PASOS
Revista de Turismo y Patrimonio Cultural
www.pasosonline.org

Vol. 23 N.º 1. Págs. 89-102. enero-marzo 2025
https://doi.org/10.25145/j.pasos.2025.23.006

Exploring tourists' intention to use smart tourism apps

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Abstract: This study investigates tourists' intention to use apps when travelling and the factors that influence this intention. Although various studies have addressed the adoption of different technologies, how tourists approach technologies featuring smart destination functions has scarcely been studied. To study this area, we used a model based on the theoretical UTAUT2 model to understand the motivations behind the adoption of these apps. An online survey was conducted, resulting in 107 responses. We then tested our model using partial least squares structural equation modelling (PLS-SEM). The results suggest that outcome expectancy, habit, and facilitating conditions positively influence intention to use tourism apps. However, we were unable to confirm that effort expectancy, social influence, hedonic motivation, and the price/value relationship affect intention to use. At the end of the article, we discuss possible practical implications for developers and tourist destination managers.

Keywords: apps; smart tourism; destination marketing; intention to use; UTAUT2

Explorando la intención de los turistas de utilizar aplicaciones de turismo inteligente

Resumen: El presente estudio investiga la intención de los turistas de usar aplicaciones durante sus viajes y los factores que influyen en dicha intención. Aunque diversos estudios han abordado la adopción de distintas tecnologías, apenas se ha estudiado el comportamiento de los turistas con el conjunto de tecnologías con funcionalidades de un destino inteligente. Para ello, se ha contrastado un modelo basado en el modelo teórico de la UTAUT2 para comprender las motivaciones para la adopción de estas aplicaciones. Se ha realizado una encuesta online con 107 respuestas. El modelo fue testado usando ecuaciones estructurales mediante PLS. Los resultados sugieren que la expectativa de resultado, el hábito y los factores condicionantes influyen positivamente en la intención de uso de las aplicaciones turísticas. Sin embargo, no se puede confirmar que la expectativa de esfuerzo, la influencia social, la motivación hedónica y la relación valor/precio, afecten a la intención de uso. También se discuten posibles implicaciones prácticas para desarrolladores y gestores de destinos turísticos.

Palabras clave: apps; turismo inteligente; marketing de destinos; intención de uso; UTAUT2

1. Introduction

Technological advances have fostered a series of changes in the sphere of tourism and play a fundamental role in the quest to make destinations more appealing (Gavilán, Martínez-Navarro & Fernández-Lores, 2017), giving rise to the reorientation of tourism ecosystems towards a smarter approach.

Within this scope, mobile apps offer a range of features that can help, for instance, to enrich the tourism experience by providing information in real time, encouraging users to interact with the destination, and aiding trip planning and organisation.

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Cite: David-Negre, T.D. & Gutiérrez Taño, D. (2025). Exploring tourists' intention to use smart tourism apps. *PASOS. Revista de Turismo y Patrimonio Cultural.* 23(1), 89-102. https://doi.org/10.25145/j.pasos.2025.23.006

Furthermore, the advancement of artificial intelligence is a driving force behind the creation of innovative apps for the sector. The availability of these apps has increased significantly and it is therefore crucial to attract and maintain users. This means that research related to the usage behaviour of this type of technology is essential for ensuring its success.

The acceptance and intention to use some of these apps have been studied separately in the tourism sector; however, no research has been carried out into the available technologies related to smart tourism destinations. This study thus investigates the determining factors of tourists' intention to use and adopt these apps. That is, what triggers a tourist to download a mobile app? What factors stop them from downloading and using it? How could this experience be improved? Answering all these questions could facilitate the successful development of and investment in such apps, and enable the tourist experience to be improved to meet requirements.

Therefore, this study intends to explain tourists' intention to use smart tourism apps when travelling in terms of effort expectancy, performance expectancy, social influence, hedonic motivation, habit, conditioning factors, and price/value relationship.

To achieve the objectives proposed, we conducted a quantitative study consisting of a self-administered online survey completed by residents of the Canary Islands over 18 years of age who had travelled for pleasure during the previous year. We obtained a total of 107 valid participants. The data were then analysed by means of the partial least squares technique (PLS-SEM), using the software Smart PLS v.4.0.8.5 (Ringle, Wende & Becker, 2022).

The conceptual model used for the study is the theory of acceptance and use of information technology (UTAUT2). We took this decision because the significant increase in tourists' preference to use apps and new technologies has favoured the formulation of different models and theories that seek to understand the motivations behind their adoption.

The results of this study have given us a greater understanding of the factors that influence the motivations, obstacles and opportunities relating to the use of mobile apps by tourists when travelling. They have also enabled us to find out to what extent people are familiar with said apps and how inclined they are to use them.

In the following sections we review the main contributions made by researchers regarding the premises that explain intention to adopt smart tourism apps when travelling; we then set out the methodology used in the study, together with the main results and findings. Finally, we discuss the results obtained, comparing them with previous research and we propose a series of practical implications derived from the results, as well as the main conclusions of our research work.

2. Literature review

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. in 2003 to study the adoption and use of technologies by employees through effort expectancy, performance expectancy, social influence, and conditioning factors. Earlier research has demonstrated that this model can explain usage intention across various technologies (Baptista & Oliveira, 2015; Lin & Anol, 2008; Marchewka & Kostiwa, 2007).

