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What Drives Tourists to Use Conversational AI? Evidence from an Extended UTAUT2 Model

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Abstract This study examines the factors shaping tourists' adoption and use of artificial intelligence (AI) tools in tourism by drawing on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Focusing on tourists visiting Fes, Morocco, AI is operationalised as a conversational assistant similar to ChatGPT that helps travellers search for information, plan itineraries, and make decisions during their trip. The research investigates how performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit influence behavioural intention and usage behaviour, and whether trust in AI technology moderates the intention–behaviour link. Data were collected through an online survey of N=183 tourists in Fes, Morocco. Respondents completed a screening question on prior use of a ChatGPT-like assistant for travel tasks. Only "Yes" respondents proceeded. Usage behavior reflects general self-reported use of AI for travel purposes, not verified frequency of use during the Fes stay. The collected data was then analyzed using a consistent "partial least squares" (PLS) SEM technique. The findings show that performance expectancy, hedonic motivation, price value, and habit significantly predict behavioural intention. Facilitating conditions and habit significantly predict usage behaviour. Effort expectancy and social influence are non-significant predictors of intention. Trust in AI technology does not significantly moderate the relationship between intention and usage behaviour. The study contributes to tourism technology literature by refining the application of UTAUT2 in an AI-intensive context and highlighting the role of habit and perceived value in tourists' continued reliance on AI assistants. Practical implications are discussed for tourism managers and destination stakeholders seeking to design and communicate trustworthy AI-based services.

Keywords AI adoption, tourism, UTAUT2, trust, behavioural intention, usage behaviour, conversational agents, ChatGPT-like assistants

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1. Introduction

The tourism industry has been profoundly reshaped by digital technologies [1]. Travellers increasingly rely on online platforms, mobile applications, and AI-based tools for information search, planning, and decision-making. Conversational agents such as ChatGPT and similar systems allow tourists to obtain personalised recommendations, refine itineraries, and translate lo-cal information in real time. For many visitors, these tools become part of the travel routine rather than a novelty. Understanding why tourists decide to adopt and effectively use AI-based tools is therefore a central question for both researchers and practitioners. Adoption is not only a matter of access to technology; it reflects expectations about usefulness, ease of use, enjoyment, social norms, trust in algorithms, and the perceived value of such tools compared to traditional sources of information.

This study examines adoption of conversational AI assistants in tourism using an extended UTAUT2 model. We focus on ChatGPT-like tools that tourists use for travel planning and trip decisions. The study contributes in three ways. First, it tests UTAUT2 in a conversational AI setting. Second, it examines whether trust in AI changes

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the link between intention and use. Third, it provides evidence from Fes, Morocco, a destination that remains underrepresented in tourism technology research.

In Morocco, tourism remains a key driver of economic activity, and destinations such as Fes attract visitors interested in cultural heritage, gastronomy, and experiences in the Medina and surrounding areas. Fes is a heritage destination where visitors often face dense urban layouts and information frictions (routes, opening hours, local norms). In such contexts, conversational AI can be valued for rapid clarification and itinerary adjustments. These benefits depend on enabling conditions, including connectivity and device access during the trip. Indeed, tourists increasingly arrive with smartphones and prior exposure to AI tools, including conversational assistants that can recommend activities, propose routes, or suggest restaurants and accommodations based on user queries. For destination stakeholders, this raises questions about how these tools are integrated into the tourist experience and what factors foster or hinder their adoption. This study addresses these questions by using UTAUT2 as the main theoretical framework to explain tourists' intention to use and actual use of AI-based tools in tourism. In our empirical context, AI is defined concretely as a conversational assistant similar to ChatGPT, which travellers can use to: obtain personalised suggestions for things to do in Fes; ask for step-by-step itineraries; compare accommodation or restaurant options and translate and interpret local information, including reviews and cultural notes.

Before starting the questionnaire, respondents answered a screening question about prior use of a ChatGPT-like conversational assistant for travel-related tasks. Only respondents who answered "Yes" completed the full survey. Respondents were instructed to answer based on their actual prior use of such tools during travel planning and/or on-site activities. The study examines the influence of UTAUT2 constructs on tourists' intention and use of AI-based conversational tools, explores the moderating role of trust in the intention–behaviour relationship, and provides empirical evidence from a North African tourism destination that remains underrepresented in technology adoption research.

The paper is structured as follows. Section 2 reviews the literature on AI in tourism, technology adoption models, and trust in AI, and develops the hypotheses. Section 3 presents the methodology, including the research context, AI scenario, measures, and data collection. Section 4 reports the results of the PLS-SEM analysis. Section 5 discusses the findings in light of existing research. Section 6 out-lines theoretical implications, Section 7 addresses practical implications, and Section 8 concludes with limitations and directions for future research.

2. Literature review and hypotheses development

2.1. AI and conversational assistants in tourism

AI has become embedded in many aspects of tourism, from recommendation engines on booking platforms to chatbots that answer questions about local ser-vices [1, 2]. Recently, general-purpose conversational assistants such as ChatGPT have enabled flexible, natural language interactions where tourists can formulate open-ended queries and receive tailored responses [3]. For instance, a traveller may ask, "I have two days in Fes, what should I not miss?" or "Can you suggest a walking route that includes the main historical sites and places to eat nearby?". Such tools can support information search (discover attractions, events, transport options), planning (day-by-day itineraries, time optimisation), decision-making (comparing services, clarifying trade-offs) and on-site support (translation, explanations of cultural norms). The perceived benefits of these assistants are likely to influence tourists' willingness to adopt and use them throughout their trip.

2.2. UTAUT2 in tourism

UTAUT2 integrates several determinants of technology adoption: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, with behavioural intention and usage behaviour [4]. UTAUT2 includes behavioural intention and usage behaviour as core outcomes. [5, 6]. This framework has been applied in various tourism settings (e.g. mobile travel apps, booking platforms, smart tourism services), showing that perceived usefulness, enjoyment, and habit are often central drivers of intention and continued use [7, 8].

Rather than claiming that UTAUT2 is rarely used in tourism, this study acknowl-edges that there is a growing body of work applying UTAUT2 in travel, hospitality, and tourism-related digital services [9, 12, 11, 10, 13]. Our contribution lies in extending this framework to an AI-intensive context in which the technology is not a static app but a conversational assistant relying on opaque algorithms and large-scale data.

