Understanding travelers' willingness to accept and purchase Artificial Intelligent travel applications using Value- based Adoption theory

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Abstract

With the rise in popularity and use of travel Artificial Intelligent (AI) applications (apps), more research is needed to acquire more knowledge about what intensions make travelers utilizing and buying special apps during their trip so that they keep behaving likewise. Based on the theory of Value-based Adoption Model (VAM) the present study empirically tests consumers' willingness to accept (WTA) and willingness to pay (WTP) for travel apps on their mobile phones while enjoying a tourism destination experience. Using an established scaled questionnaire a total of 373 users of various AI travel apps were surveyed. The findings revealed that trust(T), happiness(H), anthropomorphism (AM), perceived immersion (PIM) and estimated effort (EF) positively impact perceived value (PV), WTA and WTP for AI travel apps, while complexity (C) discourage consumers in adopting and paying for those apps. Additionally, PV was found to be one of the most important predictors in WTA and WTP adoption. This study offers valuable insights for tourism industry regarding attracting and engaging foreign travelers with their AI apps.

Keywords: tourism AI apps, perceived value, willingness to accept and pay Track: Tourism Marketing

1. Introduction

Since the usage of mobile phones has become so extensive that one-half of owners describe their device as something that they 'could not live without' according to Perrin (2017) the advent of mobile apps transformed these devices as the most omnipresent and frequently used products among consumers (De-Sola Gutierrez et al. 2016). Arguably, users' modern life has been transformed (Venkatesh et. al.,2012) since mobile apps depict the adoption of the virtually essential attachment with smartphones (Melumad & Pham, 2020).

According to Park (2020) tourism industry has adapted to advancements in information technology, such as the Internet, mobile phones, Virtual Reality (VR) and Augmented Reality (AR). According to De Carlo et. al (2021) AI in tourism can be described by the spread of ICT devices and digital technologies who transformed the environment in which both organizations and destinations compete. Currently, the completion of AI and robotics is ordinary, arising in hospitality and tourism, including accommodation, airline, and restaurant industry (Chui, et al., 2018). Due to the adoption of AI apps travelers' experiences are changing and AI robots are formulated on human- robot interactions (Tussyadiah & Wang, 2018). Moreover, according to Kim (2021) apps use can reduce tourists' stress and enhance memorable destination experiences. According to Buhalis et al. (2015) destinations try to provide tourists with valuable experiences, since positive practices is a key factor in tourism. Thus, tourism operators may challenge to approve which technologies to adopt and which to deny due to the existing plethora of such possibilities (Tuomi, 2020). Equally challenging might be the decision concerning where, when, and how a new technology should be adopted, as well as understanding what its impacts might be for the individual, the firm and the industry.

This study connects AI travel apps usage with factors that positively impact WTA and WTP attitute. The developed model examines empirically how happiness, anthropomorphism, perceived immersion, estimated effort, trust, complexity and perceived value affects willingness to accept (WTA) and willingness to pay (WTP) for AI travel apps. Thus, the specific purpose of this study is to identify whether these factors affect WTA and WTP toward AI travel apps and whether PV plays a role in enhancing WTA and WTP behaviour, by empirically analyzing the research model.

2. Conceptual framework and hypotheses

The study proposes a research framework based on the VAM, as shown in Fig. 1. (Kim et al., 2005). The beginning point of this research framework is the need to augment perceived value while using AI travel apps based on VAM. Firstly, happiness HAP is an important sub-dimension of benefits according to research (Venkatesh et al., 2012). According to Hu (2021) inner incentives describe the happiness of using new technology providing evidence to foretell in general consumers' technology use in the market. Additionally, in tourism industry the interactivity between human and robots delegates the surroundings of humanistic inner impulses (Lu et al., 2019). Thus, it is hypothesized that HAP has a positive and significant impact on WTA (H1a1), HAP has a positive and significant impact on PV (H1a2) and HAP has a positive and significant impact on WTP (H1a3). However, anthropomorphism AM, may also trigger controversial views among users. For example, the human-like characteristics can increase the perceived warmth and friendliness (van Doorn et al., 2017). Thus, next hypothesis is that AM has a positive and significant impact on WTA (H2a1), on PV(H2a2) and on WTP (H2a3). According to Zak et. al (2022) immersion is the neurologic state in which a person is attentive to an experience and it resonates emotionally. Zak developed immersion algorithm to predict actions, so he found there is a positive correlation between PIM and youtube metrics. Since consumers' emotional states influence behavioral intentions (Sung et al., 2021) we hypothesize that PIM has a positive and significant effect on WTA (Ha31), on PV (H3a2) and on WTP (H3a3). Moreover, when evaluating WTA and WTP customers care about effort expectancy (EF) which characterizes the expected effort and skills needed when using technologies in of AI apps (Venkatesh et al., 2012). Therefore, it is hypothesized that EF has a positive and significant effect on WTA (Ha41), on PV (H4a2) and on WTP (H4a3). In addition, some authors emphasize that trust (T) is an essential substance for effective relationship in marketing services (Sekhon et al., 2014). According to Siau and Wang (2018) consumers who initially use a new technological product without incident are likely to continue to use and trust it. Thereby, it is hypothesized that T has a positive and significant impact on WTA (H5a1), on PV (H5a2) and on WTP (H5a3). According to Wang et al. (2018) there is a significant negative relationship between technical complexity (C) and PV while examining GPS mobile app adoption. However, C is hypothesized to have a negative and significant impact on WTA (H6a1), on PV(H6a2) and on WTP (H6a3). There are also several studies establishing that PV has a positive effect on usage acceptance and purchase intention as a desirable customer behavior (Rust et al., 2012). According to the VAM, the PV is measured