Venkatesh et al. extended this model in 2012, enabling consumer acceptance and use of technology to be explained, and the name was changed to UTAUT2. UTAUT2, in contrast to UTAUT's primary organisational focus, directs attention towards consumers and the factors influencing their intentions to adopt new technologies. This is because the uptake of technology among employees and clients varies significantly. Clients actively opt for technology use, often selecting from a range of available options, while employees' adoption is shaped by their supervisors and factors related to their work. The extended model included hedonic motivation, habit, and price value as additional constructs to the four previous ones used to understand consumer behaviour and intentions. Moreover, this model has undergone rigorous validation in numerous studies that specifically examined the relationship between the predisposition to use specific tourism applications, such as maps, bookings, with augmented reality, content created by users, etc. (Assaker et al., 2020; Çalışkan et al., 2023; Gupta et al., 2017; Medeiros et al., 2022; Sia et al., 2023). While in certain instances, this theory undergoes slight modifications or expansions.

UTAUT2 is the latest technology adoption model and demonstrates a greater predictive validity than previous models (Venkatesh et al., 2012). The ongoing exploration and application of this model to various contexts, including tourism, signify its versatility and relevance. It is interesting to continue investigating and applying the model to other contexts such as tourism and, more specifically, the use of apps in tourism, where the utilisation of applications plays a crucial role in enhancing traveller experiences (Venkatesh y Morris, 2000). This exploration will not only contribute to the theoretical understanding of technology adoption but also provide practical implications for stakeholders within the tourism industry.

Smart apps for tourism

Tourists are increasingly using smart apps on their mobile phones when travelling to tourist destinations (Jeong & Shin, 2020), thus revolutionising the way that they travel and interact with destinations and the different agents that comprise them. This means that these technologies have a significant effect on such destinations (Huang et al., 2017), which are currently in a process of digital transformation (Buhalis, 2020). These technologies include a range of mobile apps:

- Maps and navigation: mobile apps that provide interactive maps that help users to find their location and directions to different places of interest.
- Information in real time: integration of location services and real-time data providers to give up-to-date information on traffic, the weather and local news.
- Improved tourist experiences: use of technologies such as augmented reality and audio guides to enhance visits to museums, places of interest and tourist destinations, offering additional information and a more immersive experience.
- Additional services: apps that include complementary services such as information on the availability of battery charging stations for electric vehicles, parking options, restaurant recommendations in the city, or taxi bookings.

Tourism mobile apps help to optimise and enrich the travel experience (Jeong & Shin, 2020). A number of studies have analysed tourist behaviour in terms of the use of apps relating to maps and navigation, location sharing and safety, travel bookings, taxi bookings, payments via mobile phone, medical assistance, tourism apps, mobile apps, augmented reality, privacy, travel guides, traffic, the weather, local news, enhanced tourist experiences, availability of battery charging stations, parking options, restaurant recommendations, and smart tourism technologies in general (Amaro & Duarte, 2013; Buhalis & Amaranggana, 2014; Chung et al., 2018; Gupta et al., 2017; Jeong & Shin, 2020; Khayer & Bao, 2019; Kurata & Hara, 2013; Lu & Su, 2009; Medeiros et al., 2022; Nikolskaya et al., 2019; Sia et al., 2023; Voicu et al., 2022; Weng et al., 2017).

New technologies like AI can facilitate the development of new apps that radically transform the guest's experience in the tourism and hospitality industry by enabling the creation of tailored services and dynamics, which are developed using technology and/or by humans and augmented by AI. Examples of AI applications in tourism include intelligent travel assistants, conversational systems, and language translation applications. This phenomenon arises from the capability of artificial intelligence to create solutions mimicking human behaviour, employing attributes resembling human characteristics, encapsulated within computer algorithms (Lu et al., 2019).

AI can also help us to understand individual needs and the relevant contexts in real time to empower the co-creation of value, as well as make highly effective predictions based on individual preferences, which would enable emotional and sustainability variables to be included when calculating customer lifetime value (Bulchand-Gidumal et al., 2023). Likewise, there is a growing trend in the adoption of AI-powered applications such as virtual assistants like Siri, Cortana, Alexa or Macy's (Lu et al., 2019). Tourism is already feeling the impact of technology, as it disrupts conventional practices and revolutionises the entire industry (Buhalis & Moldavska, 2022). Therefore, we must remain attentive to how these tools will adapt and be applied in the tourism sector.

Precursors of intention to use smart apps for tourism

Below we put forward a series of hypotheses related to the use of the UTAUT2 model to investigate tourist behaviour relating to the use of smart tourism apps when travelling. These hypotheses have arisen from the application of the UTAUT2 model in previous studies, which empirically showed the relationships in the model in other contexts (Gupta & Dogra, 2017).