2.3. Trust in AI technology as a moderating factor

Beyond traditional adoption factors, trust in AI technology has emerged as a central concern [14, 15, 16]. AI systems operate as "black boxes" for most users, raising questions such as: Are the recommendations accurate? Is the underlying information reliable? Will personal data be used responsibly [17, **?**]? In tourism, where decisions may involve safety, cost, or time constraints, these concerns are not trivial. We conceptualise trust in AI technology as the belief that AI algorithms and their providers are reliable, competent, and act in a way that does not harm the user's interests [19]. Trust is expected to influence whether tourists feel comfortable rely-ing on AI assistants for meaningful travel decisions rather than treating them as mere curiosities [18, 16].

From a theoretical standpoint, trust may not only affect intention but also the translation of intention into actual use. A traveller can recognise AI as useful and express a positive intention in a survey, yet still hesitate to rely on the system in real-life situations if they do not fully trust it. In other words, trust can act as a "gatekeeper" that either facilitates or inhibits the enactment of intention. Building on this reasoning, we propose that trust in AI technology moderates the link between behavioural intention and usage behaviour: when trust is high, intentions are more likely to turn into actual use; when trust is low, intentions may remain unfulfilled.

2.4. Hypotheses

Following UTAUT2, we formulate the following hypotheses regarding tourists' intention to use AI-based conversational tools in tourism:

- Performance Expectancy (PE) refers to the extent to which tourists believe that AI-powered services will enhance their travel experiences. AI applications, such as smart itinerary planners and real-time translation tools, offer personalized recommendations and operational efficiency, leading to higher adoption rates among travelers [6]. When tourists perceive AI services as useful and capable of improving their decision-making, their behavioral intention to adopt AI increases [20]. Thus, we hypothesize: H1. Performance expectancy has a positive effect on behavioural intention to use AI in tourism.
- Effort Expectancy (EE) measures the ease of use associated with AI technologies. Tourists are more likely to use AI tools if they are intuitive [21]. Simplified AI interfaces, such as automated booking systems and virtual travel assistants, significantly increase user engagement [37]. [22] demonstrate that tourists are more inclined to adopt AI technologies when these services are perceived as intuitive and easy to use. Similarly, [23] emphasizes that simplified AI interfaces, significantly enhance user engagement by reducing cognitive load. According to [20], AI tools offering personalized experiences are more accepted when they are easy to navigate. Consequently, we propose: H2. Effort expectancy has a positive effect on behavioural intention to use AI in tourism.
- Social Influence (SI) examines the impact of social circles, online reviews, and digital communities on technology adoption. Travelers rely on peer recommendations, influencer endorsements, and user-generated content when deciding to use AI-based tourism services. Moreover, younger travelers, in particular, who engage heavily with digital platforms, tend to place significant value on social validation when selecting tourism technologies [24, 20]. Based on these insights, we hypothesize: H3. Social influence has a positive effect on behavioural intention to use AI in tourism.
- Facilitating Conditions (FC) reflect the availability of resources and support systems necessary for AI adoption. Tourists require access to reliable internet connectivity, well-integrated AI applications, and responsive support services to ensure a seamless experience [21]. Indeed, access to Wi-Fi, technical support, and integration into existing digital ecosystems boosts usage [25, 26]. Therefore, we propose: H4a. Facilitating conditions have a positive effect on behavioural intention to use AI in tourism.

- Hedonic Motivation (HM) refers to the enjoyment and entertainment derived from using AI technologies. AI applications in tourism, such as virtual reality (VR) travel experiences, interactive AI tour guides, and gamified trip planning, have been shown to increase tourist engagement. [34] have developed a model of hedonic motivation in virtual reality tourism, comparing visitors and non-visitors. This study highlights those hedonic motivations strongly influence tourists' behavioral intention to use AI-based services. Similarly, the hedonic experience boosts consumer motivation, requiring less effort to adopt these technologies [27]. Tourists who perceive AI as enjoyable and engaging are more likely to develop a positive behavioral intention toward its adoption. Therefore, we hypothesize: H5. Hedonic motivation has a positive effect on behavioural intention to use AI in tourism.
- Price Value (PV) represents tourists' assessment of whether AI-powered services offer sufficient value for their cost. Studies have shown that tourists are more inclined to adopt AI-based travel tools when they believe these services enhance their experience at a reasonable cost [9]. AI-powered services that optimize travel expenses, such as dynamic pricing recommendations and personalized discounts, enhance adoption rates. A systematic review [28] examined the use of AI in dynamic pricing, showing how AI improves the effectiveness of this strategy, which can positively influence tourists' decision to adopt these services. Thus, we propose: H6. Price value has a positive effect on behavioural intention to use AI in tourism.
- Habit (H) reflects the extent to which tourists have already integrated AI-powered services into their travel routines. Travelers who regularly integrate AI-powered travel assistants, recommendation engines and smart booking platforms into their practices are more likely to continue using them on future trips. According to [29], 87% of users would be willing to interact with a travel chatbot if it could save them time and money. Moreover, the adoption of intelligent voice assistants among Airbnb customers is a testament to this trend. A study examined Airbnb customers' intentions to adopt intelligent voice assistants such as Amazon Alexa, highlighting their impact on traveler behavior [33]. Based on this, we hypothesize: H7a. Habit has a positive effect on behavioural intention to use AI in tourism.

In line with UTAUT2 [8], we also consider direct effects on usage behaviour:

- H4b. Facilitating conditions have a positive effect on usage behaviour of AI in tourism [25, 26, 21];
- H7b. Habit has a positive effect on usage behaviour of AI in tourism [33, 29];
- Behavioral Intention (BI) is a well-established predictor of actual technology adoption. Across various tourism contexts, behavioral intention translates into increased AI usage. For example, a study of the hotel industry in Pakistan revealed that factors such as PE, EE, SI, FC and Privacy Risk Perception significantly influence users' behavioral intention to adopt AI [35]. This behavioral intention, in turn, has a direct impact on the actual adoption of AI in the hospitality sector. According to [36], AI improves the travel experience by optimizing itineraries, reducing energy consumption and minimizing waste, reinforcing travelers' intention to adopt these technologies. We hypothesize: H8. Behavioural intention has a positive effect on usage behaviour of AI in tourism [29].

Finally, we introduce trust in AI technology as a moderator:

- H9. Trust in AI technology positively moderates the relationship between behavioural intention and usage behaviour of AI in tourism, such that the relationship is stronger at higher levels of trust [6, 30]

The conceptual model thus extends UTAUT2 by explicitly incorporating trust in AI as a moderating construct in an AI-based conversational assistant context. Fig 1 1 presents the research framework and the hypotheses developed in this study.

