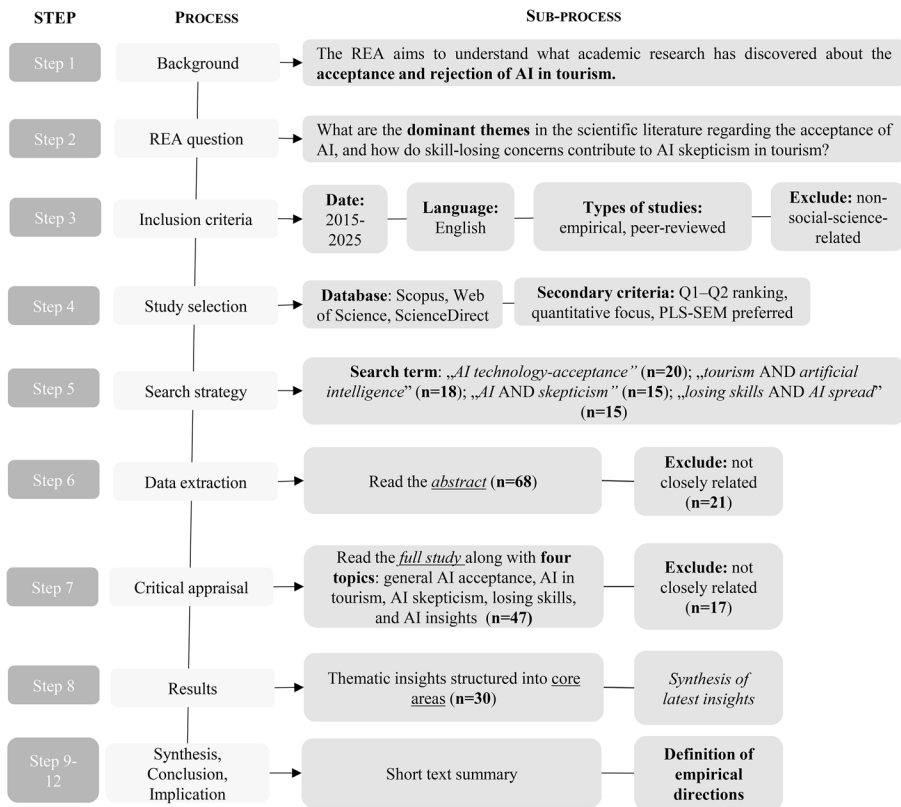
To reveal this cohort's attitude in the light of these emerging issues, this study aims to test a hypothetical model in a tourism context, using structural equation modeling approach [PLS-SEM]. With this analysis, it can be revealed how psychological concerns shape young users' willingness to engage with AI-based tourism services.

As a result, we propose the **SEAM model** [*Skill-Erosion Awareness Model*], which extends the Technology Acceptance Model [TAM] by integrating the concept of Self-Destructive Effects [SDE] as both an antecedent and a moderator of AI skepticism. The model highlights that the perceived risk of diminishing individual skills is an important driver of AI-skepticism, which has not been demonstrated by previous research, particularly in tourism context. In addition, this research is of practical value, as it shows that the uncontrolled use of AI does not necessarily lead to successful tourism experiences, due to its perceived long-term negative effects. However, it also indicates that a well-designed use can be a successful tourism development tool. This study is structured as follows: Sect. 2 presents the theoretical background. Section 3 outlines the methodology, including sample characteristics and measurement instruments. Section 4 reports the results of the measurement and structural model. Section 5 discusses the findings, theoretical and practical implications, and future research directions, limitations.

## 2 Literature review

To reveal previous findings, a Rapid Evidence Assessment [REA] was conducted, a structured, multi-step protocol provided by the Center for Evidence-Based Management [CEBMA] (Barends and Rousseau 2018) (Fig. 1).

During REA, only peer-reviewed articles, published in the last ten years (2015-), retrieved from Scopus, Web of Science [WOS], and ScienceDirect were considered.



**Fig. 1** Main steps of rapid evidence assessment [REA]. *Source:* authors’ editing, based on Barends and Rousseau (2018)

A combination of keywords with Boolean operators (e.g., “*tourism AND artificial intelligence*”) was employed to identify relevant literature (n=68). After a two-phase screening process, including abstract and full-text review, a total of 30 studies were shortlisted for final analysis. Thematic extraction focused on four core dimensions: (1) *general AI acceptance*, (2) *tourism-specific AI research*, (3) *skepticism and refusal*, and (4) *the perceived skill-losing effects related to AI use*.

**2.1 Technology-acceptance of AI-based services**

Much of current research utilizes Technology Acceptance Model [TAM] (Davis 1989) and its extensions, such as TAM<sub>2</sub> (Venkatesh and Davis 2000), TAM<sub>3</sub> (Venkatesh and Bala 2008), and UTAUT (version<sub>1</sub> – Venkatesh et al. 2003; version<sub>2</sub> –; Venkatesh et al. 2012) to reveal what affects the core variable *Behavioral Intentions to Use [BIU]*. In case of TAM-based models, *Perceived Usefulness [PU]* and *Perceived Ease of Use [PEOU]* are the main predictors, while novel constructs (e.g., *Trust*, *Perceived Risk*) have been integrated to reflect evolving user expectations.

### 2.1.1 General findings

In *higher education and learning* contexts, *Trust* has emerged as a crucial determinant of AI-acceptance (Zhao et al. 2024; Strzelecki 2024), alongside *Self-efficacy*, *Emotional Wellbeing*, and *Content Quality* (Almufarreh 2024). Similar findings have been reported in *chatbot and LLM use* (2), where variables like *Hedonic Motivation*, *Performance Expectancy*, *Habit*, and *Perceived Innovativeness* play key roles in *Intention to Use [ITU]* (Al-Emran et al. 2023; Alfaisal et al. 2024). In the context of *voice assistants and portable intelligent systems* (3), scholars have explored predictors like *Artificial Autonomy* (Pal et al. 2023) and AI-induced *Emotional Closeness* that affect positively usage intentions (Mvondo and Niu 2024). In the *healthcare system* (4), studies emphasize how *Trust* and *Attitudes* mediate AI-acceptance, particularly in ethically sensitive areas like diagnosis or patient interaction. In hospitality and customer-facing services, constructs such as *Novelty*, *Enjoyment*, and *Compatibility* help explain user satisfaction and usage (Terrah et al. 2024). From a methodological perspective, most studies adopt a PLS-SEM approach due to its flexibility with small samples and complex models (Hair et al. 2011). The dependent variables are often *Behavioral Intention to Use (BIU)* or *Actual Use (AU)*, while moderator variables include *Age*, *Gender*, *Prior Experience*, and *Digital Competence* (Obenza et al. 2024; Strzelecki 2024). These studies reflect a transition toward more affective and contextual predictors, paving the way for field-specific investigations.

