Understanding mobile augmented reality adoption in a consumer context

Abstract

Purpose

The aim of this study is to further our knowledge of what influences users to adopt Mobile Augmented Reality in Tourism (MART). A conceptual model is proposed, combining the extension of Unified Theory of Acceptance and Usage of Technology (UTAUT2) with Task Technology Fit (TTF), to explain behavioural intention and user behaviour of MART adopters.

Design/methodology/approach

A questionnaire was completed by a sample of 335 respondents in Portugal. Both UTAUT2 and TTF were combined into a new model from which several hypotheses were drawn based upon the literature.

Findings

The results have shown that the model explains 72% of the variance in behaviour intention to use MART and 45% of the variance in user behaviour.

Originality/value

MART is becoming increasingly known to travellers as it provides the user diverse and useful information with a real relationship with the world. By studying behaviour and what influences consumers to use MART, this study aims to advance the research into new technologies in tourism.

Keywords:

UTAUT2; Task Technology Fit; Augmented Reality; technology adoption.

1. Introduction

As the use of Augmented Reality (AR) travel applications continues to grow, it is crucial to understand what is important to tourists who are using or intend to use AR, with the purpose of reaching out to those who would be less likely to use it. Therefore, further research would be helpful in developing and evaluating Mobile Augmented Reality in Tourism (MART) to satisfy tourist behaviour needs (Olsson et al., 2011). Consequently, the main objective of this research is to determine what influences users to adopt MART.

This study proposes to integrate two theories: (1) the Task Technology Fit (TTF) model that states that individuals adopt a technology based on the fit between the technological characteristics and task requirements (Goodhue and Thompson, 1995); and (2) the Unified Theory of Acceptance and Usage of Technology, UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012), which analyses interactions of users using a technology and the consequent user behaviour.

This research aims to understand MART adoption through the application of two solidly grounded models, UTAUT2 and TTF. The integrated framework based on the two models provides an overview of the relevance of MART to tourism, as technology evolves to meet requirements of consumers and their uptake of immersive and engaging technological solutions that capture their attention.

2. Literature Review

2.1. Mobile Augmented Reality in Tourism (MART)

Mobile augmented reality offers the user the possibility of having a live view of their surroundings augmented with additional practical information (Kourouthanassis et al., 2014), making it possible to discover, amongst other things, museums and monuments, locations, restaurants, attractions and accommodation. Convenient information can also be obtained based on preferences and context such as Wi-Fi spots, ATMs, car parks, transportation, local news and weather (Chen, 2014).

Some of these applications allow users to create a list of their preferred points of interest (POI), tailoring information according to both preferences and context (Trojan, 2016). Moreover, since population cannot be offline these services are offering customers an immediate connection through social networks, where they may exchange information and tips (Kounavis et al., 2012).

The use of MARTs can leverage a tourist experience allowing the visitor to be more creative (Richards, 2011) and spontaneous (Wang et al, 2012). MART has been studied by some researchers, with results suggesting direct benefits for the understanding of the surrounding environment when visiting a tourist location (e.g., Lashkari et al., 2010). Nevertheless, some drawbacks often occur in mobile applications which limit user experience and context awareness, such as the lack of adaptive visualization of contents regarding the immediate surroundings (Yovcheva et al., 2012).

2.2. Technology acceptance

The unified theory of acceptance and use of technology (UTAUT) was developed to study the use of technology in an organizational context by proposing four key constructs: performance expectancy; effort expectancy; social influence and facilitating conditions as direct determinants of behaviour intention and use behaviour (Venkatesh et al., 2003). These authors have also introduced constructs of age, gender, experience and voluntariness of use acting as moderators on the impact of the four independent key constructs on the two dependent constructs.

Venkatesh et al. (2012) also developed UTAUT2, which extended the earlier theory by incorporating three additional variables: hedonic motivation; price value and habit. Consequently, this updated version is more appropriate for studying technology adoption from a consumer point of view. The hedonic motivation is crucial in consumer product or technology use (Dickinger et al., 2006), and its addition complements the strongest predictor of UTAUT which emphasizes utility. Moreover, the authors of UTAUT2 argued that adding a construct related to price or cost would complement the previous model, which was only focused on time and effort. Finally, they found that habit had a significant relationship with consumer behavioural intention and actual use of mobile Internet services.

The TTF model states that individuals adopt a technology based on the fit between the technology characteristics and the task requirements (Goodhue and Thompson, 1995). Specifically, users will not adopt an advanced technology if it does not fit with their tasks and consequently cannot improve their performance (Junglas et al., 2008; Lee et al., 2007).

Law et al. (2014) pointed out the critical relevance of mobile technology adoption in hospitality and tourism. The more recent study by Ukpabi and Karjaluoto (2016) analysed 71 studies published from 2005 to 2016 on e-tourism technology acceptance, where five of them adopted UTAUT. Interestingly, the same authors concluded that research into mobile technology acceptance in tourism is not widespread. The adoption of augmented reality in tourism was also studied by Tom Dieck and Jung (2015) and Jung et al. (2016) in a museum tour application, with their findings revealing several dimensions that need to be incorporated in mobile solutions to improve tourist acceptance, including price value and facilitating conditions

3. Conceptual Framework

Ultimately as TTF might determine performance expectancy (PE), Behavioural Intention (BI) and Use Behaviour (U), this study proposes to test UTAUT2 in MART, adding the task technology fit framework to the model. Below, each of the constructs of TTF and UTAUT2 are defined (Figure 1).

Gebauer and Ginsburg (2009) noted that task technology fit of mobile information systems is determined by task characteristics and technology performance, leading to the following hypotheses:

H_1: The influence of Task Characteristics will be positive on Task Technology fit.

H_2: The influence of Technology Characteristics will be positive on Task Technology fit.