3. Methodology

3.1. Research context and AI scenario

The empirical study was conducted among tourists in Fes, Morocco, a major cultural destination known for its historic medina, religious and educational heritage, and urban markets. Fes is not typically branded as a "smart"

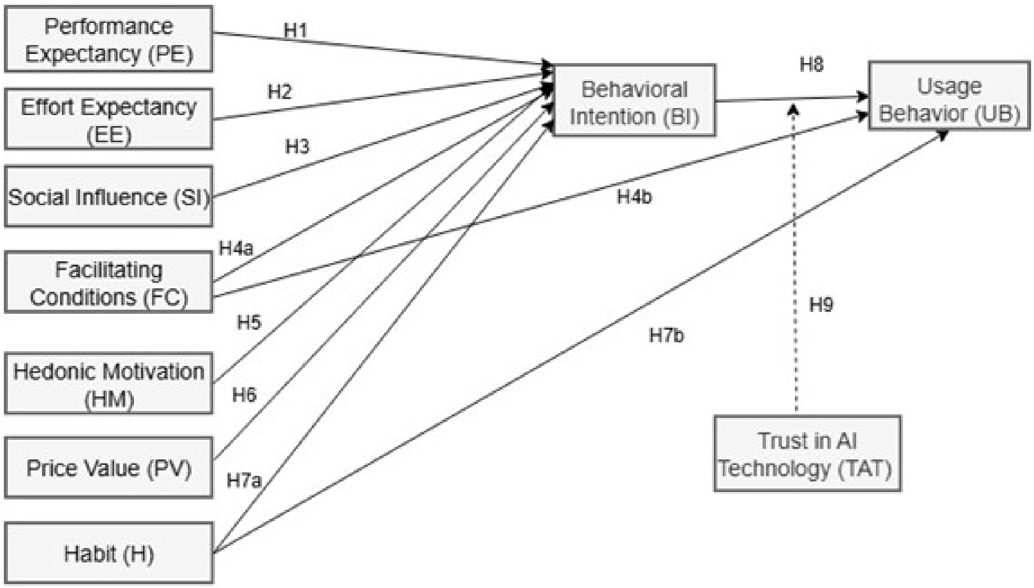

Figure 1. Research model (Source: Author's own).

or "eco" destination, yet tourists visiting the city are increasingly digitally connected and familiar with online tools. To reduce ambiguity in the notion of "AI in tourism", the questionnaire introduced a concrete AI scenario: Respondents were first asked whether they had used a conversational AI assistant similar to ChatGPT to organise and experience their trip in Fes. Only those who reported prior use were invited to complete the full survey and were instructed to base their responses on their actual travel-related experience. The AI assistant could answer questions about attractions, propose itineraries, help select restaurants or accommodations based on preferences and budget, and assist with translation and explanations of local customs. Participants were instructed to base their answers on their perceived or actual use of such an AI assistant while travelling. The scenario prompt was designed to provide a shared reference point for the technology.

3.2. Measures

The constructs were measured using multi-item Likert scales adapted from prior UTAUT2 and AI adoption studies. Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioural intention, and usage behaviour were operationalised following established scales, with items tailored to the tourism and AI assistant context (e.g. "Using AI in tourism helps me make better travel decisions"). Trust in AI technology was measured through items capturing perceived reliability of AI algorithms, data integrity, and confidence in AI developers' honesty. All items were rated on a five-point Likert scale ranging from strong disagreement to strong agreement. The full list of items and sources is provided in Table 1. In this study, price value is interpreted broadly. Respondents may consider monetary costs (e.g., subscription) and non-monetary costs (e.g., mobile data, time, and effort). This clarification matters because some conversational AI tools are free at point of use. Also, Usage behaviour items capture general self-reported use of AI for travel purposes (planning and purchasing). They do not measure verified frequency of use during the Fes stay. We interpret UB accordingly throughout the paper.

3.3. Data collection and sample

Data were collected through a structured questionnaire administered to tourists who were either currently visiting Fes or had recently visited and used AI-based tools during their travel planning or on-site activities. The translation

Table 1. Constructs and items incorporated in the questionnaire (Source: Author's own)

Variables	**Items**	**Reference**
Performance Expectancy (PE)	AI solutions are useful for me in tourism (PE1) AI systems help me accomplish tasks more quickly while traveling (PE2) AI technologies bring convenience to my work when traveling (PE3) AI can enhance the quality of tourism services (PE4)	[31, 5]
Effort Expectancy (EE)	I am ready to use AI technologies as they are easy to understand (EE1) Using AI interfaces is less complex (EE2) AI is easy to use (EE3) It is easy for me to become an expert in using AI systems in tourism (EE4)	[31, 5]
Social Influence (SI)	People around me think that AI should be used in tourism (SI1) Family and friends play an important role in my use of AI technologies for tourism (SI2) Using AI in tourism seems prestigious or admirable (SI3) I will discuss the benefits of using AI in tourism with my family and friends (SI4)	[31, 5]
Facilitating Conditions (FC)	I have access to the necessary digital devices to use AI for tourism (FC1) I have the necessary resources to use AI in tourism activities (FC2) AI systems are compatible with other technological devices I use for tourism (FC3) I can get help when I encounter difficulties using AI systems in tourism (FC4)	[31, 5]
Hedonic Motivation (HM)	Using AI in tourism is fun for me (HM1) AI-driven tourism applications are enjoyable to me (HM2) Using AI in tourism is a form of entertainment (HM3) AI use increases my overall tourism experience (HM4)	[5]
Price Value (PV)	AI solutions offer good value for money in the tourism sector (PV1) AI systems are reasonably priced compared to other alternatives in the tourism sector (PV2) AI tools in tourism are worth the cost (PV3)	[5]
Habit (H)	The use of AI in tourism has become a habit for me (H1) I must use AI when traveling (H2) I am addicted to using AI technologies for tourism due to their benefits (H3) Using AI has become natural for me when traveling (H4)	[5]
Behavioral Intention (BI)	I intend to continue using AI in the future for tourism (BI1) I plan to use AI frequently in my future travels (BI2) I predict I will use AI in tourism in the near future (BI3) I want to make others aware of the benefits of using AI in tourism (BI4)	[31, 5]
Usage Behavior (UB)	I have been using AI technologies in tourism for a considerable amount of time (UB1) I frequently use AI technologies for planning my trips (UB2) I regularly use AI technologies to purchase tourism products or services (UB3)	[31, 5, 32]
Trust in AI Technology (TAT)	I trust that AI algorithms are reliable in providing recommendations related to tourism services (TAT1) I trust that AI-based tourism software has a reliable database for making decisions (TAT2) I believe there will be government regulations to ensure the security of AI-based tourism software (TAT3) I trust that AI software developers are honest and will not misuse user data in the tourism sector (TAT4)	[38, 16]

of the survey from English to French was done using the translation/back-translation method [39]. A pilot study was conducted with 10 tourism professionals and 5 professors to ensure clarity and relevance. The survey was distributed online and began with a screening question. Only respondents who answered "Yes" to prior use of a ChatGPT-like conversational assistant for travel-related tasks were allowed to proceed to the full questionnaire.