when we count the benefits to the sacrifices associated with the final offering (Kim et al., 2007). However, PV is likely to result in WTA (H7) and WTP (H8). Since previous researchers like Hsiao and Chen (2017), Sohn and Kwon (2020) tested VAM finding that PV is a significant predictor in new ICT adoption it is hypothesized that the perceived value mediates the relationship between all indicators and the WTA (H7a- H7f) and also that the perceived value mediates the relationship between all indicators and the WTP (H8a-H8f).

3. Methodology

Based on a literature review, the items and instruments used in the questionnaire to measure the constructs were adapted from previously validated studies to maintain reliability and validity.Borrowing the milestone for the hospitality and tourism field Service Robots Integration Willingness (SRIW) scale, developed by Lu (2019) we also used three items to assess the HAP (Van Boven, 2003), four items for AM (Lu et al., 2019), four items for PIM (Jennett et al., 2008), three items for EF (Lu et al., 2019) and five items for T (Gefen, et al., 2003). We measured C with three items





adapted from Davis (1989) and Li, Buhalis (2006), three items for PV (Sirdeshmukh, et al., 2002), six items for WTA adapted from Venkatesh et al. (2012) and Lu et al. (2019) and three items for WTP adapted from Laroche et al. (2001). All the items were slightly modified to suit the AI apps context. Five-point Likert scales were used to assess all constructs. Then, the questionnaire was pretested by circulating a survey to 44 travel AI apps users via an online questionnaire instrument using Qualtrics. Four screening questions were asked to confirm that the respondents had experience with AI travel apps during travelling. Five final questions on demographic variables concluded the questionnaire. The pretest finalized the questionnaire structure to be used in the main data collection.

The questionnaire of the survey was conducted on Prolific platform, providing a medium monetary compensation to respondents. The questionnaire link was also shared among Facebook and WeChat group chats of AI app users with the help of group chat administrators. We conducted the survey online as it is the fastest way to access a large number of tourists in a short period. We distributed 900 questionnaires in two months and received 498 responses. Of these responses, 123 were excluded from the data analysis because they contained unengaged responses and missing information. Therefore, the sample used in this study consisted of 373 respondents (response rate of 41%) from 8 different European regions.

4. Results and Conclusion

The present research used AMOS 28 to assess the structural model reflecting the research hypotheses. Common method bias is a crucial issue in behavioral research. It occurs when variations in responses are triggered by the instrument rather than the actual predispositions of the respondents that the instrument tries to reveal. To address this issue, first, a special section explaining the strict confidentiality of the responses and that there were no right or wrong answers was included in the questionnaire. Additionally, we told them to remain neutral and honest while filling out the survey. Second, we conducted Harman's single-factor approach. The variance extracted using one factor is 32.862%, less than 50%, indicating no common method bias in this study (Podsakoff et al., 2003).