Task technology fit impacts user performance expectancy (Schrier et al., 2010). If a user demands fast, convenient and ubiquitous tourist services, the user is likely to feel that MART is helpful and therefore improves their performance.

H_3: The influence of Task Technology Fit will be positive on user's Performance Expectancy (PE).

A good task technology fit will improve Behavioural Intention (BI) and Use Behaviour (U), whereas a poor task technology fit will decrease user adoption intention (Lee et al., 2007).

H_4: The influence of Task Technology Fit will be positive on Behavioural Intention.

H_5: The influence of Task Technology Fit will be positive on User Behaviour.

Technology characteristics affect advantages of MART such as ubiquity and immediacy, allowing users to discover relevant information and therefore reducing their time and effort (Zhou at al., 2010).

H_6: The influence of Technology Characteristics will be positive on user Effort Expectancy (EE).

Performance Expectancy (PE) on using MART can be defined as the degree to which a user believes that using that service is helping them perform certain tasks (Venkatesh at al., 2003).

H_7: The influence of Performance Expectancy (PE) on Behavioural Intention (BI) will be positive and moderated by age and gender.

According to UTAUT, effort expectancy (EE) can be defined as the degree of ease associated with the use of a MART. It positively determines Behavioural Intention (BI) (Venkatesh at al., 2003). Furthermore, Effort Expectancy (EE) affects Performance Expectancy (PE). If users feel that MART is easy to work with and does not demand much effort, they will have high expectations towards performance.

H_8: The influence of Effort Expectancy (EE) on Behavioural Intention (BI) will be positive and moderated by age and gender.

H_9: The influence of Effort Expectancy (EE) on Performance Expectancy (PE) will be positive and moderated by age and gender.

Social Influence (SI) is similar to the subjective form of TRA (Venkatesh at al., 2003) and reflects the effort of environmental factors, such as the opinions of friends, relatives and work superiors of users (Lopez-Nicolas et al., 2008). Their opinions affect the intention of users to adopt MART (Zhou et al., 2010).

H_{10}: The influence of Social Influence (SI) on Behavioural Intention (BI) will be positive and moderated by age and gender.

Facilitating Conditions (FC) are similar to perceived behavioural control of TPB and reflects the effect of technical infrastructure to support MART, such as user knowledge, ability and resources (Venkatesh et al. 2003; Venkatesh et al. 2012). It influences behaviour intention, and therefore user behaviour.

H_{11a}: The influence of Facilitating Condition (FC) on Behavioural Intention (BI) will be positive and moderated by age and gender.

H_{11b}: The influence of Facilitating Condition (FC) on Technology Use (U) will be positive and moderated by age and gender.

Hedonic motivation (HM) that can be defined as the fun or pleasure felt from using a technology (Venkatesh et al., 2012) has been shown to play an important role in determining technology acceptance and use. In the consumer context, hedonic motivation has also been found to play an important role in technology acceptance and use (Brown and Venkatesh, 2005). Therefore, hedonic motivation is added as a predictor of the intentions of consumers to use MART.

H_{12}: The influence of Hedonic Motivation (HM) on Behavioural Intention (BI) will be positive and moderated by age and gender.

The price value (PV) is positive when the benefits of using a technology are perceived to be greater than monetary cost and such price value has a positive impact on intention (Venkatesh et al., 2012). In the case of MART, consumers usually bear the monetary cost of the data transferred over the internet. Thus, this factor must be considered.

H_{13}: The influence of Price Value (PV) on Behavioural Intention (BI) will be positive and moderated by age and gender.

Habit is a perceptual construct that reflects results of prior experiences (Venkatesh et al., 2012). Also, Kim and Malhotra (2005) found out that prior use was a strong predictor of future technology use.

H_{14a}: The influence of Habit (H) on Behavioural Intention (BI) will be positive and moderated by age and gender.

H_{14b}: The influence of Habit (H) on Technology Use (U) will be positive and moderated by age and gender.

To maintain the consistency with the underlying theory for all of the intention models, it is expected that behavioural intention will have a significant positive effect on technology use behaviour (Venkatesh et al., 2003).

H_{15}: Behavioural Intention (BI) will have a significant positive influence on Use Behaviour (U).

4. Research Methodology

All measurement items were adopted, with slight modifications, from the literature (Table 1). These were measured using a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). The developed questionnaire was first validated through a pilot survey (30 respondents). After clicking on the questionnaire URL, a page appeared with a message describing the objective of this research and a video presenting MART. Of the 402 received responses, 335 were considered valid for statistical treatment (Table 2).

When comparing the sample distributions of the first and second respondent groups, using the Kolmogorov-Smirnov (K-S) test, no non-response bias was found (Ryans, 1974). Furthermore, common method bias was also analysed using Harman's one-factor-test (Podsakoff et al., 2003), and found to be of no significance in the data set.

5. Data Analysis and Results

To analyse the relationships defined in the research model, Smart PLS 2.0 M3 (Ringle et al., 2005) was used for three different reasons: (i) not all items in the data were distributed normally ($p < 0.01$ based on Kolmogorov-Smirnov's test); (ii) the research model had not been previously developed; and (iii) the research model was considered to be complex.

Table 3 presents the loadings, *t*-values, average variance extracted (AVE), composite reliability (CR) and Cronbach's alpha (CA). Since the reliability indicator loadings must be greater than 0.7 (Henseler et al., 2009), the items FC4 (0.68), U4 (0.56), U5 (0.56), and U6 (0.66) were excluded as they presented a lower value than that required and were lacking statistical evidence. All items were statistically significant at 1% according to the analysis of the t-statistics values collected from bootstrapping with 500 iterations.