The final sample included N=183 tourists. The sample shows a gender imbalance, with 69.4% male participants and 30.6% female, indicating greater male involvement. The majority of respondents were aged 26 to 35 (39.4%), followed by 36 to 45 (30.4%) and 46 to 60 (19.5%). In terms of education, most of the participants have a master's degree (38.1%) or a doctorate (40.3%), which is typical of technology adoption studies. This sample is highly educated and predominantly male. This profile may not represent the broader tourist population. It may also reduce the salience of effort expectancy and social influence, because digitally confident users may treat ease of use as a baseline expectation and rely less on normative cues. From a professional point of view, the sample is diverse: 38.1% work in the private sector, 25.8% in the public sector, and 9.3% are entrepreneurs or liberal professionals. This wide range of professions helps to understand the adoption of AI across all sectors. Notably, 90.2% of respondents expressed interest in using AI during their travels, and 86.3% trust AI to enhance their tourism experience.

3.4. Data analysis

The data were analysed using Partial Least Squares Structural Equation Model-ling (PLS-SEM) [40] with SmartPLS [41]. A two-step procedure was followed. First, the measurement model was assessed in terms of internal consistency reliability, convergent validity, and discriminant validity (via composite reliability, Cronbach's alpha, AVE, and HTMT ratios). Second, the structural model was assessed by examining path coefficients, t-values, p-values, coefficients of determination (R^2) for endogenous constructs, and predictive relevance (Q^2). To address potential common method bias, full collinearity variance inflation factors (VIFs) were inspected for all constructs. All VIF values were below the conservative threshold, indicating that common method variance is unlikely to substantially bias the results. We applied procedural controls to reduce hypothetical bias by screening for direct prior use of conversational AI. Bootstrapping was used to assess statistical significance of path coefficients. This approach is consistent with standard PLS-SEM practice. We also note that the scenario-based nature of part of the measurement may reinforce common method concerns. However, the study remains cross-sectional and self-reported. We therefore interpret coefficients as associations rather than causal effects.

4. Results

4.1. Measurement model

To assess the convergent validity of the measurement model, we examined the loadings of the items measuring each construct. All outer loadings were above the minimum acceptable value of 0.7 [42], indicating that each item effectively represents its respective construct. Specifically, items related to PE, EE, TAT, and BI displayed excellent loadings, with values ranging from 0.759 to 0.937. Additionally, the Average Variance Extracted (AVE) for each construct exceeded the 0.5 threshold, and the Composite Reliability (CR) also exceeded the 0.7 threshold. The constructs are then well-defined and reliable. Cronbach's alpha values were calculated to ensure internal consistency across the constructs. Located between 0.791 and 0.915, they are well above the acceptable value of 0.7 [43]. Our measurement model has high internal consistency (Table 2).

Next, we compared the AVE for each construct with the squared correlations between the constructs. We computed the Heterotrait-Monotrait (HTMT) ratio, which should ideally be below 0.90 for a good structural model [44]. As shown in Table 3, all HTMT values are below the threshold of 0.90, indicating that the constructs are sufficiently distinct from one another. The study results suggested substantial discriminant validity, both at the item and construct levels of the model. Furthermore, the correlation between each item and its associated concept is higher than that observed with the other concepts. Thus, our findings confirmed the validity and reliability of the measurement model. Evaluation of the structural model is now possible.

Table 2. Convergent validity results

Constructs	Items	Loading	Cronbach's alpha	AVE	Composite Reliability
Behavioral Intention	BI1	0.925	0.925	0.818	0.928
	BI2	0.937			
	BI3	0.912			
	BI4	0.841			
Effort Expectancy	EE1	0.874	0.866	0.715	0.882
	EE2	0.862			
	EE3	0.881			
	EE4	0.759			
Facilitating Conditions	FC1	0.827	0.865	0.713	0.871
	FC2	0.895			
	FC3	0.874			
	FC4	0.775			
Habit	H1	0.888	0.877	0.731	0.889
	H2	0.863			
	H3	0.790			
	H4	0.875			
Hedonic Motivation	HM1	0.867	0.863	0.707	0.887
	HM2	0.897			
	HM3	0.758			
	HM4	0.835			
Performance Expectancy	PE1	0.902	0.911	0.789	0.911
	PE2	0.916			
	PE3	0.883			
	PE4	0.852			
Price Value	PV1	0.893	0.860	0.781	0.865
	PV2	0.895			
	PV3	0.863			
Social Influence	SI1	0.783	0.791	0.612	0.807
	SI2	0.724			
	SI3	0.812			
	SI4	0.808			
Trust in AI Technology	TAT1	0.860	0.837	0.673	0.844
	TAT2	0.860			
	TAT3	0.744			
	TAT4	0.813			
Usage Behavior	UB1	0.881	0.876	0.802	0.881
	UB2	0.925			
	UB3	0.879			

Source: Data automatically generated in SmartPLS.

Table 3. HTMT matrix

	BI	EE	FC	H	HM	PE	PV	SI	TAT	UB	TATxBI
BI											
EE	0.715										
FC	0.524	0.695									
H	0.727	0.647	0.445								
HM	0.818	0.732	0.591	0.724							
PE	0.812	0.746	0.566	0.660	0.772						
PV	0.732	0.679	0.675	0.614	0.707	0.700					
SI	0.695	0.674	0.574	0.634	0.823	0.834	0.718				
TAT	0.689	0.605	0.468	0.553	0.627	0.552	0.693	0.545			
UB	0.696	0.583	0.562	0.854	0.726	0.603	0.669	0.620	0.639		
TATxBI	0.426	0.375	0.270	0.273	0.352	0.438	0.389	0.333	0.345	0.303	

Source: Data automatically generated in SmartPLS.

4.2. Structural model

With the measurement model validated, the structural model was evaluated using several criteria, including the coefficient of determination (R^2), the Stone–Geisser cross-validation redundancy index (Q^2), and the statistical significance of the structural relationships. Multicollinearity was first assessed using the Variance Inflation Factor (VIF). All VIF values were well below the threshold of 5, indicating that multicollinearity did not bias the regression results [45].