According to Venkatesh et al. (2003) and Venkatesh et al. (2012), effort expectancy in terms of understanding a technology may influence the decision to use it, more intuitive technologies being preferred. Previous studies confirm this relationship (Ciftci et al., 2021; Moriuchi, 2021; Chi-et-al., 2020; Gupta & Dogra, 2017). We therefore propose the following hypothesis:

H1: Effort expectancy has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

A range of studies have shown that the expectancy of obtaining benefits when carrying out certain activities is the most influential factor when predicting intention to use (Venkatesh et al., 2003; Venkatesh et al., 2012). This relationship is supported by previous studies (Ciftci et al., 2021; Moriuchi, 2021; Chi-et-al., 2020; Gupta & Dogra, 2017), and we therefore put forward the following hypothesis:

H2: Performance/outcome expectancy has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

Social influence, that is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003) addresses how friends, families and other individuals affect intention to use a new system. Previous studies have confirmed a positive correlation between social influence and behavioural intentions in the use of technologies (Ciftci et al., 2021; Moriuchi, 2021; Chi-et-al., 2020; Gupta & Dogra, 2017). We have therefore formulated the following hypothesis:

H3: Social influence has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

The satisfaction that is experienced when using a technology is known as hedonic motivation and it has been proven to influence technology use (Ciftci et al., 2021; Moriuchi, 2021; Chi-et-al., 2020; Venkatesh et al., 2012). For this reason, this perceived enjoyment is also included as a determinant in the UTAUT2 model. The following hypothesis has thus been formed:

H4: Hedonic motivation has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

Habit has been defined as the tendency to exhibit behaviours automatically through learning and is sometimes likened to automaticity (Venkatesh et al., 2012). Different findings have shown that habit has an influence on technology use through different underlying processes. It has been brought to light that inclination towards technology use increases in direct proportion to past habits (Limayem et al., 2007). We therefore propose the following hypothesis:

H5: Habit has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

The way in which consumers perceive the available resources and support enabling them to perform an action is known as conditioning factors (Venkatesh et al., 2003). Previous studies (Gupta & Dogra, 2017) have shown that these conditioning factors have significant effects on the actual use of and intention to use technologies. Thus, we suggest the following hypothesis:

H6: Conditioning factors have a positive influence on tourists' intention to adopt smart tourism apps when travelling.

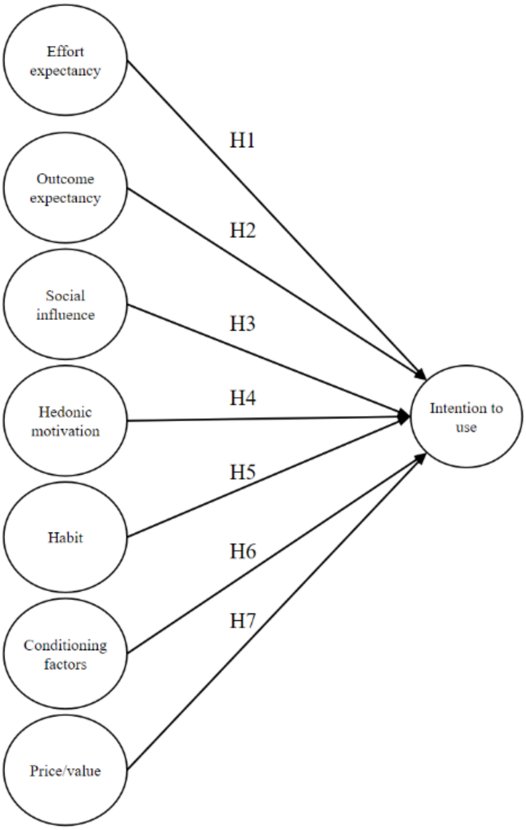
Price value takes into consideration the monetary cost that using a technology involves (Venkatesh et al., 2012). Previous studies confirm that the price value will be positive when the benefit perceived by the consumer is greater than the average cost (Gupta & Dogra, 2017). We put forward the following hypothesis:

H7: The price/value relationship has a positive influence on tourists' intention to adopt smart tourism apps when travelling.

Conceptual model

According to the literature review carried out and taking the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as a basis, in Figure 1 we outline the proposed theoretical model to explain tourists' intention to use smart tourism apps when travelling. The model suggests that intention to use depends on effort expectancy, performance expectancy, social influence, hedonic motivation, habit, conditioning factors, and value/price relationship.

Figure 1. Proposed conceptual model



Source: UTAUT2 model (Venkatesh, et al., 2012).

3. Methodology

Measurement

All the study constructs were measured using previously validated existing scales. The items were adapted from previous studies in the context of literature on intention to use and acceptance of information technology. The scales were adapted from earlier research in the areas of mobile Internet, mobile telephones, and information technology. All items of the questionnaire were sourced from prior literature and modified as needed to align with the context of this study. The items addressing the UTAUT constructs of Effort expectancy, Outcome expectancy, Social influence, Hedonic motivation, Habit and Conditioning factors were taken from the works of Venkatesh et al. (2012), Morosan (2011), Gupta and Dogra (2017) and Ciftci et al. (2021). Price/value was assessed using questions formulated by Venkatesh et al. (2012) and Gupta and Dogra (2017). The items for behavioural intentions were adopted from Moriuchi (2021), Okumus et al. (2018) and Gupta and Dogra (2017). Table 2 shows the items used in the survey. All the study construct items were measured using a 7-point Likert scale (1 = 'totally disagree' and 7 = 'totally agree').

The constructs intention to use, effort expectancy, performance expectancy, social influence, hedonic motivation, and habits were formulated as reflective (Mode A), whereas the conditioning factors and the price/value relationship were formulated as formative (Mode B) given that their items represented different dimensions.