To measure the reliability of the constructs, two indicators were taken into account: Composite Reliability (CR) and Cronbach's Alpha (CA). According to Hair et al. (2010), CR evaluates the reliability and internal consistency of each construct and the extent to which the items represent the underlying constructs. CA provides an estimate of the reliability, taking into account the indicator inter-correlations and assuming that all indicators are equally reliable (Henseler et al., 2009). As seen in Table 3, CR and CA for each construct were above the expected threshold of 0.7, thus showing evidence of internal consistency.

To assure convergent validity, AVE was examined. It must be greater than 0.5 meaning that the latent variable explains more than half of the variance of its indicators (Henseler et al., 2009). The AVE of each construct was above the expected threshold of 0.5, hence confirming convergent validity.

Finally, to test discriminant validity of the constructs the data present in Table 4 must be evaluated through two criteria: Fornell-Larker measure and cross-loadings. The first theorises that the square root of AVE must be greater than the correlations between the construct (Henseler et al., 2009), while the second requires that the loading of each indicator must be greater than all the cross-loadings (Chin, 1998). As presented in Table 4, the square roots of AVE (elements exhibited in the diagonal) were higher than the correlation between each pair of constructs (elements exhibited off-diagonal). Moreover, our findings confirmed that the patterns of loadings were greater than the cross-loadings, consequently both measures were satisfied.

In summary, the proposed conceptual model has reliability, convergent validity and discriminant validity. Thus, the constructs can be used to test the research model.

To initiate the analysis of the model it is important to verify if Chin's (1998) theory is applied, i.e. all r-squares presented are above 0.2. Task Technology Fit, Performance Expectancy, Effort Expectancy, Behavioural Intention and Use Behaviour were 0.59, 0.43, 0.24, 0.72 and 0.45, respectively, and therefore this measure was consistent in the research model.

Table 5 summarizes the results of PLS estimation and findings revealed that not all of the constructs were statistically significant – according to the calculated t-values derived from bootstrapping (500 iterations).

Task Characteristics ($\beta = 0.17$; $p < 0.01$) and Technology Characteristics ($\beta = 0.49$; $p < 0.01$) were statistically significant in explaining Task Technology Fit (TTF). Furthermore, TTF was statistically significant in explaining Behavioural Intention ($\beta =$

0.14; $p < 0.01$) for Mobile Augmented Reality in Tourism (MART), and also showed to have a positive impact on Performance Expectancy ($\hat{\beta} = 0.37$; $p < 0.01$). Technology Characteristics ($\hat{\beta} = 0.66$; $p < 0.01$) was also used to explain Effort Expectancy.

Regarding UTAUT2, not all direct effects were statistically significant. Performance Expectancy ($\hat{\beta} = 0.11$; $p < 0.10$), Facilitating Conditions ($\hat{\beta} = 0.15$; $p < 0.01$), Hedonic Motivation ($\hat{\beta} = 0.21$; $p < 0.01$), and Habit ($\hat{\beta} = 0.38$; $p < 0.01$) were significant in explaining Behavioural Intention to use MART, whereas Effort Expectancy, Social Influence and Price Value were not. Also, TTF had good indices ($\hat{\beta} = 0.14$; $p < 0.01$) for explaining Behavioural Intention to use MART. It is also important to note that Effort Expectancy ($\hat{\beta} = 0.40$; $p < 0.01$) was confirmed to explain Performance Expectancy.

Ultimately, all indicators explaining future usage of MART were confirmed, TTF ($\hat{\beta} = 0.29$; $p < 0.01$), Habit ($\hat{\beta} = 0.31$; $p < 0.01$) and Behavioural Intention ($\hat{\beta} = 0.15$; $p < 0.10$), except one – Facilitating Conditions.

Concerning UTAUT2 moderators (age and gender), they did not reach the relevant value ($\beta \geq 1.65$; $p \leq 0.10$) in any construct to be statistically significant in the research model.

6. Discussion and conclusions

6.1. Conclusions

Figure 2 shows the outcomes of the hypotheses tested. The research model proposed explains 59% of variation in TTF of MART, which therefore explains (with UTAUT2 constructs) 72% and 45% of variation in Behavioural Intention (BI) and Use Behaviour (U) of MART, respectively. TTF also explains 43% of variation in performance expectancy. Technology Characteristics is also able to explain 24% of variation in Effort Expectancy (EE). TTF has been used to study the adoption of emerging Internet services - but people are willing to adopt them only if they meet their requirements and consequently improve their performance (Lee et al., 2007; Junglas et al., 2008). Thus, this study results are in accordance with previous studies (Zhou et al., 2010).

6.2.Theoretical implications

Findings show that Facilitating Conditions (FC) have low influence on the intention to use (H_{11a}) and may even not influence use behaviour (H_{11b}), contrasting with UTAUT2 premises. Interestingly, this result is in line with the study by San Martín and Herrero (2012), which evaluated the online purchase intentions of rural accommodation by tourists, when compared to other contexts such as hospital services (Aggelidis and Chatzoglou, 2009) who found FC to influence behaviour. Such results may be explained by the maturity of tourists regarding technological innovations being at ease with mobile applications (Ukpabi and Karjaluoto, 2016). Aligned with this finding is the discovery of a correlation between TTF and UTAUT2 constructs, as Technology Characteristics strongly influence EE, suggesting that a higher level of technological maturity in mobile application users overshadows facilitating conditions, thus less effort is required by users.

The results regarding EE, Social Influence (SI), and Price Value (PV) over Behavioural Intention (BI) suggest that respondents are neither concerned with the effort taken to use MART, nor with the opinion of others – relatives, friends and colleagues – concerning these technologies or their price. Finally, considering the effects on Use Behaviour, all constructs (TTF, Habit, and BI) were significant except FC, meaning that respondents are not considering possible difficulties that may arise when adopting this technology. This further highlights the specific nature of MART, which is yet to be thoroughly studied when compared to acceptance of other mobile technologies (Han et al., 2013).