The R^2 values indicate moderate explanatory power, with $R^2 = 0.326$ for Behavioral Intention and $R^2 = 0.568$ for Usage Behavior. Both values exceed the minimum recommended threshold of 0.10, suggesting that the model explains a meaningful proportion of variance in the endogenous constructs [46]. In addition, the Q^2 values for all dependent constructs were positive, ranging from 0.024 to 0.156, confirming the predictive relevance of the model [43].

Following these assessments, the significance and relevance of the path coefficients were examined to test the research hypotheses, in line with established recommendations [43]. A bootstrapping procedure with 5,000 resamples and a 95% confidence interval was applied (Figure 2).

The results show that six of the hypothesised relationships are supported, while three are not statistically significant. As reported in Table 4, Performance Expectancy, Hedonic Motivation, Price Value, and Habit have significant positive effects on Behavioral Intention. Facilitating Conditions and Habit also exert significant effects on Usage Behavior.

Statistically significant relationships are indicated by t-values greater than 1.96 and p-values below 0.05. In particular, Hedonic Motivation ($\beta = 0.317, t = 4.445, p < 0.001$), Performance Expectancy ($\beta = 0.326, t = 3.829, p < 0.001$), and Habit ($\beta = 0.555$, $t = 9.265$, $p < 0.001$) strongly influence Behavioral Intention and Usage Behavior. In contrast, the moderating effect of Trust in AI Technology on the relationship between Behavioral Intention and Usage Behavior is not supported ($\beta = -0.010, t = 0.320, p = 0.749$).

Facilitating Conditions show a positive and significant effect on Usage Behavior ($\beta = 0.161$, $t = 2.771$, $p = 0.006$), highlighting the role of an enabling environment in AI adoption. Effort Expectancy and Social Influence do not significantly affect Behavioral Intention, suggesting a limited role for these factors in this context. Behavioral Intention does not significantly predict Usage Behavior in this sample (H8 not supported, p=0.301). Usage Behavior is explained by Habit and Facilitating Conditions. This pattern suggests that use of conversational AI for travel may be more routine-driven and infrastructure-dependent than intention-driven in this context. Hypotheses H1, H4b, H5, H6, H7a, and H7b are supported, while H2, H3, H4a, H8, and H9 are not supported.

Figure 2. Bootstrapping result of the structural model (Source: Data automatically generated in SmartPLS).

Table 4. Hypothesis testing

Hypotheses and relation	STDEV	O	t-value	p-value	Decision
H1. Performance Expectancy → Behavioral Intention	0.085	0.326	3.829	0.000	Supported
H2. Effort Expectancy → Behavioral Intention	0.067	0.094	1.404	0.160	Not supported
H3. Social Influence → Behavioral Intention	0.069	-0.075	1.088	0.277	Not supported
H4a. Facilitating Conditions → Behavioral Intention	0.058	-0.060	1.033	0.302	Not supported
H4b. Facilitating Conditions → Usage Behavior	0.058	0.161	2.771	0.006	Supported
H5. Hedonic Motivation → Behavioral Intention	0.071	0.317	4.445	0.000	Supported
H6. Price Value → Behavioral Intention	0.064	0.186	2.921	0.004	Supported
H7a. Habit → Behavioral Intention	0.060	0.172	2.850	0.004	Supported
H7b. Habit → Usage Behavior	0.060	0.555	9.265	0.000	Supported
H8. Behavioral Intention → Usage Behavior	0.072	0.075	1.034	0.301	Not supported
H9. Trust in AI Technology × Behavioral Intention → Usage Behavior	0.031	-0.010	0.320	0.749	Not supported

Source: Data automatically generated in SmartPLS (STDEV refers to the standard deviation of the bootstrap estimates).

5. Discussion

The study aimed to examine how tourists adopt and use AI-based conversational assistants in tourism, using Fes as the empirical setting. We discuss the findings by following the research model in Figure 1. We first interpret predictors of behavioural intention. We then interpret predictors of usage behaviour. We finally address the non-significant intention–use link and the non-significant trust moderation result. Several insights emerge from the analysis.

First, the strong effects of performance expectancy, hedonic motivation, price value, and habit on behavioral intention indicate that tourists are more likely to rely on AI assistants when they perceive clear benefits, such as improved decision-making and time savings, when interaction with AI is enjoyable, when the perceived cost-benefit ratio is favorable, and when AI use has become part of their travel routine. In this setting, price value likely reflects perceived net value rather than direct purchase price. Tourists may weigh benefits against time costs, data costs, or subscription costs. This framing fits the use of freemium conversational AI tools.

Second, effort expectancy and social influence do not significantly predict behavioral intention. One plausible explanation is that conversational assistants such as ChatGPT are perceived as relatively easy to use by tourists who regularly engage with digital tools [47]. Indeed, effort expectancy and social influence are non-significant in this sample. A plausible explanation is the sample profile. Respondents are highly educated and screened for direct prior use of conversational AI. For this segment, ease of use may be a basic expectation rather than a differentiator. Social influence may also be weaker when travel planning is self-directed and mediated by personalized digital tools. Several findings are better interpreted as trade-offs rather than isolated effects. Conversational AI can support personalization, but personalization can increase privacy exposure because it relies on user data. Ease of use may be treated as a baseline, yet perceived risk can still limit reliance on outputs. Also, the decision to use AI assistants may be more individual and self-directed than socially driven, particularly among travelers who plan trips independently and rely primarily on online information sources. Moreover, anthropomorphic interaction cues may support early engagement, but novelty can fade, leaving functional limits more salient. These tensions help explain why some classic UTAUT2 predictors are weak in this sample and non-significant in a mature conversational AI interface.

Third, facilitating conditions do not directly influence intention but significantly affect actual usage behavior. This suggests that once intention is formed, access to internet connectivity, appropriate devices, and technical support becomes essential for translating intention into use during the trip.

Fourth, habit emerges as a central determinant of both intention and usage behavior. Tourists who routinely consult AI tools in everyday life or during previous trips are more likely to continue using them in new destinations, reinforcing the role of habit emphasized in UTAUT2.

Trust in AI technology did not moderate the intention–use relationship. Although trust remains conceptually important and is reflected in tourists' confidence in AI tools [48], it does not significantly strengthen or weaken the translation of intention into behavior. This result suggests that trust may not act as a "gatekeeper" for use in this context. One explanation is restricted variance, because screened respondents already have direct experience with conversational AI. Another explanation is timing. Trust may shape perceived usefulness and the formation of intention, rather than the translation of intention into use. This interpretation is consistent with the view that beliefs can exert their strongest influence before behavior becomes routine.