Sampling, data collection and data analysis

To gather the study data, we conducted a self-administered online survey using the software LimeSurvey. To guarantee that all participants had an adequate understanding of what we were referring to with "apps when travelling", at the start of the survey we included a written explanation with examples.

The target population of this study was individuals aged 18 or over who lived in the Canary Islands and had a smartphone. They had to have used mobile apps on their smartphone in the previous six months and to have travelled for pleasure in the previous 12 months. Screening questions were used to filter respondents who met the requirements. In this study, we used snowball sampling, a non-probability convenience sampling technique. The responses were subject to quality controls in three areas: time taken to respond, control questions, and straightlining. A total of 107 valid responses were gathered in March 2022.

The partial least squares (PLS-SEM) technique was applied to analyse the proposed conceptual model and to test the hypotheses. To do this, we used the software Smart PLS v.4.0.8.5 (Ringle, Wende & Becker, 2022). PLS-SEM is a suitable tool when using mixed models containing both reflexive (Mode A) and formative (Mode B) constructs.

Table 1 shows the profile of the respondents whereby 50.5% were female and 49.5% male. In terms of age, 43.9% were between 18 and 24 years of age, 22.4% were aged from 25 to 44, and 33.6% were over 44. In terms of education, 57.9% were university graduates, 33.6% had A-level equivalent studies or vocational training, and 8.4% a basic primary or secondary education. Regarding financial status, 60.7% of the respondents considered theirs to be average, 13.1% below average and 26.2% above average. As far as occupation is concerned, just under half of those surveyed were employed, 38.3% were students, 5.6% unemployed, and self-employed individuals and business owners or managers each accounted for 3.7% of the sample.

Table 1: Sample structure

Options	Results
Sex:	
- Female	50.5%
- Male	49.5%
Age:	
- 18–24 years	43.9%
- 25–44	22.4%
- >44	33.6%
Education:	
- Primary/secondary	8.4%
- A-level equivalent/vocational training	33.6%
- University studies	57.9%
Financial status:	
- Below average	13.1%
- Average	60.7%
- Above average	26.2%
Occupation:	
- Business owner/manager	3.7%
- Self-employed	3.7%
- Employed	48.6%
- Student	38.3%
- Unemployed	5.6%
Total	107

4. Results

Descriptive analysis

Table 2 shows the results of the descriptive analysis (mean and standard deviation) of the construct items in the proposed model. On a scale from 1 to 7, we can see that the intention construct items obtain values between 5.50 and 5.67, which is well above the middle of the scale, thus showing that tourists have a high level of intention to use smart tourism apps when travelling.

Effort expectancy, which represents the perceived level of ease of use of the apps, also has high values ranging from 5.09 and 5.66 and we therefore can see that this type of app is relatively easy to use.

Table 2: Descriptive analysis and evaluation of the measurement model

Reflective (Mode A) constructs		Mean	Standard deviation	Loading	Composite reliability (rho_c)	Average Variance Extracted (AVE)
	Intention to use apps				0.917	0.787
IC1	I intend to use these apps when I travel next	5.67	0.998	0.914		
IC3	I plan to use these apps every time I need them when travelling	5.53	1.269	0.884		
IC4	As soon as I travel, I will use these apps	5.50	1.119	0.862		
	Effort expectancy				0.888	0.725
EE1	I find it easy to learn to use apps for the city I'm travelling to	5.09	1.418	0.858		
EE2	It wouldn't take me long to learn to use this type of apps for tourist trips	5.66	1.266	0.850		
EE3	This type of app for travelling is easy to use	5.14	1.217	0.846		
	Outcome expectancy				0.921	0.795
ER1	I find it easy to use these apps for my travels	5.68	1.170	0.922		
ER2	Using these apps helps me to save time when I'm travelling	5.65	1.158	0.910		
ER3	Apps help me to find what I'm looking for more quickly during my trip	5.90	1.098	0.841		
	Social influence				0.879	0.708
IS1	People who are important to me think that I should use these apps when travelling	4.50	1.507	0.867		
IS2	People whose opinions I value prefer me to use apps when travelling	4.64	1.383	0.870		
IS3	Most of the people I know use this type of app when travelling	4.86	1.349	0.786		
	Hedonic motivation				0.931	0.817
MH1	I think that using this type of app makes travelling more enjoyable	4.87	1.339	0.903		
MH2	I think that using this type of app makes travelling more fun	4.69	1.356	0.909		
MH3	I think that using this type of app makes travelling pleasant	5.11	1.269	0.901		
	Habit				0.899	0.748
H1	When I travel, I use these apps without even thinking about it	5.02	1.454	0.808		
H2	Using these apps is part of my routine when travelling	5.00	1.360	0.888		
H3	I usually use these apps when I travel	5.39	1.309	0.894		
2nd order formative (Mode B) constructs		Mean	Standard deviation	Weight	Sig.	VIF
	Conditioning factors					
FC1	I have the necessary resources to use these apps when I travel	5.97	1.004	0.606	***	1.216
FC2	These travel apps are compatible with other apps that I use	5.21	1.381	0.180	ns	1.203
FC3	I can get help from others when I have difficulty using these apps	5.21	1.308	0.576	***	1.056
	Price/value					
PV1	I think it's fine that ads come up when using the app as they're needed to finance it	4.34	1.962	0.744	*	1.322
PV2	I think it's fine that this type of travel app is financed by a small charge when I download it	3.10	1.743	0.046	ns	1.226
PV3	I would be willing to share my details and usage data to cover the cost of these apps	3.63	2.007	0.410	ns	1.209

Significance: * p < .05; ** p < .01; ***p < .001; ns: non-significant

The outcome expectancy items score highest on the scale. At between 5.65 and 5.90, they show the great usefulness of this type of app as perceived by tourists when travelling.