6.3.Practical implications

MART service providers should invest in studying the market with the objective of understanding the consumer types they might reach and how to please them. A tourist who is enjoying moments of spontaneity only wants to obtain the necessary information at that moment and in that place.

Despite the analysis of the moderators not reaching a significant value for the influencing part of the path analysed, a significant value was obtained regarding age over Behavioural Intention (BI), leading to the first recommendation to management to analyse the users and cluster them by age groups. People in different stages of life think differently and have specific demands and needs (i.e., a student travelling is usually more concerned with the money spent, while a professional in a mature phase of their career might prefer a user-friendly platform which offers easy access to cultural information).

Moreover, it is important to understand that consumers are becoming more demanding, and an easier way to please and captivate them could be to provide a service that is able to offer practical uses. The user feels more enthusiastic (Hedonic Motivation – HM) about using an application that shows its usefulness (Performance Expectancy – PE), and with technological developments (Facilitating Conditions – FC) an application can start helping even before the beginning of the tourist journey. Prior to a trip, users must always plan and book something (i.e., what to pack, which transport to take, book a hotel), or if they decide to make their own way, they will eventually need a navigation system. They will want to know about which places to visit, where to taste the best food and how to exploit the area (i.e. cultural guidance, restaurant advice, events in town). Consequently, communication will certainly be required when looking for specific information that cannot be easily found or simply cannot be understood in foreign language. In this case immediate translation tools would be extremely useful). In order to remember and document the trip an application selecting the best moments could give the tourist a perfect souvenir.

These applications are still in development stages, but if the tourist could get all of these services together and have the opportunity to use them, certainly MART could become part of a tourist life (TTF, BI and Habit over U).

Finally, both suppliers and tourists can benefit from the adoption of these services providing efficiency and convenience for both sides. The tourism sector can always have a line of communication to their clients whilst attracting new customers. Meanwhile tourists can see their lives simplified in various ways, giving them time to experience what they enjoy most when travelling.

6.4.Limitations and future research

While the 335 responses provided a significant overview of MART acceptance, further studies are required using a larger sample of responses to confirm the above findings. In addition, this study could be replicated in future studies in other geographical areas. Moreover, once developed, specific mobile augmented reality in tourism applications could be tested in order to assess their potential adoption by tourists. This could address not only segmentation analysis from a consumer perspective but also the classification of different solutions according to their characteristics and perceived benefits of their usage.

References

Aggelidis, V.P. and Chatzoglou, P.D. (2009), “Using a modified technology acceptance model in hospitals”, *International Journal of Medical Informatics*, Vol.78 No.2, pp.115-126.

Brown, S.A. and Venkatesh, V. (2005), “Model of Adoption of Technology in the Household: A Baseline Model Test and Extension Incorporating Household Life Cycle”, *MIS Quartely*, Vol.29 No.4, pp.399-426.

Brislin, R.W. (1970), “Back-Translation for Cross-Cultural Research”, *Journal of Cross-Cultural Psychology*, Vol.1 No.3, pp.185-216.

Chen, W. (2014), “Historical Oslo on a handheld device – A mobile augmented reality application”, *Procedia Computer Science*, Vol.35, pp.979-985.

Chin, W.W. (1998), “Issues and opinion on structural equation modeling”, *MISQuartely*, Vol.22, No.1, pp.6-15.

Dickinger, A., Arami, M. and Meyer, D. (2006), “Reconsidering the adoption process: enjoyment and social norms—antecedents of hedonic mobile technology use”, in *Proceedings of the 39th Annual Hawaii International Conference on System Sciences, 2006. HICSS'06*, IEEE.

Gebauer, J. and Ginsburg, M. (2009), “Exploring the black box of task-technology fit”, *Communications of the ACM*, Vol.52 No.1, pp.130-135.

Goodhue, D.L. and Thompson, R.L. (1995), “Task-technology fit and individual performance”, *MIS Quartely*, Vol.19 No.2, pp.213-236.

Hair, J.F.J., Black, W.C., Babin, B.J. and Anderson, R.E. (2010), *Multivariate Data Analysis (7th Edition)*, Prentice Hall, New Jersey, USA.

Han, D.I., Jung, T. and Gibson, A. (2013), “Dublin AR: implementing augmented reality in tourism”, in *Information and communication technologies in tourism 2014*, Springer, pp.511-523.

Hannam, K., Butler, G. and Paris, C. (2013), “Developments and key issues in tourism mobilities”, *Annals of Tourism Research*, Vol.44, pp.171-185.

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

Im, I., Hong, S. and Kang, M.S. (2011), “An international comparison of technology adoption: Testing UTAUT model”, *Information & Management*, Vol.48 No.1, pp.1-8.

Jung, T., tom Dieck, M.C., Lee, H. and Chung, N. (2016), “Effects of virtual reality and augmented reality on visitor experiences in museum”, in *Information and Communication Technologies in Tourism 2016*, Springer, pp.621-635.

Junglas, I., Abraham, C. and Watson, R.T. (2008), “Task-technology fit for mobile locatable information systems”, *Decision Support Systems*, Vol.45 No.4, pp.1046-1057.

Kim, S.S. and Malhotra, N.K. (2005), “A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Post-Adoption Phenomena”, *Management Science*, Vol.51 No.5, pp.741-755.

Kounavis, C., Kasimati, A. and Zamani, E. (2012), “Enhancing the tourism experience through mobile augmented reality: Challenges and prospects”, *International Journal of Engineering Business Management*, Vol.4, pp.1-6.

Kourouthanassis P., Boletsis C., Bardaki C. and Chasanidou, D. (2014), “Tourists responses to mobile augmented reality travel guides: The role of emotions on adoption behavior”, *Pervasive and Mobile Computing*, Vol.18, pp.71-87.