### 2.1.2 Tourism-related studies

The *tourism sector* has emerged as a key application field for AI. AI applications in tourism range from chatbots, voice assistants, and personalized recommendation systems to autonomous vehicles and smart destination tools (Stankov et al. 2025). These innovations aim not only to improve convenience and efficiency but also to offer highly tailored, immersive experiences (Topsakal and Çuhadar 2024; Vinasco and Al Ghofaili 2024). Scholars found that *Performance Expectancy* and *Hedonic Motivation* strongly influenced tourists' willingness to use AI-supported travel applications (Topsakal and Çuhadar 2024). Chiengkul et al. (2025) emphasized the role of *Emotional Bond* in enhancing tourists' satisfaction. Beyond these psychological factors, structural conditions also influence AI adoption. Vinasco and Al Ghofaili (2024) highlighted the importance of social influence and facilitating conditions, noting that tourists are more likely to accept AI when they perceive sufficient support infrastructure and social endorsement. *Trust* and *Transparency* remain critical: several studies emphasize that privacy concerns and ethical doubts can significantly hinder adoption (Ferhataj and Memaj, 2024; Della Corte et al. 2023).

Advanced theoretical models such as UTAUT2 and the Stimulus–Organism–Response (S-O-R) framework have been used to explain how external stimuli (e.g., *AI design features* or *Usage Contexts*) affect internal responses (e.g., *Emotions*, *Trust*) and lead to behavioral outcomes (Vinasco and Al Ghofaili 2024; Chiengkul et al. 2025). In terms of highly automated vehicles powered by AI (AVs), *Perceived Risk* and *Trust*, are identified as critical determinants of autonomous vehicle (AV) adoption (Kenesei et al. 2022). A novel model called the Technology Acceptance

Model of Autonomous vehicles for Tourism purposes [TAMAT] (Jászberényi et al. 2022) highlights that *Openness to Tourism Usage* positively affects *Perceived Ease of Use* and *Perceived Usefulness*, consequently enhancing tourists' intention to use AVs. Additionally, tourists' openness to AV adoption is higher in *Unusual Surroundings*. At the same time, concerns about *cultural homogenization and the dehumanization of tourism services* – such as unstaffed hotels or automated guides – are becoming more pronounced in recent studies (Pinheiro et al. 2021). A growing number of tourism studies seek to integrate technological innovation with broader behavioral and sustainability outcomes. For instance, Jiang et al. (2025) explored how virtual reality can foster more sustainable travel decisions by simulating eco-friendly adventures, emphasizing both hedonic appeal and pro-environmental engagement. These insights underscore that technology acceptance in tourism is increasingly shaped not only by utilitarian benefits, but also by experiential, emotional, and ethical dimensions, particularly among younger cohorts such as Gen Z.

Despite this growing body of research, few studies have examined general openness toward AI-based services as a domain-specific attitudinal construct. While existing work has addressed tourists' readiness to adopt technologies such as virtual assistants, VR/AR, or recommender systems, the empirical gap between general technology acceptance and context-specific digital receptiveness remains underexplored. Addressing this gap may help capture the nuanced motivations and reservations of travelers, especially those in digitally native segments like Gen Z.

## 2.2 Drivers of AI skepticism

Skepticism towards AI has emerged as a significant research focus in parallel with the growing deployment of AI systems. Studies emphasize that AI systems trained on incomplete or biased datasets may replicate and even *exacerbate existing social inequalities*, such as those based on race or gender (Dwork and Minow 2022). These concerns are compounded by the lack of transparency in algorithmic processes – the so-called “black box” phenomenon – which prevents users from understanding decisions made by AI systems (Salloum et al. 2024). Another major driver of skepticism involves *concerns over autonomy and privacy*. As AI technologies increasingly rely on personal data, users may feel that their control over personal information is eroding, and that their behavioral patterns are being manipulated (Cho and Hooi 2023). *Media and cultural narratives* also significantly shape public perceptions. Fictional portrayals of AI as autonomous, threatening, or socially disruptive contribute to a generalized sense of unease, particularly among younger generations more exposed to dystopian narratives (Bo et al. 2025).

Concerns over *job displacement* are another recurring theme. As AI becomes increasingly capable of automating cognitive and service-oriented tasks, fear of human obsolescence has become widespread (Cho and Hooi 2023). This is particularly important in industries such as tourism, where human interaction is traditionally central to the customer experience. *Ethical concerns* also contribute to a growing discourse around AI misuse, especially in relation to surveillance, weaponization, and decision-making without accountability (Zlateva et al. 2024). Several studies highlight the role of *psychological variables in shaping AI skepticism*. Traits such

as neuroticism, algorithm aversion, and AI-specific anxiety have been shown to correlate with higher levels of doubt and resistance toward AI (Stănescu and Romaşcanu 2024). These findings underscore the emotional dimensions of skepticism, which are often overlooked in rational-choice models of technology-acceptance.

Beyond structural and cultural dimensions, a growing body of research underscores the role of psychological variables in shaping AI skepticism. Traits such as neuroticism, algorithm aversion, and AI-specific anxiety have been shown to correlate with higher levels of doubt and resistance (Stănescu and Romaşcanu 2024). These findings highlight the emotional and cognitive aspects of AI resistance, which are often overlooked in rational-choice models of technology acceptance. Supporting this perspective, recent research suggests that psychological comfort and emotional safety significantly influence how users perceive and adopt AI-driven solutions. For example, Nam et al. (2024) demonstrated that familiarity with the destination moderated users' acceptance of VR applications in heritage tourism. Their study highlights how affective bonds and prior knowledge shape digital trust and satisfaction, indicating that successful adoption depends not only on system functionality but also on users' emotional readiness.

Building on this idea, another underexplored dimension of AI skepticism may stem from perceived threats to *human autonomy and competence*. Carr (2020) warned that automation could weaken critical thinking and attentional control, while Susskind and Susskind (2022) argued that technological displacement undermines professional and interpersonal skills. Although such concerns have been discussed in education and labor contexts, their psychological resonance in leisure-oriented domains like tourism remains largely unexamined. The notion that AI might not merely assist but gradually replace human agency introduces a deeper layer of resistance, one rooted in perceived personal atrophy and skill erosion.

### 2.3 Consequences of excessive AI-usage

While a growing number of scholars have acknowledged AI's potential to reduce human agency or social connection, few have operationalized these perceptions into measurable psychological constructs that could be systematically linked to behavioral intentions. Recent psychological and human-computer interaction research highlights growing concerns about digital overreliance, a condition in which users experience diminished cognitive or social functioning due to excessive dependence on automated systems (Stănescu and Romaşcanu 2024). Based on this, the overuse of AI might *impair real-world problem-solving skills, communication abilities on the long run*. In addition, the risk of individuals becoming cognitively passive, emotionally disengaged, or socially isolated in environments dominated by AI-services might be a rising issue in the near future. Studies across various fields warn that automation may lead to measurable skill erosion – especially in tasks previously learned through repetition, mentoring, or direct engagement. In fields such as accounting or auditing, for instance, *the automation of repetitive processes has been found to reduce opportunities for skill acquisition and professional development* (Ardichvili 2022). Scholars (Ahmad et al. 2023) also caution that *cognitive functions, decision-making*

*capabilities* may be undermined when these are consistently delegated to intelligent systems.

