Predicting the intentions to use chatbots for travel and tourism

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Predicting the intentions to use chatbots for travel and tourism

As with other businesses, tourist companies are taking advantage of modern technologies. Chatbots are a recent technology that hotels, travel agencies, and airline companies are adopting. Despite this industry-wide implementation, there is no evidence about the factors that explain why consumers are willing to interact with chatbots. This work proposes a theoretical model to explain chatbot usage intention. The model and its hypotheses were tested by structural equations with the PLS technique. The study was conducted on a sample of 476 individuals who had traveled on vacation in the previous 12 months. The study reveals that the intentions behind using chatbots are directly influenced by the following factors: the chatbots' expected performance, the habit of using chatbots, the hedonic component in using them, the predisposition to using self-service technologies, the social influences, and the fact that the chatbot behaves like a human. The inconvenience and problems related to communicating with the chatbot were found to have a negative influence. Lastly, the possibility that chatbots could replace jobs had a surprisingly positive influence, and not a negative one.

Keywords: Chatbots, SSTs, client interaction, anthropomorphism, automation

Introduction

Everyone would agree with the proposition that companies should interact with their clients. In the case of the tourist industry, this is even more relevant. Technology has always been a useful tool for this purpose. Phones and email are clear examples of technology's usefulness. Traditionally, many of these interactions have been based on human skills, but self-service technologies (hereafter SSTs) also provide the opportunity for company-client interactions to be performed. For example, in tourism touch screens are a well-known option for guests to interact with hotels and airports (Bulchand-Gidumal & Melián-González, 2015).

Recently, companies have started to adopt an additional SST: chatbots. According to Shawar and Atwell (2007: 29), a chatbot is ' …a software program that interacts with users using natural language' . Other names for this technology are virtual agents and chatterbots. Currently, chatbots are common in mobile applications and text messaging systems deployed in companies' websites. More recent formats are physical objects based on cloud technology such as Alexa and Google Home, that seem like a simple speaker.

A quick search on the reviews that consumers upload to TripAdvisor reflects that guests of hotels, restaurants, transportation, and leisure companies are using chatbots. Some of these uses were voluntary (i.e., the users chose to do so), while others were mandatory (i.e., the users were forced to do so, since there were no other options available to communicate with the company). Many content management professionals are working on chatbot implementations (The Content Wrangler, 2018) and there are relevant cases about its use in the tourism industry (Deloitte, 2017; WorldHotels, 2018). Chatbots have been claimed to be the next popular technology and its spread is considered unavoidable (Daniel, Matera, Zaccaria, & Dell'Orto, 2018).

Most of the current research on chatbots is focused on the technical aspects of this technology (Sheehan, 2018), on the users' attributions of human qualities to chatbots, and its effects on communication (Hill, Ford, & Farreras, 2015). Nevertheless, there is hardly any research about the factors that explain its use by consumers. When important technologies begin to be used, researchers analyze why individuals adopt them. This was the case for corporate websites (Lee, 2009; Lubbe, 2007), social media (Lorenzo-Romero, Constantinides, & Alarcón-del-Amo, 2011; Martins Rodrigues Pinho & Soares, 2011; Parra-López, Bulchand-Gidumal, Gutiérrez-Taño, & Díaz-Armas, 2011), and mobile applications (Kang, Mun, & Johnson, 2015; Ozturk, Bilgihan, Nusair, & Okumus, 2016; Taylor & Levin, 2014). Understanding why consumers use these technologies will allow companies to implement the suitable practices for their clients to adopt them.

Evidence indicates that consumers' attitudes to information technologies vary (Curran & Meuter, 2005; Curran, Meuter, & Surprenant, 2003). In other words, the fact that guests are willing to use a hotel's webpage does not imply that they will accept using a chatbot to communicate with the same hotel. Considering the relevant figures about chatbot usage in tourism (e.g. Kayak, 2017; Phocuswright, 2018), it is necessary to know the factors that explain its acceptance by consumers. This research seeks to fill this gap, based mostly on one of the most extended models used to explain technology usage: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Other factors were also taken into consideration, due to chatbots' peculiarities and the differences among consumers regarding IT usage.