Law, R., Buhalis, D. and Cobanoglu, C. (2014), “Progress on information and communication technologies in hospitality and tourism”, *International Journal of Contemporary Hospitality Management*, Vol.26 No.5, pp.727-750.

Lashkari, A.H., Parhizkar, B. and Mohamedali, M.A. (2010), “Augmented reality tourist catalogue using mobile technology”, in *Second International Conference on Computer Research and Development*, IEEE, pp.121-125.

Lee, C.C., Cheng, H.K. and Cheng, H.H. (2007), “An empirical study of mobile commerce in insurance industry: Task-technology fit and individual differences”, *Decision Support Systems,* Vol.43 No.1, pp.95-110.

Lopez-Nicolas, C., Molina-Castillo, F.J. and Bouwman, H. (2008), “An assessment of advanced mobile services acceptance: Contributions from TAM and diffusion theory models”, *Information & Management*, Vol.45 No.6, pp.359-364.

Martins, C., Oliveira, T. and Popovic, A. (2014), “Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application”, *International Journal of Information Management*, Vol.34 No.1, pp.1-13.

Olsson, T., Lagerstam, E., Karkkainen, T. and Vaananen-Vainio-Mattila, K. (2013), “Expected user experience of mobile augmented reality services: a user study in the context of shopping centres”, *Personal and Ubiquitous Computing*, Vol.17 No.2, pp.287-304.

Podsakoff, P.M., MackKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), “Common method biases in behavioral research: a critical review of the literature and recommended remedies”, *Journal of Applied Psychology*, Vol.88 No.5, pp.879-903.

Richards, G. (2011), “Creativity and tourism: The state of the art”, *Annals of Tourism Research*, Vol.38 No.4, pp.1225-1253.

Ringle, C.M., Wende, S. and Will, A. (2005), *SmartPLS 2.0 (M3)*, Beta, Hamburg,Germany.

Ryans, A.B. (1974), “Estimating consumer preferences for a new durable brand in an established product class”, *Journal of Marketing Research*, pp.434-469.

San Martín, H. and Herrero, Á. (2012), “Influence of the user’s psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework”, *Tourism Management*, Vol.33 No.2, pp.341-350.

Schrier, T., Erdem, M. and Brewer, P. (2010), “Merging task-technology fit and technology acceptance models to assess guest empowerment technology usage in hotels”, *Journal of Hospitality and Tourism Technology*, Vol.1 No.3, pp.201-217.

tom Dieck, M.C. and Jung, T. (2015), “A theoretical model of mobile augmented reality acceptance in urban heritage tourism”, *Current Issues in Tourism*, doi:10.1080/13683500.2015.1070801.

Trojan, J. (2016), “Integrating AR services for the masses: geotagged POI transformation platform”, *Journal of Hospitality and Tourism Technology*, Vol.7 No.3, pp.254-265.

Ukpabi, D.C. and Karjaluoto, H. (2016), “Consumers’ acceptance of information and communications technology in tourism: A review”, *Telematics and Informatics*, doi:10.1016/j.tele.2016.12.002.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), “User acceptance of information technology: Toward a unified view”, *MIS Quarterly*, Vol.27 No.3, pp.425-478.

Venkatesh, V., Thong, J.Y. and Xu, X. (2012), “Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology”, *MIS Quartely*, Vol.36 No.1, pp.157-178.

Wang, D., Park, S. and Fesenmaier, D. (2012), “The role of smartphones in mediating the touristic experience”, *Journal of Travel Research*, Vol.51 No.4, pp.371-387.

Yovcheva, Z., Buhalis, D. and Gatzidis, C. (2012), “Overview of smartphone augmented reality applications for tourism”, *e-Review of Tourism Research (eRTR)*, Vol.10 No.2, pp.63-66.

Zhou, T., Lu, Y. and Wang, B. (2010), “Integrating TTF and UTAUT to explain mobile banking user adoption”, *Computers in Human Behavior*, Vol.26, pp.760-767.

Table 1 - Items for all constructs.

Constructs	Items		Source
Performance Expectancy (PE)	I find mobile internet useful in my touristic activities	PE1	Venkatesh et al. (2003), Venkatesh et al. (2012)
	I think that mobile internet increases my chances of achieving things that are important to me in my touristic activities	PE2	
	I think mobile internet would enable me to conduct touristic activities more quickly	PE3	
Effort Expectancy (EE)	Learning how to use mobile internet for touristic activities is easy for me	EE1	
	My interaction with mobile internet in touristic activities is clear and understandable	EE2	
	I find mobile internet easy to use in touristic activities	EE3	
	It is easy for me to become skilful at using mobile internet in touristic activities	EE4	
Social Influence (SI)	People who influence my behaviour think that I should use mobile internet in my touristic activities	SI1	
	People who are important to me think that I should use mobile internet in my touristic activities	SI2	
	People in my environment who use mobile internet services in touristic activities have more prestige than those who do not	SI3	
	Having mobile internet services in touristic activities is a status symbol in my environment	SI4	
Facilitating Conditions (FC)	I have the necessary resources to use mobile internet in touristic activities	FC1	
	I have the necessary knowledge to use mobile internet in touristic activities	FC2	
	Mobile internet in touristic activities is compatible with other technologies I use	FC3	
	I can get help from others when I have difficulties using mobile internet in touristic activities	FC4	
Hedonic Motivation (HM)	Using mobile internet in touristic activities is fun	HM1	Venkatesh et al. (2012)
	Using mobile internet in touristic activities is enjoyable	HM2	
	Using mobile internet in touristic activities is very entertaining	HM3	
Price Value (PV)	Mobile internet for touristic activities is reasonably priced	PV1	
	Mobile internet for touristic activities is a good value for the money	PV2	
	At a current price, mobile internet for touristic activities provides a good value	PV3	
Habit (H)	The use of mobile internet in touristic activities has become a habit for me	H1	
	I am addicted to using mobile internet in touristic activities	H2	
	I must use mobile internet in touristic activities	H3	
	Using mobile internet in touristic activities has become natural to me	H4	
Behavioural Intention (BI)	I intend to continue using mobile internet in touristic activities in the future	BI1	Venkatesh et al. (2003), Martins et al. (2014)
	I will always try to use mobile internet in my touristic life	BI2	
	I plan to continue to use mobile internet frequently in touristic activities	BI3	