Taken together, these debates suggest that AI overreliance may foster not only cognitive disengagement but also a broader fear of losing one's sense of control and authenticity during travel. This type of psychological cost, distinct from practical usability concerns, may play a pivotal role in shaping Gen Z's attitudes toward AI. Yet, to date, models of technology acceptance have not explicitly accounted for this phenomenon, despite its growing salience in critical technology discourses.

## 2.4 Research gap

While previous studies have significantly advanced the understanding of how users engage with AI technologies, several important gaps remain:

- *AI skepticism is under-theorized in empirical models:* Although skepticism toward AI has gained attention, most empirical studies continue to treat it as a secondary attitude or a by-product of other variables. There is a lack of studies that position skepticism as a central construct within acceptance models.
- *Concerns about the erosion of human skills:* These phenomena have not been systematically studied in tourism-focused AI research. Although related fields such as psychology and education have explored digital overreliance, these perspectives have not yet been operationalized in tourism-specific models, despite its strong reliance on authentic, human-centric experiences.
- *Existing studies focus on macro-level concerns:* Algorithmic bias, ethical dilemmas, job displacement, or data security are primarily in focus, while micro-level anxieties related to personal competence, communication, and autonomy remain underrepresented in AI-acceptance models.
- *There is limited understanding of how such psychological concerns moderate adoption pathways:* Most TAM-based models emphasize direct, linear predictors of Behavioral Intention to Use, without testing how deeper fears – such as perceived skill erosion – may amplify skepticism or weaken openness toward AI.
- *Tourism-specific acceptance models rarely address critical resistance factors:* Given the sector's emphasis on sensory, interpersonal, and experiential value, user resistance rooted in fears of over-automation deserves stronger attention.

Drawing on these insights, we introduce the concept of *Self-destructive Effects* [SDE] to describe perceived threats to human cognitive, interpersonal, and experiential competencies due to AI usage. This construct reflects concerns such as weakened communication, diminished autonomy, reduced real-world engagement, and a declining appreciation for authenticity – all of which may contribute to skepticism and resistance toward AI in tourism and beyond.

### 3 Conceptual framework development

This study builds on the TAM-concept to develop a conceptual framework (Fig. 2) for understanding how Gen Z tourists perceive AI-based services in tourism context.

As seen from the REA (*section: 2*), literature on AI-acceptance does not pay proper attention to concerns about the *potential disruption of human skills* by AI-usage. While previous studies have explored skepticism toward AI (e.g., ethical, privacy, and transparency issues), there has been little focus on how *cognitive concerns about human skill degradation* affect behavioral outcomes. Based on these, the variables to be tested and the hypothetical connections among them are presented below:

- Consistent with the TAM (Davis 1989), the theoretical model includes *Perceived Ease of Use [PEOU]* and *Perceived Usefulness [PU]* as key constructs of behavioral intention. *PEOU* refers to the degree to which individuals believe that interacting with AI systems would be free of effort, while *PU* reflects the belief that using AI would make tasks more efficient. These constructs are widely validated predictors and are expected to positively influence Intention to Use [ITU] (Venkatesh and Davis 2000; Topsakal and Çuhadar 2024).
- *ITU* is theorized to be a key predictor of *Actual Use [AU]*. Furthermore, the mod-

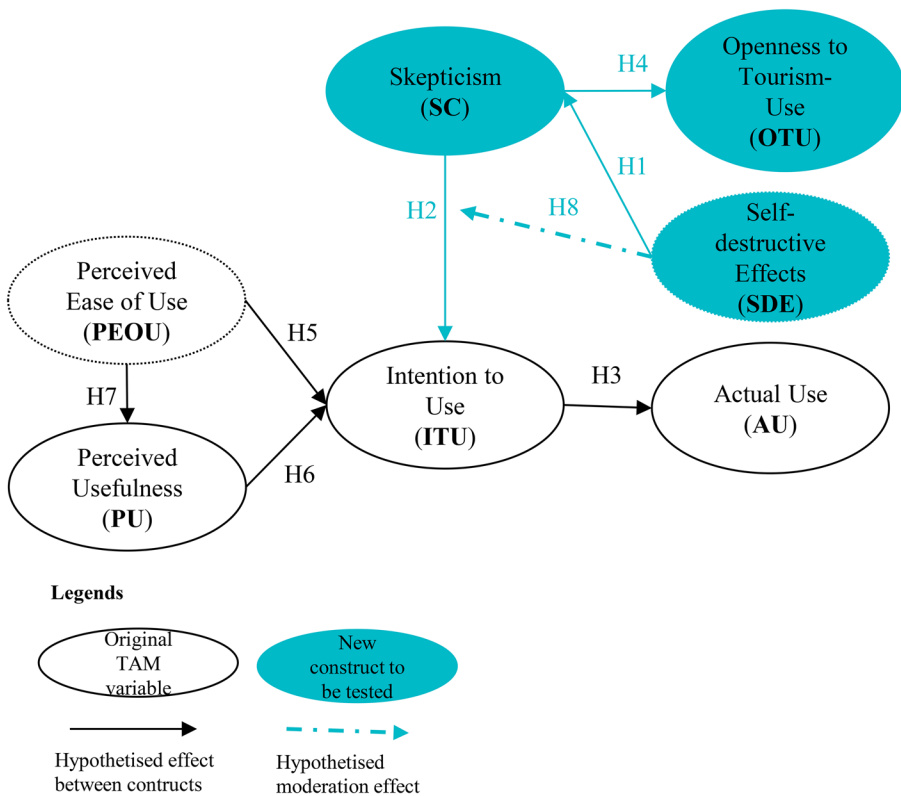


Fig. 2 Proposed model and hypothesized relationships. Source: authors' editing

el includes Openness Toward Tourism Use [OTU] to capture the domain-specific digital receptiveness in tourism contexts (Jászberényi et al. 2022; Jiang et al. 2025). While prior studies emphasize the role of emotional and experiential expectations, few have conceptualized openness as a discrete attitudinal construct.