6. Theoretical implications

Figure 1 helps interpret where the model aligns with UTAUT2 and where it diverges. At the intention stage, performance expectancy, hedonic motivation, price value, and habit remain relevant. At the use stage, the mechanism shifts. Habit and facilitating conditions explain usage behaviour, while behavioural intention is not significant. This suggests a more routinized adoption process for conversational AI in travel, where access and routine override planned intention. The findings contribute to the literature on tourism and technology adoption in several ways.

First, the study confirms the relevance of UTAUT2 in an AI-intensive context by showing that performance expectancy, hedonic motivation, price value, and habit remain key determinants of behavioral intention, while habit and facilitating conditions explain actual usage behavior. This supports the extension of general technology adoption mechanisms to AI-based conversational assistants in tourism.

Second, the non-significant effects of effort expectancy and social influence call for a more nuanced interpretation of UTAUT2 in contexts characterized by relatively high digital literacy and individualized technology use. Two paradoxes help interpret the results. Personalization depends on data, which can raise privacy concerns. This can weaken the role of trust as a moderator when users treat trust as a baseline condition. At the same time, conversational AI can reduce friction in information search, yet heavy reliance can reduce autonomy for some users. These paradoxes suggest the intention–use link may weaken when use becomes habitual and infrastructure-driven. Adoption drivers may show threshold or non-linear patterns that are not captured in a linear PLS-SEM specification. Future research could examine conditions under which effort expectancy and social influence regain explanatory power, such as among less digitally experienced travelers or in group travel settings.

Third, the study contributes to the growing discussion on trust in AI by operationalizing trust as a moderating factor in the intention–behavior relationship. Although the moderation hypothesis is not supported, this result suggests that trust may operate as a background condition shaping initial intention rather than as a distinct mechanism influencing implementation. This opens avenues for alternative model specifications, including positioning trust as an antecedent of perceived usefulness, perceived risk, or habit.

Finally, by focusing on tourists visiting Fès, the study provides empirical evidence from a North African destination that remains underrepresented in tourism and AI research, thereby contributing to a broader geographical coverage of studies on AI adoption in tourism.

7. Practical implications

The findings suggest three priorities.

- First, destination stakeholders can strengthen performance expectancy by offering a destination-specific assistant with verified local information (routes, opening hours, norms). Access can be delivered through official channels and on-site QR codes in hotels and visitor points.
- Second, developers can support habit formation by reducing friction across devices. Tourists often switch between desktop planning and mobile on-site use. Cross-platform continuity supports routine use.
- Third, facilitating conditions remain critical. Local tourism actors can support use by investing in visible Wi-Fi hotspots in tourist zones and by partnering with operators for short-term data plans.

Operational transparency should be concrete. Provide short "why this was recommended" explanations. Offer basic controls for personalization. Provide a visible escalation option to a human agent for complaints or exceptions. As a decision rule, automate low-empathy and high-frequency tasks, and keep human support for exceptions and emotionally sensitive situations.

8. Limitations and future research directions

This study has limitations.

- First, the data are cross-sectional and self-reported. This limits causal inference. Although we assessed common method bias using collinearity checks, shared-method measurement remains possible.
- Second, the study uses a scenario prompt. The usage behaviour items capture general self-reported travel AI use, not verified on-site use in Fes. The findings therefore reflect intention and general usage propensity. Future research should measure in-situ use through diary studies, experience sampling, or usage logs.
- Third, the sample is highly educated and predominantly male. This limits generalizability. It may also reduce the explanatory power of effort expectancy and social influence.

- Fourth, price value is conceptually complex for freemium tools. Future research can refine measurement to separate monetary cost from non-monetary costs such as mobile data, time, and privacy exposure.
- Finally, the non-significant trust moderation suggests alternative model specifications. Trust may operate as an antecedent of usefulness, perceived risk, or intention, or it may develop from repeated use over time.

9. Conclusion

This study examined conversational AI adoption in tourism by extending UTAUT2 with trust in AI technology. Based on survey data from N=183 tourists in Fes, the findings show that performance expectancy, hedonic motivation, price value, and habit influence behavioural intention. Usage behaviour is explained by habit and facilitating conditions, while behavioural intention is not a significant predictor of usage behaviour in this sample. Trust in AI technology does not significantly moderate the intention–usage relationship.

Overall, the results suggest that conversational AI tools such as ChatGPT are more likely to be integrated into tourists' experiences when they are perceived as useful, enjoyable, and as providing good value in terms of time and effort, and when their use becomes habitual. For researchers, the study highlights both the relevance and the limits of UTAUT2 in AI-intensive contexts and points to future research directions related to trust, non-linear effects, and cross-destination comparisons.

These findings should be read in light of limitations. The data are cross-sectional and self-reported. The sample is highly educated and predominantly male. Usage behaviour reflects general travel AI use among screened users and does not verify in-situ frequency during the Fes stay. Future studies should collect in-situ data and test more heterogeneous samples.