Constructs	Items		Source
Use Behaviour (U)	Please choose your usage frequency for each of the following:		Im et al. (2011)
	Maps	U1	
	Attractions	U2	
	Where to eat?	U3	
	Where to sleep?	U4	
	Transports	U5	
	Events	U6	
Task Characteristics (TKC)	I need to obtain touristic information anytime	TKC1	Goodhue and Thompson (1995), Zhou et al., (2010)
	I need to obtain touristic information anywhere	TKC2	
Technology Characteristics (TC)	Mobile internet provides ubiquitous services in tourism activities	TC1	
	Mobile internet provides a real time services in tourism activities	TC2	
	Mobile internet provides a quick service in tourism activities	TC3	
	Mobile internet provides a secure service in tourism activities	TC4	
Task-Technology Fit (TTF)	In helping complete my touristic activities, the functions of mobile internet are enough	TTF1	
	In helping complete my touristic activities, the functions of mobile internet are appropriate	TTF2	
	In general, the functions of mobile internet fully meet my touristic needs	TTF3	

Table 2 - Demographic data and characterization of respondents.

Gender		
Male	125	37.3 %
Female	210	62.7%

Age		
<21	19	5.7%
22-25	121	36.1%
26-30	66	19.7%
31-40	96	28.7%
>40	33	9.9%

Education		
Elementary & High School	44	13.1%
Undergraduate Degree	130	38.8%
Graduate Degree	96	27.8%
Post-Graduate Diploma	59	17.6%
Doctoral Degree	8	2.4%
Other	1	0.3%

Professional Status (according to CAE)		
Other	71	21.2%
Student	69	20.6%
Financial activities	38	11.3%
Health and Social Services	24	7.2%
Collective, social and personal services	19	5.7%
Education	16	4.8%
Unemployed	16	4.8%
Public Administration	14	4.2%
Wholesale and retail trade	12	3.6%
Construction	10	3%
Transports, storage and communications	8	2.4%
Processing industries	8	2.4%
Agriculture, Animal Production, Hunting, Forestry	6	1.8%
International Organisations & other institutions	6	1.8%
Retired	6	1.8%
Real estate market, renting and services to businesses	5	1.5%
Accommodation and restaurants	3	0.9%
Production and distribution of electricity, water and gas	2	0.6%
DK / NA = Do not know / No answer	2	0.6%
Fishing	0	-
Extractive industries	0	-
Stay at home parent	0	-

Owning a smartphone and/or portable device		
Yes	314	93.7%
No	21	6.3%

Use of a smart & portable device - tourism		
Always	175	52.2%
Often	85	25.4%
Sometimes	42	12.5%
Rarely	6	1.8%
Never	27	8.1%

Table 3 - Loadings of the measurement model and reliability measures (CR and CA) and AVE.

Construct	Item	Loading	*t*-Value	AVE	CR	CA
Task Characteristics (TKC)	TKC1	**0.9599**	97.98	0.93	0.96	0.92
	TKC2	**0.97**	151.17			
Technology Characteristics (TEC)	TecC1	**0.85**	33.58	0.80	0.94	0.92
	TecC2	**0.93**	93.00			
	TecC3	**0.93**	97.58			
	TecC4	**0.87**	48.57			
Task Technology Fit (TTF)	TTF1	**0.95**	118.04	0.89	0.96	0.94
	TTF2	**0.95**	88.98			
	TTF3	**0.93**	75.64			
Performance Expectancy (PE)	PE1	**0.89**	61.34	0.82	0.93	0.89
	PE2	**0.93**	83.36			
	PE3	**0.89**	54.45			
Effort Expectancy (EE)	EE1	**0.91**	65.55	0.83	0.95	0.93
	EE2	**0.91**	54.75			
	EE3	**0.90**	44.19			
	EE4	**0.92**	57.53			
Social Influence (SI)	SI1	**0.90**	63.86	0.71	0.91	0.87
	SI2	**0.92**	84.11			
	SI3	**0.78**	24.50			
	SI4	**0.75**	20.54			
Facilitating Condition (FC)	FC1	**0.84**	37.75	0.69	0.90	0.85
	FC2	**0.89**	63.20			
	FC3	**0.90**	83.01			
Hedonic Motivation (HM)	HM1	**0.96**	147.63	0.89	0.96	0.94
	HM2	**0.95**	127.41			
	HM3	**0.93**	83.80			
Price Value (PV)	PV1	**0.93**	68.77	0.90	0.96	0.94
	PV2	**0.96**	147.46			
	PV3	**0.94**	99.80			
Habit (H)	H1	**0.91**	85.50	0.77	0.93	0.90
	H2	**0.81**	36.94			
	H3	**0.86**	39.11			
	H4	**0.93**	126.25			
Behavioural Intention (BI)	BI1	**0.89**	56.50	0.82	0.93	0.89
	BI2	**0.89**	65.30			
	BI3	**0.93**	87.50			
Usage Behaviour (U)	U1	**0.89**	19.09	0.00	0.00	0.00
	U2	**0.86**	17.66			
	U3	**0.72**	11.24			

Table 4 - Means, standard deviations, correlations and discriminant validity measures.