- *Skepticism [SC]* is conceptualized as a negative attitudinal response shaped by emotional factors (e.g., distrust, anxiety, and algorithm aversion). Based on prior literature (e.g., Alfaisal et al. 2024; Nam et al. 2024), skeptic feelings are expected to directly reduce ITU, especially when emotional discomfort or lack of familiarity undermines trust in AI-based systems.
- *Self-Destructive Effects [SDE]* represent a novel construct, reflecting concerns over human cognitive and interpersonal atrophy due to overreliance on intelligent systems. These concerns are also linked to emotional ambivalence and resistance described in recent research on AI-induced technostress. While related concepts exist in the literature, Self-Destructive Effects (SDE) provide a theoretically distinct lens on AI-induced resistance. Unlike technological over-reliance, which primarily captures habitual dependence on digital tools in everyday practices (Stănescu and Romaşcanu 2024), SDE emphasizes the perceived long-term erosion of fundamental human competencies such as decision-making, orientation, and interpersonal communication. In contrast to cognitive laziness (Ahmad et al. 2023), which denotes a temporary reduction in cognitive effort due to the availability of automated solutions, SDE reflects irreversible atrophy and loss of human skills that are seen as difficult to recover once displaced by AI. While algorithm aversion focuses on a lack of trust in AI outputs or reluctance to rely on machine-generated decisions (Stănescu and Romaşcanu 2024), SDE goes beyond distrust by capturing self-directed fears of diminished autonomy, competence, and authenticity. In this sense, SDE constitutes a novel construct that systematically connects psychological resistance to AI with the perceived weakening of human agency, offering a unique contribution to technology acceptance research. Importantly, *tourism* represents a particularly sensitive context for the manifestation of *Self-Destructive Effects [SDE]*. Travel situations often require autonomous decision-making in unfamiliar environments, real-time problem solving, spatial orientation, and interpersonal communication with service providers (Kenesei et al. 2022; Jászberényi et al. 2022). When AI-based systems increasingly guide navigation, recommendations, and service interactions, concerns about diminishing orientation skills, reduced spontaneity, or weakened interpersonal engagement may become more salient than in routine daily technology use. Consequently, tourism offers a revealing domain in which perceived skill erosion may directly shape experiential expectations and behavioral intentions.

Based on these, the following hypotheses are proposed:

- **H1:** *Self-Destructive Effects [SDE]* positively influence *AI Skepticism [SC]*.
- **H2:** *AI Skepticism [SC]* negatively influences *Intention to Use [ITU]*.
- **H3:** *Intention to Use [ITU]* positively influences *Actual Use [AU]*.
- **H4:** *AI Skepticism [SC]* negatively influences *Openness Toward Tourism Use [OTU]*.

- **H5:** *Perceived Ease of Use [PEOU]* positively influences *Intention to Use [ITU]*.
- **H6:** *Perceived Usefulness [PU]* positively influences *Intention to Use [ITU]*.
- **H7:** *Perceived Ease of Use [PEOU]* positively influences *Perceived Usefulness [PU]*.

An additional contribution of this study is the inclusion of a moderating effect: we hypothesize that *SDE* strengthens the negative relationship between *SC* and *ITU*. In other words, individuals who are more concerned about the skill-destructive effects of AI-usage are more likely to let their skepticism shape their behavioral intentions.

- **H8:** *Self-Destructive Effects [SDE]* moderate the relationship between *SC* and *ITU*, such that the negative effect of *SC* on *ITU* is stronger when *SDE* is high.

## 4 Data and Methods

Figure 3 represents the main steps of data collection and analysis.

### 4.1 Research design and data collection

Data were collected between November-December 2024 through an online survey (*Qualtrics platform, license provided by the university*). Survey was distributed among students of Corvinus University of Budapest, Hungary's top-ranked private university specializing in business and social sciences (QS World University Ranking 2025). The target population consisted of Generation Z respondents (born between 1995 and 2010), who had *participated in at least one tourism-related trip in the past*

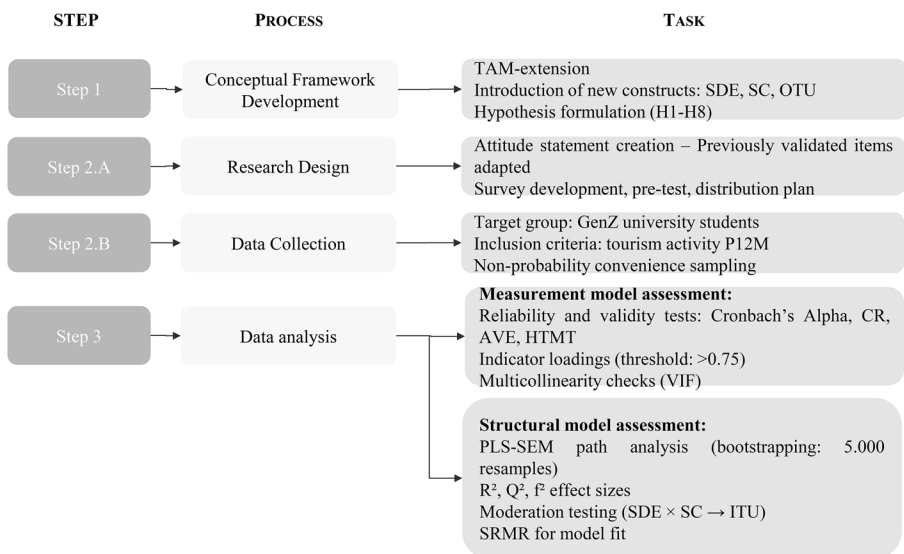


Fig. 3 Data collection and analysis. *Source:* authors' editing

12 months. This inclusion criterion ensured relevance to the research context of AI-supported tourism consumption. For the fieldwork, a non-probability convenience sampling method (Malhotra et al. 2020) was employed. Participants were recruited via targeted invitations disseminated through the university’s internal newsletter system, reaching students across multiple faculties and study programs. Participation was voluntary and anonymous. Respondents were informed about the academic purpose of the research and provided informed consent before beginning the survey. The study design followed the ethical standards of the institution and aligns with the Declaration of Helsinki guidelines (ec.europa.eu 2021) for social science research. After data cleaning and preparation using IBM SPSS (version: 29.0.2.0, license provided by the university) (removing incomplete responses, ensuring uniform scales, and recoding demographic variables), the final dataset contained 420 valid responses. Descriptive statistics of the sample showed diversity in gender, age, educational background, and place of residence (Table 1).

All measurement items were based on 7-point Likert scales ranging from 1= “strongly disagree” to 7= “strongly agree”. The final structural model included seven latent constructs (Table 2). Although SDE and Skepticism items reflect general concerns about AI use, their inclusion in this study is grounded in the assumption that such concerns may be amplified in *tourism contexts*, where autonomy, experiential authenticity, and interpersonal interaction are central to value creation (Seyfi et al. 2023). Thus, the measurement framework captures both general AI-related anxieties and their specific relevance to tourism-related decision-making.

## 4.2 Data analysis

Partial Least Squares Structural Equation Modeling [PLS-SEM] was employed to test the model and hypotheses, using SmartPLS 4 (version: 4.1.1.1). PLS-SEM was selected due to its suitability for analyzing complex models with multiple latent constructs, its flexibility regarding data distribution, and its predictive orientation, which aligns with the exploratory nature of this research (Hair et al. 2011). Scholars have extensively employed PLS-SEM to examine how users adopt and utilize technologies across various sectors, including healthcare (e.g., Terrah et al. 2024), education (e.g., Almufarreh 2024), and tourism-related mobility (e.g., Jászberényi et al. 2022). The analytical procedure consisted of the following steps (Table 3) following the guidelines of Chin (1998) and Hair et al. (2011):

**Table 1** Demographic characteristics of the sample ( $n=420$ )

Variable	Categories	Percentage (%)
Gender	Female	75.1
	Male	24.9
Type of Residence	Capital	57.9
	County seat	5.3
	City	8.9
	Village	27.9
Marital Status	Single	49.0
	In a relationship	51.0