Social influence obtained one of the lowest scores; however, it is still above the middle of the scale at between 4.50 and 4.86, which implies that the opinion of people who are close to the respondents is not very important in this regard.

The hedonic motivation items also have relatively low scores ranging from 4.69 to 5.11, which suggests that this type of app is not strongly associated with experiencing an activity that is fun, or which provides self-gratification or pleasure.

The habit construct items score just over 5, which suggests a relatively habitual use of these apps by the tourists who responded to the survey.

The conditioning factors referring to perception of available resources and support for the use of these apps obtained high scores between 5.21 and 5.97.

Finally, the price/value relationship items obtained the lowest scores of all the constructs, ranging from 3.10 to 4.34, which suggests that tourists are not willing to make an effort to fund this type of apps.

Evaluation of the overall model

The results revealed SRMR model fit values of 0.076, whereby a value less than 0.08 can be considered acceptable for PLS-SEM (Henseler, Hubona & Ray, 2016). We also confirmed that there were no signs of multicollinearity between the antecedent variables of each of the endogenous constructs, as all the VIF (Variance Inflation Factor) values are below 3.

Evaluation of the measurement model

Reflective (Mode A) constructs:

The individual reliability of the indicators of the reflective (Mode A) constructs is evaluated by examining the loadings (λ) of the indicators with their respective construct. Table 2 shows that all the item loadings in the measurement model are greater than 0.707 (Carmines & Zeller, 1979).

In Table 2, we analyse construct reliability and we can see that all of the composite reliability scores (Dijkstra & Henseler, 2015) are greater than the minimum cut-off point of 0.70 (Fornell & Larcker, 1981). All the latent variables achieve convergent validity as their AVE scores are over 0.5 (Fornell & Larcker, 1981).

The results in Table 3 show that the constructs examined achieve discriminant validity as they exceed the heterotrait-monotrait (HTMT) ratio of correlations (scores below 0.85, Kline, 2011). Therefore, the measurement model was satisfactory and provided sufficient evidence in terms of reliability and convergent and discriminant validity.

Table 3: Heterotrait-monotrait ratio (HTMT)

	Effort expectancy	Outcome expectancy	Habit	Social influence	Behavioural intention	Hedonic motivation
Effort expectancy						
Outcome expectancy	0.550					
Habit	0.415	0.742				
Social influence	0.249	0.730	0.764			
Behavioural intention	0.363	0.841	0.815	0.635		
Hedonic motivation	0.198	0.598	0.637	0.742	0.644	

Formative (Mode B) constructs:

Regarding the formative (Mode B) constructs, Table 2 shows that all the VIFs of the construct items are less than 3.3 (Diamantopoulos & Siguaw, 2006) and, therefore, we can guarantee that there is no multicollinearity between the indicators. Table 2 also shows the contribution and significance of the construct items and we can see that all of them make a positive contribution, although not all of them are significant.

The contributions to the conditioning factors of the items FC1 (0.606) and FC3 (0.576) are relevant and significant, whereas the contribution of the item FC2 is not significant. Item PV1 (0.744) is the only one to make a significant contribution to the price/value construct.

Evaluation of the structural model

The relationships in the structural model were evaluated by means of bootstrapping (Hair et al., 2011), analysing the significance of the path coefficients. Given that the hypotheses specify the direction of the relationships between the variables, we used a one-tailed Student's t test with n-1 degrees of freedom, whereby n is the number of subsamples. 10,000 bootstrap samples (Hair et al., 2021) were used with the same number of cases as observations in the original sample.

Table 4: Results of the hypothesis test, variance decomposition, Q2 redundancy

Hypothesis	Relationships	Path Coefficient	Sig.	T Statistics	Variable Correlation	R^2	Q^2
	Intention to use apps					**0.701**	**0.64**
H1	Effort expectancy -> Behavioural intention	-0.094	ns	1.533	0.306	-0.029	
H2	Outcome expectancy -> Behavioural intention	0.465	***	5.438	0.745	0.346	
H3	Social influence -> Behavioural intention	-0.128	ns	1.453	0.530	-0.068	
H4	Hedonic motivation -> Behavioural intention	0.113	ns	1.301	0.570	0.064	
H5	Habit -> Behavioural intention	0.358	***	4.406	0.704	0.252	
H6	Conditioning factors -> Behavioural intention	0.222	***	3.295	0.551	0.122	
H7	Price/value -> Behavioural intention	0.050	ns	0.773	0.255	0.013	