	Mean	SD	TKC	TEC	TTF	PE	EE	SI	FC	HM	PV	Habt	BI	U	Gender	Age
TKC	4.5	1.75	**0.96**													
TEC	4.64	1.49	0.59	**0.90**												
TTF	4.72	1.51	0.56	0.76	**0.94**											
PE	5.08	1.60	0.58	0.60	0.55	**0.90**										
EE	5.40	1.48	0.34	0.49	0.45	0.56	**0.91**									
SI	3.49	1.85	0.36	0.43	0.41	0.48	0.31	**0.84**								
FC	5.12	1.62	0.35	0.48	0.48	0.46	0.71	0.31	**0.83**							
HM	4.67	1.65	0.50	0.54	0.56	0.68	0.50	0.50	0.50	**0.95**						
PV	3.59	1.60	0.21	0.39	0.31	0.33	0.29	0.27	0.37	0.31	**0.95**					
H	3.68	1.85	0.64	0.59	0.56	0.69	0.47	0.52	0.50	0.68	0.32	**0.88**				
BI	5.04	1.70	0.53	0.61	0.59	0.67	0.54	0.45	0.57	0.71	0.31	0.76	**0.91**			
U	3.42	1.07	0.60	0.54	0.54	0.53	0.36	0.31	0.35	0.45	0.25	0.57	0.54	**NA**		
Gender	0.37	0.48	-0.08	0.02	0.08	0.02	0.00	-0.04	0.05	-0.04	-0.04	-0.01	0.03	-0.05	**NA**	
Age	30.09	8.93	-0.15	-0.10	-0.09	-0.03	-0.09	-0.06	-0.11	-0.05	0.02	-0.11	-0.05	-0.03	0.16	**NA**

Table 5 - Structural Model results for TTF + UTAUT 2.

Hypotheses	Path	Findings			Moderators	Conclusion
		R^2	$\hat{\beta}$	*t*-value		
	Task Technology Fit	59%				
H1	Task Characteristics		0.17	3.15 ***	None	Supported
H2	Technology Characteristics		0.49	8.50 ***	None	Supported
	Performance Expectancy	43%				
H3	Task Technology Fit		0.37	6.06 ***	None	Supported
H9	Effort Expectancy		0.40	6.37 ***	Age, Gender	Partially supported *
	Effort Expectancy	24%				
H6	Technology Characteristics		0.66	14.21 ***	None	Supported
	Behavioural Intention	72%				
H4	Task Technology Fit		0.14	2.80 ***	None	Supported
H7	Performance Expectancy		0.11	1.76 *	Age, Gender	Partially supported *
H8	Effort Expectancy		0.01	0.10	Age, Gender	Not supported
H10	Social Influence		-0.01	0.23	Age, Gender	Not supported
H11a	Facilitating Conditions		0.15	2.68 ***	Age, Gender	Partially supported *
H12	Hedonic Motivation		0.21	3.64 ***	Age, Gender	Partially supported *
H13	Price Value		-0.03	0.75	Age, Gender	Not supported
H14a	Habit		0.38	6.89 ***	Age, Gender	Partially supported
	Use Behaviour	45%				
H5	Task Technology Fit		0.29	3.82 ***	None	Supported
H11b	Facilitating Conditions		-0.02	0.27	Age, Gender	Not supported
H14b	Habit		0.31	4.75 ***	Age, Gender	Partially supported *
H15	Behavioural Intention		0.15	1.65 *	None	Supported

Notes:

* Effect not significant with moderators

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; all other path coefficients are insignificant