Source: Authors’ editing

**Table 2** Measurement items (latent constructs) and observed variables

Latent variable name		Observed variables related	
SDE	Self-destructive effects	SDE1	In the long run, the use of AI-based tools tends to have a negative impact on human intelligence and skills.
		SDE2	AI-based tools diminish the possibilities for traditional experience (e.g., admiring the physical environment).
		SDE3	AI-based tools can impair people's ability to thrive in the "real" world (e.g., orientation, object recognition).
		SDE4	Reliance on AI-based tools impairs people's ability to communicate.
		SDE5	Reliance on AI-based tools impairs interpersonal relationships (e.g., people become alienated from each other, preferring to enjoy virtuality).
SC	Skepticism	SC1	The use of artificial intelligence raises several ethical issues and is not well regulated.
		SC2	AI can use too much personal data, which is why I am afraid of its use.
		SC3	The spread of AI will only increase socio-economic inequalities in the long term, which is why I do not think it is a good idea to use it.
		SC4	AI-based tools only increase people's vulnerability to digital, machine-based tools.
ITU	Intention to Use	ITU1	I am open to trying out AI-based tools.
		ITU2	I am open to using AI-based tools on a regular basis.
		ITU3	I intend to use AI-based tools in everyday activities.
AU	Actual Use	AU1	I have used AI-based tools in my work-related activities.
		AU2	I have used AI-based tools in my daily activities.
		AU3	AI-based tools have become part of my everyday activities.
OTU	Openness towards Tourism Use	OTU1	I am open to AI-based tools that help me plan my travel.
		OTU2	I am open to AI-based tools that help me book tourist services (e.g., flights, accommodation, entrance tickets).
		OTU3	I am open to AI-based tools to help with check-in and check-out at hotels.
		OTU4	I am open to AI-based tools that assist in the back-office processes of tourist services (e.g., room service, cleaning, catering, serving).
		OTU5	I am open to AI-based tools that help me to participate in sightseeing tours as a substitute for a tour guide.
PEOU	Perceived Ease of Use	PEOU1	I find the use of the currently available AI-based tools simple and easy to understand.
		PEOU2	Learning to interact with AI-based services is easy for me.
		PEOU3	It is easy for me to become skillful at using AI-based services.
PU	Perceived Usefulness	PU1	Artificial intelligence can help to do some everyday tasks faster and more efficiently (for example: searching for information on the internet).
		PU2	Artificial intelligence can help to work more efficiently.
		PU3	AI-based services enhance my effectiveness when planning.
		PU4	Overall, AI-based tools are useful in everyday context.

Source: Authors' editing

**Table 3** Key assessment steps

Analysis aspect	Analysis	Threshold
<b>Measurement model evaluation</b>		
Indicator reliability	Standardized factor loadings	>0.75
Internal consistency	Cronbach's alpha ( $\alpha$ ), Composite Reliability (CR), Average Variance Extracted (AVE)	$\alpha > 0.50$ CR > 0.70, AVE > 0.50
Collinearity diagnostics	VIF	all values < 5
Discriminant validity	HTMT criterion	< 0.85
<b>Structural model evaluation</b>		
Path coefficients	bootstrapping with 5.000 resamples	
Coefficient of determination ( $R^2$ )	to evaluate explanatory power	
Predictive relevance ( $Q^2$ )	via blindfolding procedure	$Q^2 > 0$ indicates predictive power
Effect sizes ( $f^2$ )	to measure the impact of each exogenous construct on endogenous constructs.	
<b>Robustness checks of structural model</b>		
Collinearity diagnostics	VIF	all values < 5
Model fit evaluation	SRMR	< 0.08

Source: Authors' editing

## 5 Results

### 5.1 Measurement model evaluation

*Factor loadings* exceeding 0.75 in all cases, and most items loading are above 0.80. All constructs met the recommended thresholds for *internal consistency and convergent validity* (Table 4). To ensure the absence of *multicollinearity*, VIF values were checked. All constructs showed VIF values well below the conservative threshold of 3.3 (Hoyle 2012), confirming no collinearity concerns.

*Discriminant validity* was tested using the Heterotrait–Monotrait [HTMT] ratio. All HTMT values were below the threshold of 0.85 (Table 5) (Henseler et al. 2015), supporting discriminant validity between all constructs.

### 5.2 Structural model [SEAM] evaluation

Following the assessment of the measurement model, the structural model was evaluated (Fig. 4) to test the hypothesized relationships among constructs and to assess the model's explanatory power and predictive relevance.

**Table 4** Construct reliability and convergent validity

Construct	Indicator	Loading	Cronbach's Alpha	CR	AVE	VIF
Perceived Ease of Use	PEOU1	0.801	0.837	0.896	0.683	2.108
	PEOU2	0.874				
	PEOU3	0.831				
Perceived Usefulness	PU1	0.892	0.860	0.916	0.730	2.426
	PU2	0.853				
	PU3	0.805				
	PU4	0.874				
Skepticism	SC1	0.783	0.862	0.901	0.644	2.321
	SC2	0.827				
	SC3	0.788				
	SC4	0.810				
Self-Destructive Effects	SDE1	0.847	0.885	0.921	0.697	2.645
	SDE2	0.856				
	SDE3	0.862				
	SDE4	0.775				
	SDE5	0.807				
Intention to Use	ITU1	0.843	0.877	0.922	0.747	2.119
	ITU2	0.881				
	ITU3	0.878				
Actual Use	AU1	0.887	0.885	0.925	0.754	2.132
	AU2	0.873				
	AU3	0.858				
Openness Towards Tourism Use	OTU1	0.823	0.903	0.927	0.718	2.386
	OTU2	0.851				
	OTU3	0.842				
	OTU4	0.871				
	OTU5	0.857				

Source: Authors' editing

**Table 5** Discriminant validity [HTMT criterion]

	PU	PEOU	SC	SDE	ITU	AU	OTU
<b>PU</b>	X						
<b>PEOU</b>	0.792	X					
<b>SC</b>	0.229	0.202	X				
<b>SDE</b>	0.164	0.162	0.670	X			
<b>ITU</b>	0.634	0.487	0.512	0.438	X		
<b>AU</b>	0.566	0.436	0.483	0.379	0.707	X	
<b>OTU</b>	0.574	0.427	0.461	0.344	0.688	0.655	X

Source: Authors' editing

### 5.2.1 Path coefficients, determination ( $R^2$ ) and predictive relevance ( $Q^2$ )

The analysis was performed using SmartPLS 4, applying a bootstrapping procedure with 5.000 subsamples to determine the statistical significance of path coefficients. The model explained a substantial proportion of variance in the key endogenous vari-