Figure 2. Structural model results

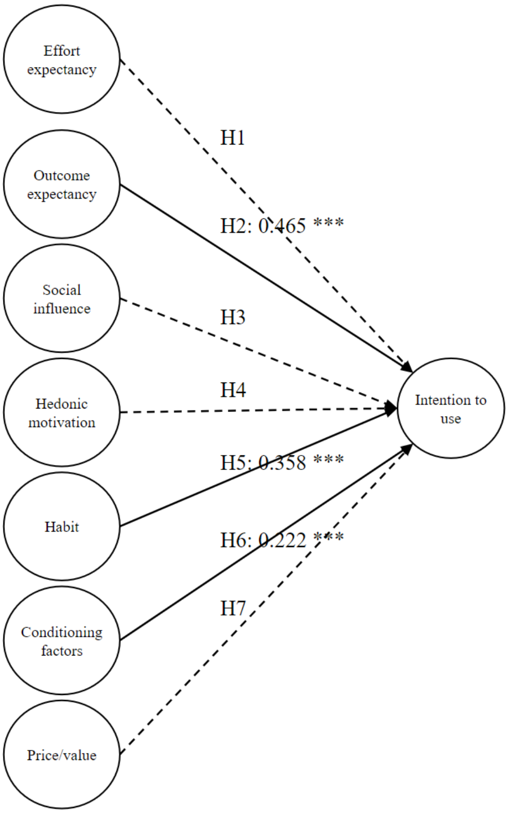


Table 4 and Figure 2 show the results of the proposed relationships in the model.

Outcome expectancy clearly has a positive influence on intention to use apps (H2: β=0.465, p<0.001). Habit also has a positive influence on intention to use apps (H5: β=0.358, p<0.001), as do conditioning factors (H6: β=0.222, p<0.001). However, we were unable to confirm the influence that the variables effort expectancy, social influence, hedonic motivation, and price/value relationship have on intention to use.

There is sufficient evidence to accept research hypotheses H2, H5 and H6, but we were unable to confirm hypotheses H1, H3, H4 and H7.

The determination coefficient (R2) represents a measurement of predictive power that indicates the amount of variance of a construct, which is explained by the predictive variables of said endogenous construct in the model. The proposed model explains 70.1% of tourists' intention to use smart apps when travelling, which is considered to be a high score (Chin, 1998) (Table 4).

As a criterion to measure the predictive relevance of the constructs, we used the Stone-Geisser test (Stone, 1974; Geisser, 1975), and Table 4 shows that the Q2 value is greater than zero, which indicates that the model has predictive power.

5. Discussion

The main findings of this study coincide with previous research; however, we have also identified several significant differences regarding the adoption of technologies by tourists. Hypotheses H2, H5 and H6 were confirmed, meaning that outcome expectancy, habit and conditioning factors have a positive influence on intention to use tourist apps when travelling. These findings suggest consistency in the importance of these factors in technology adoption in different tourism contexts and reinforce the validity of our results.

Outcome expectancy clearly has the biggest influence on tourists' intention to use smart apps and similar results have been found in previous studies (Antunes & Amaro, 2016; Oliveira et al., 2014). Therefore, we can conclude that the greater the perception of usefulness of the technology, the greater tourists' intentions to use apps when travelling. This further highlights the critical link between perceived usefulness and tourists' inclination to utilise app technology while travelling.

The results also suggest that habit is a great predictor of intentions to use smart tourism apps. These results are consistent with previous research (e.g. Gupta & Dogra, 2017; Arenas-Gaitán, Peral-Peral & Ramón-Jerónimo, 2016). Thus, habitual use of apps implies that tourists' intention to use them when travelling is greater. Furthermore, this result highlights the importance of considering users' past behaviour when predicting their future behaviour in relation to technology adoption in tourism.

Facilitating conditions are another highly significant precursor to behavioural intentions, which coincides with the results of previous studies (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Venkatesh et al., 2012). Thus, tourists may have a greater intention to use travel apps when they feel that they have the necessary resources and support to do so. In accordance with these findings, it becomes essential for stakeholders in the tourism sector to guarantee the availability of sufficient resources and support mechanisms, thus enabling tourists to effectively utilise travel apps and enhancing their overall travel experience.

The results revealed that there is not a significant relationship between four of the UTAUT2 constructs and behavioural intentions, specifically effort expectancy, social influence, hedonic motivation, and price/value.

The effort expectancy finding coincides with the findings of several existing studies (Baptista & Oliveira, 2015; Faria, 2012; Zhou et al., 2010). This is probably due to the high level of use of other mobile technologies that users find very easy to operate and become accustomed to very quickly. This may be related to the proliferation of smartphones and mobile applications in modern society, in which users have become accustomed to different interfaces and functionalities that prioritise simplicity and convenience.

The non-significant relationship between social influence and behavioural intentions is consistent with previous research findings (Baptista & Oliveira, 2015; Wang & Yi, 2012). Previous literature suggests that as experience with technology increases over time, social influence decreases (Venkatesh & Morris, 2000). This may be because users rely more on their own experience and judgement when evaluating the usefulness and desirability of a technology, rather than relying exclusively on social influence.

The price/value finding was consistent with previous research (Baptista & Oliveira, 2015; Yang et al., 2012). The possible reason for this could be the low cost of technology and the wide availability of tourism apps, which are generally free of charge, on mobile devices.