The study assessed reliability, convergent validity, and discriminant validity which are crucial prerequisites for achieving valid results (Ringle et al., 2015). We verified the scales' reliability and convergent validity by employing the three normal criteria: item reliability of the measures by using factor loading (>0.5), Cronbach's alpha and the composite reliability (CR) of the constructs (>0.7), and the average variance extracted (AVE) (>0.5). The latent variables ranged from 0.718 to 0.843, showing statistically significant loading. Cronbach's alpha ranged from 0.789 to 0.912, and CR ranged from 0.790 to 0.912, confirming their reliability. Moreover, AVE ranged from 0.557 to 0.638, above the threshold level of 0.50. For discriminant validity two methods were applied. The first is the Fornell and Larcker method, and the second is the heterotrait- monotrait (HTMT). In the Fornell and Larcker method, the square root of each latent variable's AVE is greater than the correlation of its coefficient, indicating discriminant validity in our research (Fornell & Larcker, 1981). Henseler et al. (2015) stated that the HTMT values must be lower than 0.85, which is the case in our study, indicating discriminant validity. The values on the diagonal representing the square root of the average variance extracted HAP=0.784, AM=0.798, PIM=0.777, EF=0.789, T= 0.799, C=0.746, PV=0.788, WTA= 0.796 and WTP=0.813. The variance inflation factor (VIF), was

also examined detecting multicollinearity in regression analysis. The values did not exceed the threshold of 5; therefore, multicollinearity was acceptable in this study.

According to Hair et al.'s (2011) rule of thumb, 0.25, 0.50, and 0.75 denote small, medium, and large effects, respectively. The analysis highlighted that the endogenous constructs, namely PV (0.508), WTA (0.450), WTP (0.563), reflected a medium effect size, indicating that the regression model is acceptable. To test the hypotheses, statistical bootstrap technique was applied with the recommended 5000 sample size (Ringle et al., 2015). The hypotheses H1a1-H1a3 as shown on Table 1 are being supported ($\beta = 0.138$, 0.228, and 0.127 i.e., WTA,

PV and WTP) which means that the inner impulse of happiness is appeared to be one of the most significant factors of technology use (Venkatesh et al., 2012).

Results also support H2a1-H2a3, AM ($\beta =$ 0.148, 0.116, and 0.120) where it is revealed that these human-like features may influence consumers' acceptance of using AI apps and of purchasing them (Hu et al., 2021). The results outlined that the hypotheses H3a1-H3a3 named PIM ($\beta =$ 0.124, 0.265, and 0.110) directly increase customers' adoption of AI apps and WTP, suggesting that tourists are likely to be affectively committed when experiencing perceived immersion. The hypotheses H4a1-H4a3 claiming that the effort involved in utilizing and acquiring knowledge about new technologies (Heerink et al., 2010) affects WTA and WTP is been supported EF Table 1: Hypotheses testing Direct & Indirect Effect

Hypotnesis Relationships Beta Error Values H1a1 HAP \Rightarrow WTA 0.138 0.043 3.209 H1a2 HAP \Rightarrow WTA 0.138 0.043 3.209 H1a2 HAP \Rightarrow WTP 0.228 0.042 5.429 H1a3 HAP \Rightarrow WTP 0.127 0.039 3.256 H2a1 AM \Rightarrow WTA 0.148 0.042 3.524 H2a2 AM \Rightarrow WTA 0.148 0.042 3.524 H2a3 AM \Rightarrow WTP 0.116 0.043 2.698 H2a3 AM \Rightarrow WTP 0.120 0.043 2.791 H3a1 PIM \Rightarrow WTA 0.124 0.057 2.175 H3a2 PIM \Rightarrow PV 0.265 0.037 7.162 H3a3 PIM \Rightarrow WTP 0.110 0.040 2.750 H4a1 EF \Rightarrow WTA 0.124 0.039 3.179 H4a2 EF \Rightarrow WTP 0.136 0.039 3.487	Values ** ** ** ** ** ** ** ** ** **
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H5a1 T → WTA 0.111 0.041 2.707	**
H5a2 T → PV 0.146 0.041 3.561	••••
H5a3 T→WTP 0.116 0.039 2.974	**
H6a1 C→WTA 0.001 0.026 0.038	NS
H6a2 C → PV 0.024 0.027 0.889	NS
H6a3 C→WTP -0.051 0.031 -1.645	NS
H7 PV → WTA 0.196 0.044 4.455	•••
H8 PV → WTP 0.320 0.037 8.649	•••
indirect Std. Std. T	P
Hypothesis Relationships Beta Error Value	Values
H7a Hap → PV → WTA 0.045 0.014 3.207	•••
H7b ATP → PV → WTA 0.023 0.010 2.254	**
H7c PIM → PV → WTA 0.052 0.016 3.185	***
H7d EFT → PV → WTA 0.026 0.012 2.169	**
H7e TST → PV → WTA 0.029 0.008 3.248	***
H7f CMP → PV → WTA 0.005 0.006 0.754	NS
H8a Hap → PV → WTP 0.073 0.017 4.147	•••
H8b ATP → PV → WTP 0.037 0.015 2.458	**
H8c PIM → PV → WTP 0.085 0.018 4.564	•••
H8d EFT → PV → WTP 0.042 0.017 2.352	
H8e TST → PV → WTP 0.047 0.013 3.613	••
H8f CMP → PV → WTP 0.008 0.011 0.729	•••