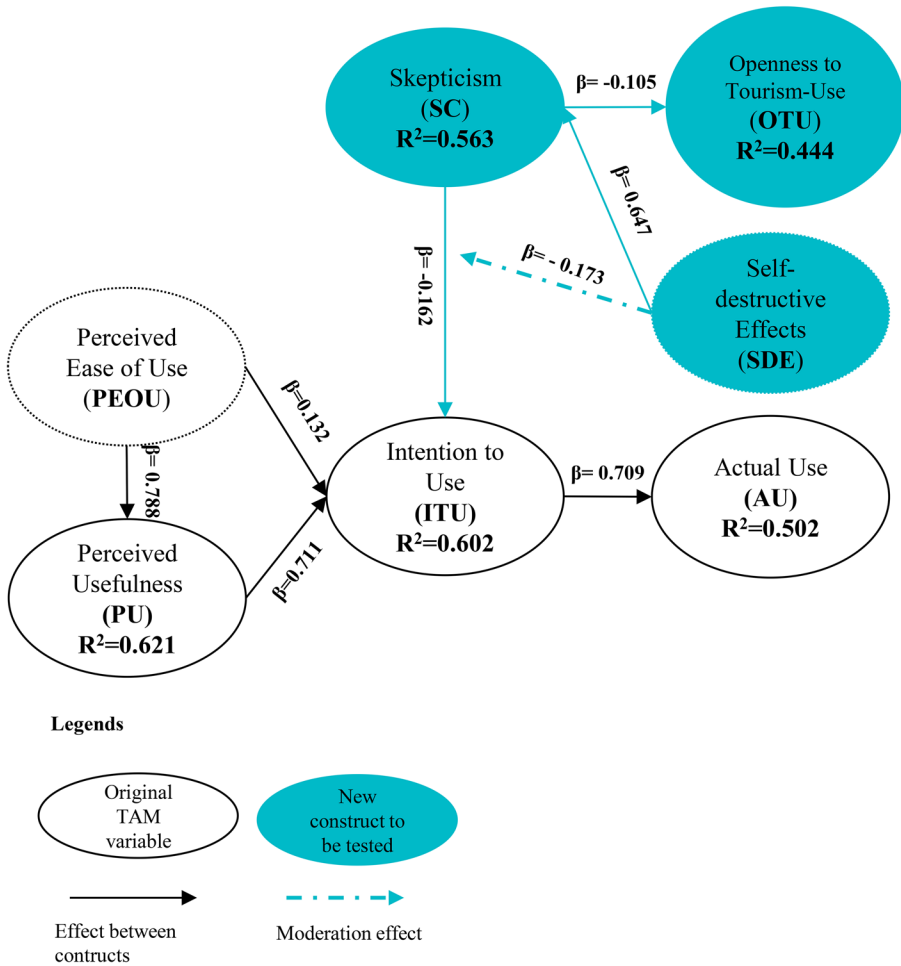


Fig. 4 SEAM model [skill-erosion Awareness model]. Source: authors’ editing

ables. As shown in Table 6,  $R^2$  values ranged from moderate to substantial, while the  $Q^2$  values confirmed predictive relevance across all constructs ( $Q^2 > 0$ ).

The results of the hypothesis testing are summarized in Table 7 All hypothesized relationships were statistically significant, supporting the proposed conceptual model.

Table 6  $R^2$  and  $Q^2$  values of endogenous constructs

Construct	$R^2$	Interpretation	$Q^2$	Predictive relevance
SC	0.563	Moderate	0.260	Yes
ITU	0.602	Substantial	0.370	Yes
AU	0.502	Moderate	0.403	Yes
OTU	0.444	Moderate	0.375	Yes
PU	0.621	Substantial	0.335	Yes

Source: Authors’ editing

**Table 7** Path coefficients and hypothesis testing

Hypothesis	Path	$\beta$	SE	t-value	p-value	$f^2$	Supported
H1	SDE $\rightarrow$ SC	0.647	0.038	17.03	<0.001	0.42	Yes
H2	SC $\rightarrow$ ITU	-0.162	0.042	4.91	<0.001	0.04	Yes
H3	ITU $\rightarrow$ AU	0.709	0.038	18.66	<0.001	0.42	Yes
H4	SC $\rightarrow$ OTU	-0.105	0.042	4.20	<0.001	0.01	Yes
H5	PEOU $\rightarrow$ ITU	0.132	0.041	3.22	<0.001	0.02	Yes
H6	PU $\rightarrow$ ITU	0.711	0.042	17.04	<0.001	0.45	Yes
H7	PEOU $\rightarrow$ PU	0.788	0.036	21.73	<0.001	0.62	Yes
H8	SC $\times$ SDE $\rightarrow$ ITU	-0.173	0.041	4.22	<0.001	0.03	Yes

Source: Authors' editing

**Table 8** Moderation result – SC  $\times$  SDE  $\rightarrow$  ITU

Path	$\beta$	SE	t-value	p-value	95% CI	Interpretation
SC $\times$ SDE $\rightarrow$ ITU	-0.173	0.041	4.22	<0.001	[-0.263, -0.084]	<b>Significant negative moderation</b>

Source: Authors' editing

## 5.2.2 Moderating Effects

To further explore the dynamics of resistance to AI-based tourism services, we tested whether *Self-Destructive Effects [SDE]* moderate the relationship between *AI Skepticism [SC]* and *Intention to Use [ITU]*. The moderating hypothesis (H8) proposed that higher perceptions of SDE would *strengthen the negative effect* of *Skepticism* on *Intention to Use [ITU]*. Moderation analysis was conducted using the product indicator approach in SmartPLS4, and bootstrapping with 5.000 subsamples was used to assess the statistical significance of the interaction term  $[SC \times SDE]$  (Table 8).

The results confirmed a statistically significant interaction effect ( $\beta = -0.173$ ,  $p < 0.001$ ), supporting H8. The direction of the effect indicates that the negative impact of *Skepticism* on *ITU* is amplified when concerns about *Self-Destructive Effects [SDE]* are high. In other words, individuals who are more worried about AI degrading human skills and autonomy are more strongly influenced by their skeptical attitudes, resulting in lower behavioral intention to adopt AI-based tourism technologies. This moderating relationship confirms the theoretical assumption that perceived *SDE* act not only as antecedents of *Skepticism* [H1] but also as intensifiers of its behavioral effects [*ITU*, *AU*].

## 5.2.3 Effect sizes ( $f^2$ ) and hypothesis Interpretation

Following Cohen's (2013) benchmarks, effect sizes ( $f^2$ ) of 0.02, 0.15, and 0.35 can be interpreted as small, medium, and large, respectively. The analysis of effect sizes therefore provides a more nuanced understanding of the relative explanatory power of the predictors within the SEAM framework beyond mere statistical significance. According to these thresholds, several relationships can be classified as *large effects*. *Perceived Usefulness  $\rightarrow$  Intention to Use* ( $f^2 = 0.45$ ), *Intention to Use  $\rightarrow$  Actual Use*

( $f^2=0.42$ ), and *Self-Destructive Effects* → *Skepticism* ( $f^2=0.42$ ) all exceed the 0.35 benchmark, indicating substantial practical relevance. These findings confirm that utilitarian evaluations and psychologically grounded resistance mechanisms represent the dominant explanatory forces in the model. In contrast, the effects of *Perceived Ease of Use* → *Intention to Use* ( $f^2=0.02$ ) and *Skepticism* → *Intention to Use* ( $f^2=0.04$ ) fall within the small range. While statistically significant, these effects suggest limited incremental explanatory contribution relative to *Perceived Usefulness*. Similarly, the path from *Skepticism* → *Openness Toward Tourism Use* ( $f^2=0.01$ ) falls slightly below Cohen's small-effect threshold. Although its magnitude is minimal in practical terms, its theoretical importance lies in demonstrating that *skepticism extends beyond general adoption intention and subtly constrains domain-specific openness within tourism*. The moderating effect ( $SDE \times SC \rightarrow ITU$ ;  $f^2=0.03$ ) also falls within the small range. However, moderation effects in behavioral research are typically expected to be modest in size, and even small interaction effects may carry meaningful theoretical implications when they reveal conditional dynamics within the model. Taken together, the effect size analysis reveals a *layered structure of influence*. Core TAM drivers and SDE exert substantial practical impact, while resistance-based pathways and moderation effects contribute primarily at the theoretical level by refining the explanatory architecture of AI acceptance. This distinction between statistical significance, theoretical contribution, and practical magnitude is crucial for interpreting the SEAM model appropriately.