This article is structured as follows: the first section tackles the literature review and describes the proposed theoretical model, the next section explains the methodology, then the results are described, and the conclusions and limitations are presented.

Literature review

Chatbots

As was stated previously, chatbots are software programs (robots, or bots) that have conversations in natural language with users (chats). These chatbots can be currently found in several places: websites, mobile applications, and smart speakers, amongst others.

It is important to note that in text chats, there is occasionally a combination of robots and humans. In these cases, there is usually a robot that is in charge of the initial portion of the conversation and tries to classify the user request. The conversation is then transferred to a human if the robot is unable to address the request. In some cases, and in colloquial conversations, this whole system is called a chatbot. However, strictly speaking only the part of the conversation in which there is interaction with a robot could be defined as chatbot.

Originally, chatbots were developed for fun and were based on simple keyword matching techniques (Shawar & Atwell, 2007). Nevertheless, modern chatbots have significantly improved their capabilities in written and voice dialogue due to progress in fields such as natural language processing and artificial intelligence (Shah, Warwick, Vallverdú, & Wu, 2016). Thus, companies from different industries are taking advantage of these capabilities and are using chatbots for client interactions (Forbes, 2017; Følstad & Brandtzæg, 2017). In turn, consumers state that they mostly use chatbots for customer service purposes (Elsner, 2017).

Winkler and Söllner (2018) described four main advantages to chatbots. Firstly, this technology saves customer service costs by replacing personal assistants. Secondly, chatbots increase user satisfaction through interactions in real time and by being available twenty-four hours a day. Thirdly, chatbots can predict customer questions, and thus can interact proactively with users and provide the information that they need. Fourthly, chatbots allow sophisticated analysis, since conversations are registered and can be automatically analyzed to better understand customer requirements, and therefore improve products and services.

According to Daniel et al. (2018: 1), chatbots ' are expected to irreversibly permeate both our private and our professional interactions of tomorrow' . Gartner estimated that, by 2020, 85% of customer requests in companies will be handled by chatbots (Inbenta Technologies Inc., 2016). Følstad and Brandtzæg (2017) mentioned that important companies such as Google, Facebook, and Microsoft see chatbots as the next popular technology. According to Facebook IQ, from January 2017 to January 2018, discussions on the subject of chatbots have risen almost six times (Chatbots Magazine, 2018). A survey of content management professionals found that 95% of them were planning to adopt chatbots to deliver content to their customers before the end of 2019 (The Content Wrangler, 2018).

Some uses of this technology reveal its importance to the tourism industry. Deloitte (2017) mentioned the case of Oyo Rooms, which operates a network of 70,000 rooms in over 200 Indian cities, and uses chatbots for their clients' search for and booking of hotels. WorldHotels (2018) mentioned the chatbots launched by important companies such as Booking.com and Kayak. The report also mentioned a particular chatbot that allows its users to interact with more than 4700 hotels. Marriot has started to use a chatbot for hotel reservations that has successfully provided assistance in stay and reservation issues to 44% of its registered clients (Nguyen, 2017). Finally, Amadeus has implemented a chatbot to help travel agents in real-time, to solve doubts about common issues (De la Rosa, 2019).

UTAUT2 model

Based on eight models frequently used to explain technology acceptance, Venkatesh et al. (2003) proposed the Unified Theory of Adoption and Use of Technology (UTAUT). This model included four core determinants of intention and usage, and up to four moderators of key relationships. Years later, Venkatesh, Thong, and Xu (2012) extended the UTAUT model by adding three new constructs and tailoring the model to the consumer use context. This new model (UTAUT2) provided better explanations for behavioral intention and technology use than UTAUT.