*Indicates significant paths: *p<0.05, **p<0.01, ***p<0.001, NS = not significant Model fit 1/ 511.048. df=459. p<0.001. RMSEA=0.017. CFI=0.992. SRMR=0.0297

 $(\beta = 0.124, 0.131, \text{ and } 0.136)$. The findings further revealed that T positively impacts WTA, PV and WTP supporting H5a1- H5a3 while T ($\beta = 0.111, 0.146, 0.116$). These findings suggest that T, which reflects a psychological motivation to be in a long-term relationship, plays a crucial role in adoption behaviors. Testing H6a1- H6a3 indicated that C has a negative and insignificant impact on WTA, PV and WTP since it is shown that the complexity of the

innovation has a significant negative relationship with the adoption of the new apps (Rogers, 1995). The results outlined that both the hypotheses H7 and H8 named PV ($\beta = 0.196$) and ($\beta = 0.320$) relatively directlry lead to WTA and WTP attitude, evaluating acceptance of AI app use (Gursoy et al., 2019) and the chance of buying subscription to use AI apps (Lazarus, 1991). Results also support the mediation effect results are shown in Table 1. The findings demonstrated that PV mediates the relationship between the H7a-H7e estimated HAP \Rightarrow PV \Rightarrow WTA ($\beta = 0.045$), ATP \Rightarrow PV \Rightarrow WTA ($\beta = 0.023$), PIM \Rightarrow PV \Rightarrow WTA ($\beta = 0.052$), EF \Rightarrow PV \Rightarrow WTA ($\beta = 0.026$), T \Rightarrow PV \Rightarrow WTA ($\beta = 0.029$), except from H7f, C \Rightarrow PV \Rightarrow WTA ($\beta = 0.005$) which is not supported. These findings are reasonable because when consumers are experiencing a perceived value they are feeling more satisfied and willing to adopt and pay for using those tested AI travel apps (Doss, 2015).

Additionally, the results are similar for H8a-H8f since PV mediates the relationship between the H8a-H8e estimated HAP \rightarrow PV \rightarrow WTA ($\beta = 0.073$), ATP \rightarrow PV \rightarrow WTA ($\beta = 0.037$), PIM \rightarrow PV \rightarrow WTA ($\beta = 0.085$), EF \rightarrow PV \rightarrow WTA ($\beta = 0.042$), T \rightarrow PV \rightarrow WTA ($\beta =$ 0.047), except from H7f, C \rightarrow PV \rightarrow WTA ($\beta = 0.008$) which is not supported. A plausible explanation for these nonsignificant relationships is that perceived complexity opinions about tourism apps is perceived as a burden accepting their utility. Affectively committed tourists purchase the service of the tourism app after experiencing the perceived value.

5. Discussion

This research aimed at empirically testing the assumption that investing in perceived valued experiences leads to positive acceptance outcomes. Our findings empirically confirm for the first time this claim and show that perceived value can represent a driver of AI travel apps adopting and purchasing outcome. The positive impact of perceived value orientation on tourism apps should alert practicing the tourism industry to the fact that customer acceptance should not be neglected when dealing with the adoption on ICT innovations. No app can win the mind and heart of consumers, unless engaged tourism companies promise and internalize what it stands for. As such, travel apps wishing to improve their customers' acceptance need to carefully adopt an orientation to ensure that they create feelings of happiness, trust and perceived immersion to the users. Accordingly, it is suggested that those apps having human-like characteristics, may minimize the effort expectancy while been used. Since in hospitality surroundings, optimizing customer experience will continue to require technology inspiration melted into various aspects of services it is a fact that hospitality services thrive on providing interpersonal interactions to create customer value (Lu, 2019).

Our results also corroborate studies emphasizing the necessity of introducing the use of AI in tourism marketing by knowing customer emotions, defining manufacturing chances in using AI, explaining consumer needs and fulfilling them, having electronic word-of-mouth awareness, ameliorating merchandise achievements, utilizing AI in branding and in strategic marketing, checking and improving consumer faithfulness and reliance, introducing AI in services and changing perspectives in consumer's whole experience moving one step forward the science of marketing (Mustak et al., 2021). The present study examined the willingness to accept and the willingness to purchase AI travel apps as an impact of perceived value. It is also revealed that the mediating role of perceived value offers empirical evidence on this acceptance of AI apps use, augments sales leading to business success. However, the relationships investigated are by no means exhaustive. Further research should investigate possible antecedents of willingness to accept the use and the purchase of AI travel apps and assess this orientation along with other important marketing constructs. Future studies focusing on specific sectors or industries would help generalize the strategic importance of AI enabled technology which has metamorphosed the retailing perspective by enriching customer-company interaction through reality-enhancing online interfaces (Kaplan & Haenlein, 2020).