### 5.2.4 Multi Group Analysis [MGA]

To examine whether the structural relationships vary across different user profiles, a Multi-Group Analysis [MGA] was conducted using SmartPLS4's non-parametric bootstrapping procedure. Two grouping variables were tested: (1) the primary *source of AI-related information* and (2) *type of residence*. This analysis aimed to explore whether background factors influence the strength of key model relationships.

**5.2.4.1 Group comparison 1: information source (media vs. Professional)** Respondents were grouped based on whether they primarily obtained information about AI from *mass media sources* (e.g., social media, news portals) or from *professional/scientific channels* (e.g., academic articles, expert forums). The following significant difference was found (Table 9):

This result indicates that the effect of *Intention to Use* [ITU] on *Actual Use* [AU] is significantly stronger among respondents who rely on media for AI information. These individuals may be more exposed to persuasive, experience-focused narratives that encourage the practical application of AI, translating their intention more readily into action.

**Table 9** Result of MGA – information source

Path	Media group	Professional group	p-value	Significance
ITU → AU	0.53	0.31	0.037	Yes

Source: Authors' editing

**Table 10** Result of MGA – place of residence

Path	Urban group	Rural group	p-value	Significance
SC → ITU	-0.19	-0.36	0.042	Yes

Source: Authors' editing

**Table 11** Robustness check results

Construct path	VIF
PEOU → PU	2.01
PU → ITU	2.24
SC → ITU	2.37
SDE → SC	1.89
SC×SDE → ITU ( <i>Moderation</i> )	1.21

Source: Authors' editing

**5.2.4.2 Group comparison 2: type of residence (Urban vs. Rural)** To assess contextual effects related to access, digital infrastructure, and norms, participants were also categorized as urban (living in towns or cities) or rural (villages or smaller settlements). A statistically significant difference emerged in the following path (Table 10):

The negative effect of *Skepticism [SC]* on *Intention to Use [ITU]* was significantly stronger among rural participants, suggesting that in less urbanized areas, skepticism toward AI more heavily undermines AI-acceptance. This may reflect contextual factors such as less frequent exposure to AI-based services, or greater attachment to traditional human-centered service models.

### 5.2.5 Robustness check

To assess the statistical robustness and reliability of the model, two commonly recommended diagnostic procedures were applied: (1) *collinearity diagnostics* and (2) *model fit evaluation* (Hoyle 2012). These tests help ensure that the estimated relationships are not distorted by multicollinearity or poor model specification. Variance Inflation Factor [VIF] values were examined to detect any potential multicollinearity issues among predictor constructs. As recommended by Hair et al. (2011), VIF values below the conservative threshold of 3.3 (or the more liberal threshold of 5.0) indicate acceptable levels of collinearity. All VIF values ranged between 1.21 and 2.37 (Table 11), confirming that no multicollinearity issues were present in the structural model. These values provide strong evidence that the predictor constructs are sufficiently distinct, and their effects on the dependent variables are not inflated by collinearity.

Although PLS-SEM does not emphasize global model fit indices as strongly as CB-SEM (Hair et al. 2011), the Standardized Root Mean Square Residual [SRMR] is widely accepted as a practical approximation of overall fit. An SRMR value below 0.08 indicates an acceptable model fit (Henseler et al. 2015). The model's SRMR value was 0.064, which is well below the threshold, indicating a *good model fit* and alignment between the empirical data and the proposed theoretical structure.

## 6 Discussion and conclusion

This study explored how skepticism shapes Gen Z tourists' willingness to use AI-based services, focusing especially on how concerns about the loss of human skills influence their attitudes. Based on a survey among university students ( $n=420$ ), we extended the traditional Technology Acceptance Model [TAM] by introducing a novel psychological construct: *Self-Destructive Effects* [SDE], referring to the perceived erosion of human skills and autonomy through the excessive AI use. Importantly, the findings emphasize that not all AI-based innovations lead to improved tourism experiences. Particularly for Gen Z tourists – who are digitally fluent but emotionally discerning – excessive automation may reduce perceived authenticity and human connection. This suggests that tourism innovation strategies must critically evaluate not only what AI can do, but what travelers truly value in an experience-driven sector. The resulting **SEAM model** (*Skill-Erosion Awareness Model*) integrates both utilitarian predictors (*Perceived Usefulness and Perceived Ease of Use*) and resistance-based constructs (*Skepticism and SDE*) within a unified structural framework. Using PLS-SEM, we found that *Perceived Usefulness* was the strongest positive predictor of *Intention to Use* ( $\beta=0.711$ ), while *Skepticism* had a significant negative effect ( $\beta=-0.162$ ). SDE significantly predicted *Skepticism* ( $\beta=0.647$ ) and intensified its negative impact on *Intention to Use* (interaction  $\beta=-0.173$ ). These results highlight the dual nature of AI-acceptance, shaped by both performance expectations and psychological concerns, and underline the value of incorporating resistance mechanisms into tourism research.

### 6.1 Sector-specific relevance

*Tourism* is an experience-driven sector in which authenticity, human interaction, and personal agency are core value components (Seyfi et al. 2023; Nam et al. 2024). Unlike many everyday digital contexts, travel frequently involves uncertainty and reliance on one's own cognitive and interpersonal skills. Tourists must navigate unfamiliar environments, interpret cultural cues, solve unexpected problems, and engage with service providers in real time. In such settings, the perceived delegation of orientation, decision-making, or social interaction to AI systems may generate stronger concerns about competence loss and diminished experiential richness than in routine daily technology use.

*Recent tourism research* has highlighted how AI applications, from intelligent recommender systems to autonomous service encounters increasingly shape destination experiences and visitor satisfaction (Topsakal and Çuhadar 2024; Stankov et al. 2025). However, much of this literature has focused primarily on performance expectancy, hedonic motivation, or service efficiency. By contrast, the present study demonstrates that tourism is not merely another application field for AI adoption models, but a *sector in which psychological resistance may be especially salient*. Because *tourism consumption* is deeply intertwined with identity construction, memory formation, and perceived authenticity (Nam et al. 2024), concerns about skill erosion or reduced autonomy may directly *influence how travelers evaluate AI-mediated experiences*.