Regarding hedonic motivation, the results obtained contradict those of previous studies (Baptista & Oliveira, 2015; Raman & Don, 2013; Venkatesh et al., 2012). The lack of influence of hedonic motivation on intention to use smart tourism apps may be explained by the functional nature of these apps, extensive prior experience of the technology, and the context of use, which implies more usefulness than pleasure or fun.

6. Implications

The findings of this study may provide useful ideas for professionals, as understanding the constructs that are significant to technology acceptance may be useful for developing and/or improving new apps, which may in turn lead to greater acceptance by tourists. The high usage intention and favourable perception of smart tourism applications among tourists have important practical implications for tourism service providers and application developers. These findings suggest that there is a real demand and potential market for these types of technologies. Due to the lack of social influence, traditional marketing strategies that focus on peer influence may not be effective in promoting the use of these applications among tourists. Likewise, the perception of a lack of resources could indicate the need to provide greater support and training for their use.

Therefore, we suggest that tourism app developers could incorporate extremely useful features that meet tourist requirements, exploring the possibility of including them in a single app so that travellers do not have to search through other apps to find the information they require and will eventually form the habit of using these apps when travelling.

Likewise, app developers should place emphasis on providing effective, useful and trustworthy information which would result in a greater acceptance of the apps by travellers. We also suggest that marketing specialists should focus on raising awareness of the usefulness and potential of travel apps so that more tourists adopt this technology. Thus, this study presents a series of practical implications that are of interest to tourism companies, destination marketing organisations and app developers.

7. Conclusions

Our society is faced with an increase in digitalisation and with it the challenge of being able to manage many new apps so that appropriate investment can be made in that area. Is our society predisposed to the acceptance and adoption of digitization? In this study, we tested the UTAUT2 model to analyse the factors that have a bearing on the acceptance and adoption of smart tourism apps by tourists when travelling. Due to the scarcity of previous research on this subject, this study can enrich our understanding of user needs and demands in terms of services provided by travel apps at smart destinations.

We can conclude that the tourists in the sample studied show a high degree of intention to use smart tourism apps when travelling, perceiving them to be easy to use and highly useful. This finding is significant in the current context of the digitalization of the tourism sector, where technologies play an increasingly important role in the travel experience. We also found that they are not influenced by those around them as far as this usage is concerned and they do not perceive that they have the available resources or support to use them when travelling. These findings shed light on the factors that may affect the actual adoption of digital technologies in the context of smart tourism. We must also mention that these apps do not bring them enjoyment and they are not willing to invest in them even though they use them habitually. Raising questions about the effectiveness and perceived usefulness of these applications, despite their prevalence in today's tourism market. This could lead to a poor user experience and a negative perception of its usefulness.

While this study provides valuable insights into the acceptance and adoption of smart tourism apps, some limitations warrant consideration: the sample size, which may be insufficient to generalise the results; the sample selection, potentially introducing biases; and the fact that only intention was measured and not the actual behaviour of the participants. Likewise, in future studies, novel variables should be incorporated into the UTAUT2 model to enrich the research. In doing so, we can deepen our comprehension of user preferences and behaviours within the dynamic realm of smart tourism technology, thereby bolstering the advancement and deployment of impactful digital solutions within the tourism industry.

References

Amaro, S., & Duarte, P. (2013). Online travel purchasing: A literature review. *Journal of Travel & Tourism Marketing*, 30(8), 755-785.

Assaker, G., Hallak, R., & El-Haddad, R. (2020). Consumer usage of online travel reviews: Expanding the unified theory of acceptance and use of technology 2 model. *Journal of Vacation Marketing*, 26(2), 149-165.

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior,* 50, 418-430.

Buhalis, D., & Amaranggana, A. (2014). Smart tourism destinations. In Information and Communication Technologies in Tourism 2014: Proceedings of the International Conference in Dublin, Ireland, January 21-24, 2014 (553-564). Springer International Publishing.

Buhalis, D., & Moldavska, I. (2022). Voice assistants in hospitality: using artificial intelligence for customer service. *Journal of Hospitality and Tourism Technology*, 13(3), 386-403.

Buhalis, D. (2020). Technology in tourism-from information communication technologies to eTourism and Smart tourism towards ambient intelligence tourism: A perspective article. *Tourism Review,* 75(1), 267-272.

Bulchand-Gidumal, J., William Secin, E., O'Connor, P., & Buhalis, D. (2023). Artificial intelligence's impact on hospitality and tourism marketing: exploring key themes and addressing challenges. *Current Issues in Tourism,* 1-18.

Carmines, E. G., & Zeller, R. A. (1979). Reliability and validity assessment. *Sage publications.*

Chi, O. H., Gursoy, D., & Chi, C. G. (2020). Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. *Journal of Travel Research, 61(1), 170-185.*

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research,* 295(2), 295-336.

Chin, W. W. (2009). How to write up and report PLS analyses. In Handbook of partial least squares: Concepts, methods and applications (pp. 655-690). Berlin, Heidelberg: Springer Berlin Heidelberg.

Ciftci, O., Choi, E. K. C., & Berezina, K. (2021). Let's face it: are customers ready for facial recognition technology at quick-service restaurants?. *International Journal of Hospitality Management*, 95, 102941.

Chung, N., Lee, H., Kim, J. Y., & Koo, C. (2018). The role of augmented reality for experience-influenced environments: The case of cultural heritage tourism in Korea. *Journal of Travel Research,* 57(5), 627-643.