UTAUT2 has been used to explain the adoption of a great variety of technologies such as software (Raman & Don, 2013), mobile applications (Yuan, Ma, Kanthawala, & Peng, 2015; Tak & Panwar, 2017), social networking sites (Herrero & San Martín, 2017), online games (Xu, 2014), Internet banking (Arenas Gaitán, Peral Peral, & Ramón Jerónimo, 2015), technology for collaborative learning (Goh, Tang, & Lim, 2016), near field communication (NFC), mobile payments (Morosan & DeFranco, 2016), and service robots (Lu, Cai, & Gursoy, 2019). The model includes seven constructs (Venkatesh et al., 2012). The following paragraphs detail these seven constructs and explain which of them will be used in our model.

Performance expectancy. Performance expectancy refers to the degree to which using a technology will benefit consumers in performing certain activities. Previous research reveals that performance expectancy is the strongest predictor of behavioral intentions to use new technology (Venkatesh et al., 2003) and has extensively been used in tourism research (Chung, Lee, Kim, & Koo, 2018). In particular, it has predicted the usage intention of the technologies mentioned in the previous paragraph. Because customer service chatbots are designed to help clients, our first hypothesis states that this construct predicts chatbot usage intentions.

H1: There is a positive relationship between performance expectancy and chatbot usage intentions.

Effort expectancy. Effort expectancy refers to the degree of ease associated with consumers' use of technology. This construct has explained the usage intention of software (Raman & Don, 2013), mobile applications (Tak & Panwar, 2017), and Internet banking (Arenas Gaitán et al., 2015). In a similar vein, it is reasonable to expect that consumers who think that chatbots are complex will tend to use them less. This leads to our second hypothesis.

H2: There is a positive relationship between ease of use and chatbot usage intentions.

Social influence. Social influence refers to the degree to which consumers perceive that others who they think are important believe that they should use a particular technology. This construct has explained the usage intention of online games (Xu, 2014), NFC mobile payments (Morosan & DeFranco, 2016), and mobile applications (Tak & Panwar, 2017). Likewise, this construct can also condition the intention to use chatbots, which is considered in the next hypothesis.

H3: There is a positive relationship between social influence and chatbot usage intentions.

Hedonic motivations. Hedonic motivation refers to the degree to which individuals experience fun or pleasure when they use a technology. This motivation seems obvious when dealing with technologies that involve enjoyment, such as online games (Xu, 2014) and social networking sites (Herrero & San Martín, 2017). However, it has been demonstrated to be relevant in the use of very different technologies such as NFC mobile payments (Morosan & DeFranco, 2016). Therefore, it is expected that this intrinsic motivation could also be relevant in explaining chatbot usage intention.

H4: There is a positive relationship between hedonic motivation and chatbot usage intentions.

Habit. Habit refers to the degree to which individuals tend to use a particular technology. It has been demonstrated to be relevant in the usage intention of NFC mobile payments (Morosan & DeFranco, 2016), social networking sites (Herrero & San Martín, 2017), and online games (Xu, 2014). Because habit is relevant to consumers' past and present behavior, it is expected that the more consumers use chatbots, the greater their intention to use them.

H5: There is a positive relationship between habit and chatbot usage intentions.

The UTAUT2 model includes two additional constructs: facilitating conditions and price value. The former construct was not included because chatbot usage does not require any type of support. It simply involves typing or speaking. The price value factor assumes that consumers must pay for the technology usage. Because this is not the case for commercial chatbots, it was not taken into consideration. It is true that the use of chatbots usually requires an IT device that must be paid for (e.g. computer, laptop, smartphone, tablet, speaker), but the payment is made for the device and not for the use of the chatbot.

Additional drivers of chatbots adoption

In addition to the drivers included in the UTAUT2 model, we understand that there are other five drivers that may explain chatbot usage. We detail them in the following paragraphs.

Perceived innovativeness. Although we are in the IT era, consumers differ in the extent to which they use IT (Rogers, 2010). Thus, there are consumers who tend to use any original technology, while others reject or delay adopting it (Laukkanen, Sinkkonen, & Laukkanen, 2008). Rogers and Shoemaker (1971) defined innovativeness as the extent to which individuals tend to adopt new ideas, compared to other members of their social system. Goldsmith and Hofacker (1991) highlighted that innovativeness can be domain-specific. Regarding IT usage, Agarwal and Prasad (1998: 209) described perceived innovativeness as ‘ the willingness of an individual to try out any new information technology.’ For example, San Martín and Herrero (2012) found that innovativeness was positively related to the intention of tourists to use technology for online purchases. In turn, Dabholkar and Bagozzi (2002) posited that the trend of testing new technologies involves a positive intention to use any SST. These authors found that consumers who scored low in this characteristic were reluctant to use a touch screen for ordering food. In this regard, hypothesis 6 states that individuals that tend to test new technologies will demonstrate a high intention to use chatbots.