Furthermore, tourism differs from other AI adoption domains (e.g., education or workplace settings) in that it is voluntary, leisure-oriented, and emotionally charged. Tourists do not seek optimization alone; they seek immersion and personal growth. Therefore, the psychological costs associated with excessive automation (e.g., diminished spontaneity or reduced human interaction) may carry greater experiential weight. In this sense, *tourism provides a particularly revealing empirical setting for examining Self-Destructive Effects (SDE)*, as it amplifies tensions between technological efficiency and human-centered value creation.

By *situating SDE within the tourism domain*, this study contributes to a more nuanced understanding of AI acceptance in experience-based industries. The findings suggest that resistance to AI in tourism is not merely functional or trust-based, but deeply experiential and identity-related, reinforcing the need for tourism-specific theoretical models that account for emotional and autonomy-related concerns.

## 6.2 Theoretical contributions

This study addresses a critical gap in the AI acceptance literature by *foregrounding psychological resistance rooted in fears of skill degradation and human irrelevance*. Although prior research has extensively relied on TAM and its extensions (Venkatesh and Davis 2000; Venkatesh and Bala 2008), most models emphasize utilitarian drivers such as Perceived Usefulness and Perceived Ease of Use. *In tourism contexts*, AI-related studies similarly focus on performance expectancy, hedonic motivation, and trust (Topsakal and Çuhadar 2024; Vinasco and Al Ghofaili 2024; Terrah et al. 2024), while *deeper autonomy-related anxieties remain largely underexplored*.

By *introducing Self-Destructive Effects (SDE)* as both an antecedent and a moderator of AI Skepticism, the *SEAM model expands the theoretical boundaries of TAM-based research*. Existing studies have examined constructs such as AI anxiety, neuroticism, and algorithm aversion (Stănescu and Romaşcanu 2024), as well as concerns about cognitive laziness or skill displacement (Ahmad et al. 2023; Ardichvili 2022). However, these perspectives have *rarely been systematically embedded within formal acceptance models, particularly in tourism*. Conceptualizing and empirically validating perceived skill erosion as a distinct latent construct contributes to resistance-based theorizing by linking macro-level automation concerns to individual-level behavioral intentions.

The *inclusion of a moderating mechanism* further refines the explanatory architecture of AI acceptance. Whereas many TAM-derived models assume primarily linear predictor–outcome relationships (Venkatesh et al. 2003, 2012), the present findings demonstrate that resistance operates conditionally: *the behavioral impact of skepticism intensifies when concerns about skill erosion are high*. Although advanced tourism models have applied frameworks such as UTAUT2 or S-O-R to capture emotional responses (Nam et al. 2024; Jiang et al. 2025), the dynamic amplification of skepticism through perceived long-term competence loss has not been previously addressed.

*Positioning the model within tourism also enriches ongoing debates on AI-powered tourism experiences* (Stankov et al. 2025; Topsakal and Çuhadar 2024). While earlier research has highlighted efficiency gains and experiential enhancement, the present study demonstrates that acceptance in experience-based sectors is simulta-

neously shaped by perceived experiential costs. This aligns with emerging discussions on authenticity, emotional engagement, and human-centered value creation in tourism (Seyfi et al. 2023; Nam et al. 2024), suggesting that *AI adoption cannot be understood solely through performance metrics*.

The results further complicate common portrayals of Generation Z as uniformly technology-embracing. Although Gen Z is frequently characterized as digitally fluent and innovation-oriented (Seyfi et al. 2023), the *findings reveal a pattern of digital ambivalence in which appreciation of usefulness coexists with concerns about autonomy and competence erosion*. This contributes to a more differentiated understanding of young tourists' technology acceptance and underscores the importance of integrating emotional and experiential dimensions into AI adoption research.

### 6.3 Practical contributions

The practical relevance of the findings is summarized as follows. Consistent with prior tourism AI research emphasizing trust and emotional engagement (Nam et al. 2024; Stankov et al. 2025), successful AI implementation in tourism requires more than technological efficiency; it requires psychological reassurance and the preservation of user agency.

*Tourism providers* should therefore emphasize AI's complementary role to human skills, using clear communication strategies to counteract psychological resistance. As previous studies on AI adoption in tourism highlight the importance of performance expectancy and trust (Topsakal and Çuhadar 2024; Vinasco and Al Ghofaili 2024), our findings suggest that *communication should also explicitly address autonomy-related concerns. Messaging that reassures users about the continued presence of human oversight and frames AI as augmenting, rather than replacing human judgment may help mitigate skepticism*.

To preserve a sense of agency, *AI tools such as chatbots, recommendation systems, or self-check-in kiosks should be implemented with user-empowerment features*. Providing options to override AI suggestions, choose manual alternatives, or access transparent explanations aligns with research emphasizing the role of perceived control and emotional comfort in technology acceptance (Nam et al. 2024). Encouraging active engagement with AI, rather than passive reliance, may help prevent perceived skill erosion and sustain user confidence.

Overall, *tourism development strategies* should address the potential experiential trade-offs associated with excessive automation. While AI-enhanced services can improve efficiency and personalization (Stankov et al. 2025), over-automation may risk diminishing authenticity and interpersonal interaction, elements central to *tourism value creation* (Seyfi et al. 2023). Strategic planning must therefore balance innovation with human-centered design principles to ensure that AI enhances the experiential core of tourism.

### 6.4 Limitations and future research directions

This study has several limitations. The sample was restricted to students from a single Hungarian university, with a strong female overrepresentation (75%), which limits

generalizability and cross-cultural validity. University students represent a specific and relatively homogeneous subgroup of Generation Z; therefore, the findings may not fully reflect the attitudes of working, less educated, or culturally diverse Gen Z populations. Future research should apply stratified and cross-cultural sampling strategies to test the robustness of the SEAM model across broader socio-demographic contexts. Some structural relationships exhibited small effect sizes. Future studies should therefore explore additional contextual moderators and boundary conditions to clarify when psychological resistance translates into substantial behavioral change. Finally, longitudinal or experimental designs could further strengthen causal interpretation and reveal how perceptions of skill erosion evolve over time or through direct AI experiences. Mixed-method approaches may also provide deeper insight into the emotional and experiential dimensions underlying resistance in tourism contexts.

**Author contributions** 1. Márk Miskolczi: Conceptualization; Methodology; Software; Validation; Formal analysis; Investigation; Resources; Data curation; Writing – original draft; Writing – review & editing; Visualization; Project administration. 2. Melinda Jászberényi: Conceptualization; Supervision; Funding acquisition. 3. Krisztina Keller: Investigation (data collection). 4. Coronel Padilla Monica Fabiola: Investigation (data collection). 5. Lívia Pintér Szabóné: Investigation (data collection). 6. László Kökény: Conceptualization; Methodology.

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**Data availability** The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Ethics statement** All participants provided informed consent prior to participation. The study was conducted in accordance with the Declaration of Helsinki. All data were anonymized and handled confidentially.

**Competing interests** The authors declare no competing interests.

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