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REFERENCES

1. S. Wang, Q. Wang, Q. Cui, and T. Lan, *Artificial Intelligence in Tourism: A Systematic Literature Review and Future Research Agenda*, *Sustainability*, vol. 17, no. 20, p. 9080, 2025. DOI: https://doi.org/10.3390/su17209080.
2. M. Chung, E. Ko, H. Joung, and S. Kim, *Chatbot E-Service and Customer Satisfaction Regarding Luxury Brands*, *Journal of Business Research*, vol. 117, pp. 587–595, 2018. DOI: https://doi.org/10.1016/j.jbusres.2018.10.004.
3. K. Volchek and S. Ivanov, *ChatGPT as a Travel Itinerary Planner*, in *Information and Communication Technologies in Tourism 2024*, pp. 365–370, 2024. DOI: https://doi.org/10.1007/978-3-031-58839-6_38.
4. B. D. Tran and D. H. Vu, *Gen-Y Behavioral Intention to Adopt Mobile Tourism Apps: Extending UTAUT2 with Trust and Security*, *International Journal of Data and Network Science*, vol. 8, no. 4, pp. 2173–2184, 2024. DOI: https://doi.org/10.5267/j.ijdns.2024.6.014.
5. V. Venkatesh, J. Y. L. Thong, and X. Xu, *Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology*, *MIS Quarterly*, vol. 36, no. 1, pp. 157–178, 2012. DOI: https://doi.org/10.2307/41410412.
6. P. Y.-H. Sia, S. S. Saidin, and Y. H. P. Iskandar, *Smart Mobile Tourism App Featuring Augmented Reality and Big Data Analytics: An Empirical Analysis Using UTAUT2 and PCT Models*, *Journal of Science and Technology Policy Management*, vol. 15, no. 6, pp. 1363–1386, 2023. DOI: https://doi.org/10.1108/JSTPM-05-2022-0088.
7. A. Gupta and N. Dogra, *Tourist Adoption of Mapping Apps: A UTAUT2 Perspective of Smart Travellers*, *Tourism and Hospitality Management*, vol. 23, no. 2, pp. 145–161, 2017. DOI: https://doi.org/10.20867/thm.23.2.6.
8. B. Foroughi, M. Iranmanesh, S. Asadi, M. Al-Emran, M. Ghobakhloo, and A. Batouei, *Extending UTAUT2 to Explore Intention to Use ChatGPT for Travel Planning: A Hybrid PLS-ANN Approach*, *Journal of Tourism Futures*, pp. 1–23, 2025. DOI: https://doi.org/10.1108/JTF-11-2023-0256.
9. M. Çuhadar, *Usage Intention of Tourists Regarding the Acceptance of Artificial Intelligence Enhanced Tour Guides Apps*, *Current Issues in Tourism*, pp. 1–17, 2024. DOI: https://doi.org/10.1080/13683500.2024.2375361.
10. W. Chiengkul, P. Kumjorn, T. Tantipanichkul, and K. Suphan, *Engaging with AI in Tourism: A Key to Enhancing Smart Experiences and Emotional Bonds*, *Asia-Pacific Journal of Business Administration*, ahead-of-print, 2025. DOI: https://doi.org/10.1108/APJBA-09-2024-0488.

11. Y. Dikhanbayeva, *Has the Importance of Technology in Tourism Been Realized after Covid-19? Opportunities and Challenges*, *Journal of Tourism Theory and Research*, vol. 11, no. 1, pp. 1–8, 2025. DOI: https://doi.org/10.24288/jttr.1514704.
12. I. Prawira, N. A. C. Andryani, and E. Yufriadi, *Technology Acceptance Readiness Analysis in the Context of Digital Tourism Village Using Machine Learning Approach*, in *Proceedings of the 2024 International Conference on Information Management and Technology (ICIMTech)*, pp. 94–98, 2024. DOI: https://doi.org/10.1109/ICIMTech63123.2024.10780442.
13. R. Karim, G. G. G. Goh, Y. L.-E. Lee, and A. Zeb, *To Be Digital Is to Be Sustainable—Tourist Perceptions and Tourism Development Foster Environmental Sustainability*, *Sustainability*, vol. 17, no. 3, p. 1053, 2025. DOI: https://doi.org/10.3390/su17031053.
14. I. Tussyadiah and G. Miller, *Perceived Impacts of Artificial Intelligence and Responses to Positive Behaviour Change Intervention*, in *Information and Communication Technologies in Tourism 2019*, J. Pesonen and J. Neidhardt, Eds., pp. 359–370, Cham: Springer International Publishing, 2019. DOI: https://doi.org/10.1007/978-3-030-05940-8_28.
15. S. M. C. Loureiro, J. Guerreiro, and I. Tussyadiah, *Artificial Intelligence in Business: State of the Art and Future Research Agenda*, *Journal of Business Research*, vol. 129, pp. 911–926, 2021. DOI: https://doi.org/10.1016/j.jbusres.2021.02.019.
16. T. Tanantong and P. Wongras, *A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand*, *Systems*, vol. 12, no. 1, p. 28, 2024. DOI: https://doi.org/10.3390/systems12010028.
17. D. Buhalis and I. Moldavska, *Voice Assistants in Hospitality: Using Artificial Intelligence for Customer Service*, *Journal of Hospitality and Tourism Technology*, vol. 13, no. 3, pp. 386–403, 2021. DOI: https://doi.org/10.1108/JHTT-03-2021-0104.
18. U. Gretzel, M. Sigala, Z. Xiang, and C. Koo, *Smart Tourism: Foundations and Developments*, *Electronic Markets*, vol. 25, no. 3, pp. 179–188, 2015. DOI: https://doi.org/10.1007/s12525-015-0196-8.
19. A. P. Tedjakusuma, L.-W. Liu, I. J. Eunike, and A. D. K. Silalahi, *Rethinking Information Quality: How Trust in ChatGPT Shapes Destination Visit Intentions*, *Tourism and Hospitality*, vol. 6, no. 4, p. 178, 2025. DOI: https://doi.org/10.3390/tourhosp6040178.
20. S. V. Hanji, N. Navalgund, S. Ingalagi, S. Desai, and S. S. Hanji, *Adoption of AI Chatbots in Travel and Tourism Services*, in *Proceedings of the Eighth International Congress on Information and Communication Technology*, X.-S. Yang, R. S. Sherratt, N. Dey, and A. Joshi, Eds., pp. 713–727, Singapore: Springer Nature, 2024. DOI: https://doi.org/10.1007/978-981-99-3236-8_57.
21. G. Çalışkan, İ. Yayla, and H. Pamukçu, *The Use of Augmented Reality Technologies in Tourism Businesses from the Perspective of UTAUT2*, *European Journal of Innovation Management*, ahead-of-print, 2023. DOI: https://doi.org/10.1108/EJIM-04-2023-0271.
22. S. Kamboj and R. Joshi, *Examining the Factors Influencing Smartphone Apps Use at Tourism Destinations: A UTAUT Model Perspective*, *International Journal of Tourism Cities*, ahead-of-print, 2020. DOI: https://doi.org/10.1108/IJTC-05-2020-0094.
23. I. Tussyadiah, *A Review of Research into Automation in Tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism*, *Annals of Tourism Research*, vol. 81, p. 102883, 2020. DOI: https://doi.org/10.1016/j.annals.2020.102883.
24. S. Gupta, T. Sufi, and P. Gautam, *Role of Technological Transformation in Shaping Millennials' Travel Behaviour: A Review*, in *Proceedings of the International Conference on Reliability, Infocom Technologies and Optimization (ICRITO)*, pp. 1–6, 2022. DOI: https://doi.org/10.1109/ICRITO56286.2022.9965175.
25. A. Q. Tran, L. H. Nguyen, H. S. A. Nguyen, C. T. Nguyen, L. G. Vu, M. Zhang, T. M. T. Vu, S. H. Nguyen, B. X. Tran, C. A. Latkin, R. C. M. Ho, and C. S. H. Ho, *Determinants of Intention to Use Artificial Intelligence-Based Diagnosis Support System Among Prospective Physicians*, *Frontiers in Public Health*, vol. 9, p. 755644, 2021. DOI: https://doi.org/10.3389/fpubh.2021.755644.
26. W. Wu, B. Zhang, S. Li, and H. Liu, *Exploring Factors of the Willingness to Accept AI-Assisted Learning Environments: An Empirical Investigation Based on the UTAUT Model and Perceived Risk Theory*, *Frontiers in Psychology*, vol. 13, p. 870777, 2022. DOI: https://doi.org/10.3389/fpsyg.2022.870777.
27. K. H. Bhuiyan, S. Ahmed, and I. Jahan, *Consumer Attitude toward Using Artificial Intelligence (AI) Devices in Hospitality Services*, *Journal of Hospitality and Tourism Insights*, vol. 7, no. 2, pp. 968–985, 2024. DOI: https://doi.org/10.1108/JHTI-08-2023-0551.
28. R. Chenavaz and S. Dimitrov, *Artificial Intelligence and Dynamic Pricing: A Systematic Literature Review*, *Journal of Applied Economics*, vol. 28, 2025. DOI: https://doi.org/10.1080/15140326.2025.2466140.
29. M. Khan, Z. Irfan, and K. Muley, *Chatbot Adoption in Travel and Tourism Services*, 2023.
30. T. Tanantong, *An Extended UTAUT Model for Analyzing Users' Acceptance Factors for Artificial Intelligence Adoption in Human Resource Recruitment: A Case Study of Thailand*, Preprints, 2023. DOI: https://doi.org/10.20944/preprints202311.1612.v1.
31. V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, *User Acceptance of Information Technology: Toward a Unified View*, *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003. DOI: https://doi.org/10.2307/30036540.
32. M. B. Ali, M. R. Tuhin, M. A. Alim, M. Rokonuzzaman, S. Rahman, and M. Nuruzzaman, *Acceptance and Use of ICT in Tourism: The Modified UTAUT Model*, *Journal of Tourism Futures*, 2022. DOI: https://doi.org/10.1108/JTF-06-2021-0137.
33. D. Cao, Y. Sun, E. Goh, R. Wang, and K. Kuiavska, *Adoption of Smart Voice Assistants Technology among Airbnb Guests: A Revised Self-Efficacy-Based Value Adoption Model (SVAM)*, *International Journal of Hospitality Management*, vol. 101, p. 103124, 2022. DOI: https://doi.org/10.1016/j.ijhm.2021.103124.
34. M. J. Kim and C. M. Hall, *A Hedonic Motivation Model in Virtual Reality Tourism: Comparing Visitors and Non-Visitors*, *International Journal of Information Management*, vol. 46, pp. 236–249, 2019. DOI: https://doi.org/10.1016/j.ijinfomgt.2018.11.016.
35. M. Abubakar, M. Zafar, Z. Asghar, and A. Malik, *Determining Behavioral Intention to Use Artificial Intelligence in the Hospitality Sector of Pakistan: An Application of the UTAUT Model*, *Journal of Tourism, Hospitality, and Services Industries Research*, vol. 4, p.