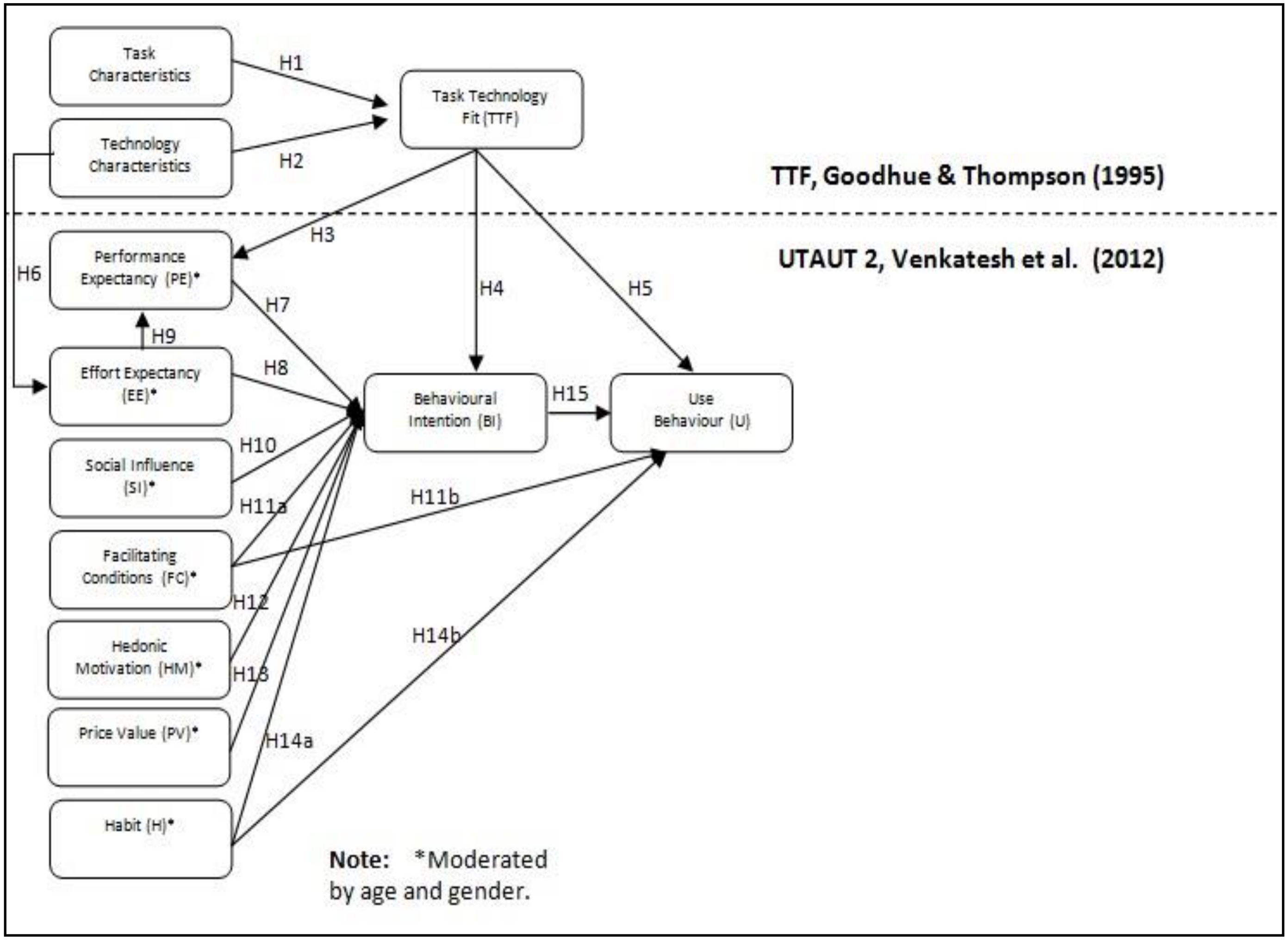

Figure 1 - Research Model.

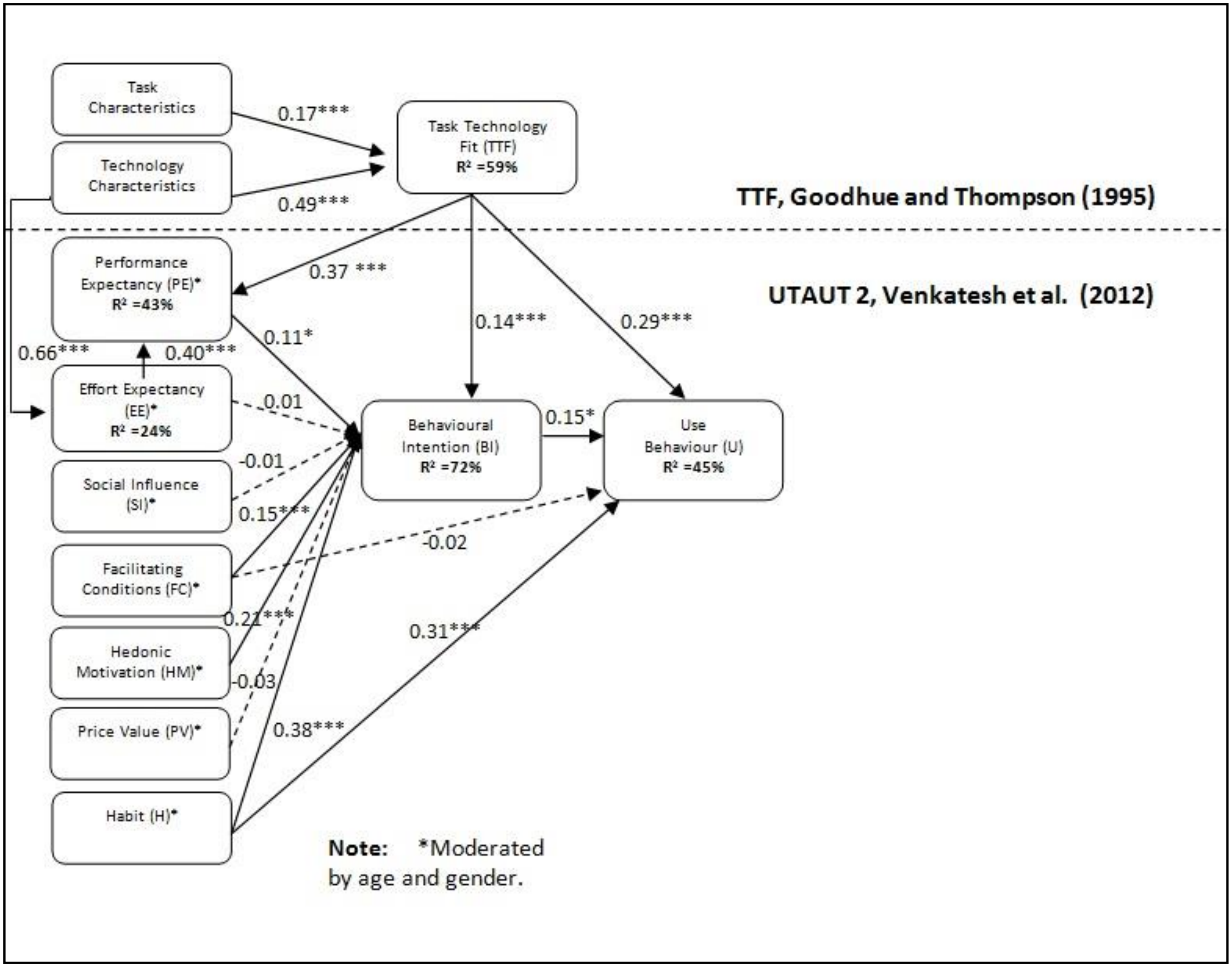

Figure 2 - Structural Model results for TTF + UTAUT 2 with path coefficients and r-squares.