Çalışkan, G., Yayla, İ., & Pamukçu, H. (2023). The use of augmented reality technologies in tourism businesses from the perspective of UTAUT2. *European Journal of Innovation Management*.

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management,* 17(4), 263-282.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly,* 39(2), 297-316.

do Valle, P. O., & Assaker, G. (2015). Using partial least squares structural equation modeling in tourism research: A review of past research and recommendations for future applications. *Journal of Travel Research,* 55(6), 695-708.

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management,* 43, 70-88.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research,* 18(1), 39-50.

Foroughi, B., Sitthisirinan, S., Iranmanesh, M., Nikbin, D., & Ghobakhloo, M. (2023). Determinants of travel apps continuance usage intention: extension of technology continuance theory. *Current Issues in Tourism,* 1-17.

Gavilan, D., Martínez-Navarro, G., & Fernández-Lores, S. (2017). Influencia social online: nuevas tecnologías en la comunicación del sector turístico. Revista ICONO 14. *Revista Científica de Comunicación y Tecnologías Emergentes,* 15(2), 138-167.

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American Statistical Association,* 70(350), 320-328.

Gupta, A., & Dogra, N. (2017). Tourist adoption of mapping apps: A UTAUT2 perspective of smart travellers. *Tourism and Hospitality Management,* 23(2), 145-161.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Evaluation of reflective measurement models. In Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R (75-90). Springer, Cham.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice,* 19(2), 137–149.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial Management & Data systems,* 116(1), 2-20.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing,* 20, 277-319.

Huang, C. D., Goo, J., Nam, K., & Yoo, C. W. (2017). Smart tourism technologies in travel planning: The role of exploration and exploitation. *Information & Management,* 54(6), 757-770.

Jeong, M., & Shin, H. H. (2020). Tourists' experiences with smart tourism technology at smart destinations and their behavior intentions. *Journal of Travel Research,* 59(8), 1464-1477.

Kenny, D. A., & Judd, C. M. (2019). The unappreciated heterogeneity of effect sizes: Implications for power, precision, planning of research, and replication. *Psychological Methods,* 24(5), 578.

Khayer, A., & Bao, Y. (2019). The continuance usage intention of Alipay: Integrating context-awareness and technology continuance theory (TCT). *The Bottom Line,* 32(3), 211-229.

Kline, R. B. (2011). Principles and practice of structural equation modeling (3. Baskı). New York, NY: Guilford, 14, 1497-1513.

Kurata, Y., & Hara, T. (2013). CT-planner4: Toward a more user-friendly interactive day-tour planner. In Information and Communication Technologies in Tourism 2014: Proceedings of the International Conference in Dublin, Ireland, January 21-24, 2014 (73-86). *Springer International Publishing.*

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. MIS Quarterly, 705-737.

Lin, C. P., & Anol, B. (2008). Learning online social support: an investigation of network information technology based on UTAUT. *CyberPsychology & behavior*, 11(3), 268-272.

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, 80, 36-51.

Lu, H. P., & Su, P. Y. J. (2009). Factors affecting purchase intention on mobile shopping websites. *Internet Research,* 19(4), 442-458.

Marchewka, J. T., & Kostiwa, K. (2007). An application of the UTAUT model for understanding student perceptions using course management software. *Communications of the IIMA*, 7(2), 10.

Medeiros, M., Ozturk, A., Hancer, M., Weinland, J., & Okumus, B. (2022). Understanding travel tracking mobile application usage: An integration of self determination theory and UTAUT2. *Tourism Management Perspectives,* 42, 100949.

Nikolskaya, E. Y., Lepeshkin, V. A., Blinova, E. A., Kulgachev, I. P., & Ilkevich, S. V. (2019). Improvement of digital technology in the tourism sector. *Journal of Environmental Management & Tourism*, 10(6 (38)), 1197-1201.

Moriuchi, E. (2021). An empirical study of consumers' intention to use biometric facial recognition as a payment method. *Psychology & Marketing*, 38(10), 1741-1765.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management,* 12(4), 531-544.

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies,* 6(7), 157-164.

Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. Oststeinbek: SmartPLS GmbH. J. Appl. Struct. Equ. Model., http://www.smartpls.com.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research,* 69(10), 3998–4010.

Sia, P. Y. H., Saidin, S. S., & Iskandar, Y. H. P. (2023). 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.*

Stone, M. (1974). Cross-validation and multinomial prediction. *Biometrika*, 61(3), 509-515.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 115-139.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157-178.
Voicu, M. C., Bărbulescu, A., & Abrudan, D. (2022). On a City Guide App Model. *Sustainability*, 14(23), 15758.
Weng, G. S., Zailani, S., Iranmanesh, M., & Hyun, S. S. (2017). Mobile taxi booking application service's continuance usage intention by users. *Transportation Research Part D: Transport and Environment*, 57, 207-216.
Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: implications for designing mobile shopping services. *Journal of Consumer Marketing*, 27(3), 262-270.
Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760-767.

Disclosure statement

The authors report there are no competing interests to declare.

Recibido: 18/12/2023
Reenviado: 11/03/2024
Aceptado: 10/04/2024
Sometido a evaluación por pares anónimos