References

Buhalis, D., & Amaranggana, A. (2015). Smart tourism destinations enhancing tourism experience through personalisation of services. In Information and communication technologies in tourism. *Springer International Publishing*

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340

De Carlo, M., Ferilli, G., d'Angella, F., & Buscema, M. (2021). Artificial intelligence to design collaborative strategy: An application to urban destinations. *Journal Of Business Research*, 129, 936-948.

Doss, S. K. (2015). "Spreading the good word": Toward an understanding of brand evangelism. In The sustainable global marketplace (p. 444). *Springer International Publishing*.

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

Gursoy, D., Chi, O., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal Of Information Management*, 49, 157-169.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis (7th ed.). New Jersey: Pearson.

Heerink, M., Kröse, B., Evers, V., Wielinga, B., 2010. Assessing acceptance of assistive social agent technology by older adults: the almere model. Int. J. Soc. Robot. 2 (4), 361–375 Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal Of Information Management*, 56, 102250.

Jennett, C., Cox, A. L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T., et al. (2008). Measuring and defining the experience of immersion in games. *International Journal of HumanComputer Studies*, 66(9), 641–661.

Kim, S.S., Malhotra, N.K., (2005). A longitudinal model of continued is use: an integrative view of four mechanisms underlying postadoption phenomena. *Management Science*. 51, 741–755.

Kim, H., Koo, C., & Chung, N. (2021). The role of mobility apps in memorable tourism experiences of Korean tourists: Stress-coping theory perspective. *Journal Of Hospitality And Tourism Management*, 49, 548-557.

Laroche, M., Bergeron, J., & Goutaland, C. (2003). How intangibility affects perceived risk: The moderating role of knowledge and involvement. *Journal of Services Marketing*, 17(2), 122–140.

Lazarus, R. S. (1991). Cognition and motivation in emotion. *American Psychologist*, 46(4), 352–367.

Li, L., & Buhalis, D. (2006). E-commerce in China: The case of travel. *International Journal of Information Management*, 26(2), 153–166.

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

Melumad, S., & Pham, M. T. (2020). The Smartphone as a Pacifying Technology. *Journal of Consumer Research*, 47(2), 237–255.

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research*, 124, 389–404.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, 88(5), 879.

Rogers, E. M. (1995). Diffusion of innovations (4th ed.). New York, NY: Free Press.

Rust, R. T., & Huang, M.-H. (2012). Optimizing service productivity. *Journal of Marketing*, 76(2), 47–66.

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing*, 66(1), 15–37.

Sung, E., Bae, S., Han, D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal Of Information Management*, 60, 102382. https://doi.org/10.1016/j.ijinfomgt.2021.102382

Tuomi, A., Tussyadiah, I., & Stienmetz, J. (2020). Leveraging LEGO® Serious Play® to embrace AI and robots in tourism. *Annals Of Tourism Research*, 81, 102736.

Tussyadiah, I.P., Wang, D., Jung, T.H., tom Dieck, M.C., 2018. Virtual reality, presence, and attitude change: empirical evidence from tourism. *Touristic Management*. 66, 140–154.

Van Boven, L. and Gilovich, T. (2003), "To do or to have? That is the question", *Journal of Personality and Social Psychology*, Vol. 85 No. 6, pp. 1193-1202.

van Doorn, J., Mende, M., Noble, S.M., Hulland, J., Ostrom, A.L., Grewal, D., Petersen, J.A., (2017). Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences. *J. Serv.* Res. 20 (1), 43–58.

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and user of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36, 157–178.

Vishwakarma, Pankaj, Srabanti Mukherjee, and Biplab Datta. "Travelers' Intention to Adopt Virtual Reality: A Consumer Value Perspective." *Journal of Destination Marketing & Management* 17 (September 2020).

Zak, Paul J., Robert Kurzban, Sheila Ahmadi, Ronal S. Swerdloff, Jang Park, Levan Efremidze, Karen Redwine, Karla Morgan, and William Matzner. "Testosterone Administration Decreases Generosity Generosity in the Ultimatum Game." PLoS One 4, no. 12 (2009): e8330.