64, 2024. DOI: https://doi.org/10.52461/jths.v4i01.3041.
36. S. Sharma, D. Sood, and N. Kumar, *The Smart Traveler: Impact of Artificial Intelligence on Tourist Behavior*, in *Artificial Intelligence in Tourism and Hospitality*, pp. 191–206, 2024. DOI: https://doi.org/10.4018/979-8-3693-3972-5.ch008.
37. E. Fernando, R. B. Ikhsan, and D. R. Parlindungan, *Analysis Intention to Use of Smart Tourism Application with Model Extended UTAUT2 Approach*, in *2023 International Conference on Information Management and Technology (ICIMTech)*, pp. 36–41, 2023. DOI: https://doi.org/10.1109/ICIMTech59029.2023.10278022.
38. H. Choung, P. David, and A. Ross, *Trust in AI and Its Role in the Acceptance of AI Technologies*, *International Journal of Human–Computer Interaction*, vol. 39, no. 9, pp. 1727–1739, 2023. DOI: https://doi.org/10.1080/10447318.2022.2050543.
39. R. W. Brislin, *Translation and Content Analysis of Oral and Written Materials*, in *Handbook of Cross-Cultural Psychology*, vol. 2, H. C. Triandis and J. W. Berry, Eds., pp. 389–444, Boston, MA: Allyn and Bacon, 1980.
40. J. F. Hair, C. M. Ringle, and M. Sarstedt, *PLS-SEM: Indeed a Silver Bullet*, *Journal of Marketing Theory and Practice*, vol. 19, no. 2, pp. 139–152, 2011. DOI: https://doi.org/10.2753/MTP1069-6679190202.
41. C. M. Ringle, S. Wende, and J.-M. Becker, *SmartPLS 4*, Computer software, SmartPLS GmbH, Bönningstedt, Germany, 2024. Available at: https://www.smartpls.com/.
42. C. Fornell and D. F. Larcker, *Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics*, *Journal of Marketing Research*, vol. 18, no. 3, pp. 382–388, 1981. DOI: https://doi.org/10.1177/002224378101800313.
43. J. F. Hair, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*, Cham: Springer International Publishing, 2021. DOI: https://doi.org/10.1007/978-3-030-80519-7.
44. J. Henseler, C. M. Ringle, and M. Sarstedt, *A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling*, *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015. DOI: https://doi.org/10.1007/s11747-014-0403-8.
45. N. Kock and G. Lynn, *Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations*, *Journal of the Association for Information Systems*, vol. 13, no. 7, pp. 546–580, 2012. DOI: https://doi.org/10.17705/1jais.00302.
46. W. W. Chin, *The Partial Least Squares Approach for Structural Equation Modeling*, in *Modern Methods for Business Research*, G. A. Marcoulides (Ed.), Lawrence Erlbaum Associates, Mahwah, NJ, pp. 295–336, 1998.
47. B. Neuhofer, D. Buhalis, and A. Ladkin, *Smart Technologies for Personalized Experiences: A Case Study in the Hospitality Domain*, *Electronic Markets*, vol. 25, no. 3, pp. 243–254, 2015. DOI: https://doi.org/10.1007/s12525-015-0182-1.
48. T. A. Bach, A. Khan, H. Hallock, G. Beltrão, and S. Sousa, *A Systematic Literature Review of User Trust in AI-Enabled Systems: An HCI Perspective*, *International Journal of Human–Computer Interaction*, vol. 40, no. 5, pp. 1251–1266, 2024. DOI: https://doi.org/10.1080/10447318.2022.2138826.