H6: There is a positive relationship between perceived innovativeness and chatbot usage intentions.

Attitude towards SSTs. Individuals' attitudes towards an object have been widely recognized as a direct antecedent of their behavioral intention (Ajzen, 1991). Therefore, hypothesis 7 posits that a positive attitude towards SSTs could also mediate the previous relationship between consumers' propensity to test new IT and the intention to use SST such as chatbots. This involves two hypotheses.

H7a: There is a positive relationship between perceived innovativeness and attitude towards SSTs.

H7b: There is a positive relationship between attitude towards SSTs and chatbot usage intentions.

Particular technologies may require the consideration of other factors in addition to the more general factors, such as the two previously described and those included in a global model such as UTAUT2. Lu et al. (2019) studied the willingness to use service robots (i.e., robots that are physically present at service encounters) and considered the anthropomorphism factor in addition to those described in the UTAUT2. Morosan and DeFranco (2016) included general privacy, system-related privacy, and perceived security in their explanation of the usage intention of NFC mobile payments. Chatbots also have peculiarities that suggest other variables that can contribute to understanding consumers' usage intention.

Inconveniences. Although consumers may consider that using chatbots is easy, certain characteristics of chatbots can affect the way that people express their thoughts. Consumers must type their thoughts (or express their ideas loudly, in a way that is understandable by the bot), which demands more effort than natural and oral communication. In addition, if consumers are aware that they are interacting with a machine, they may think that they should express their ideas differently. In fact, Hill et al. (2015) found that people use more words, longer words, and words associated with positive emotions when they communicate with people, compared to when they communicate with chatbots. This suggests that individuals change their communication style when interacting with a chatbot. All these changes can slow down the interaction with chatbots, which has been found to affect clients' satisfaction with SSTs (Collier & Kimes, 2013). In fact, Hill et al. (2015) found that chatbot interactions contain a higher percentage of swear words, which could indicate that people do not find the answers that they expect. In addition, as often happens with other SSTs, consumers may prefer to interact with employees (Walker & Johnson, 2006). Because consumers can find that chatbots interactions are not as convenient as other means of communication, we posit hypothesis 8.

H8: There is a negative relationship between chatbots' inconveniences and chatbot usage intentions.

Anthropomorphism. A key feature of chatbots is that they aim to appear human-like when interacting with individuals (Shawar & Atwell, 2007; Daniel et al., 2018; Hill et al., 2015). In fact, there are contests based on the Turing Test (Oppy & Dowe, 2016), in which chatbots compete against each other to be undistinguishable from humans (e.g. The Loebner Prize, Chatbottle).

Sheehan (2018) suggested that because chatbots are capable of free-form conversation, they can generate anthropomorphism within the human user. Anthropomorphism refers to the process by which individuals attribute human-like characteristics to a non-human entity (Waytz et al., 2010). Van Doorn et al. (2017) and Araujo (2018) posited that the extent to which machines make consumers feel like they are interacting with another human can increase their engagement and satisfaction. In the case of social robots, Ho and MacDorman (2017) found that individuals favorably appreciate robots' humanness up to a point, after which higher perceptions of humanness are associated with eerie feelings. Nevertheless, chatbots are not human-like robots and these feelings could not rise. In fact, Sheehan (2018) found that users' perceptions of chatbots' anthropomorphism explained their adoption and recommendation intentions. Similarly, Araujo (2018) found that individuals' perceptions that they are interacting with other social beings have positive effects on the emotional connection with the company using a chatbot. This leads us to hypothesis 9.

H9: There is a positive relationship between chatbots' anthropomorphism and chatbot usage intentions.

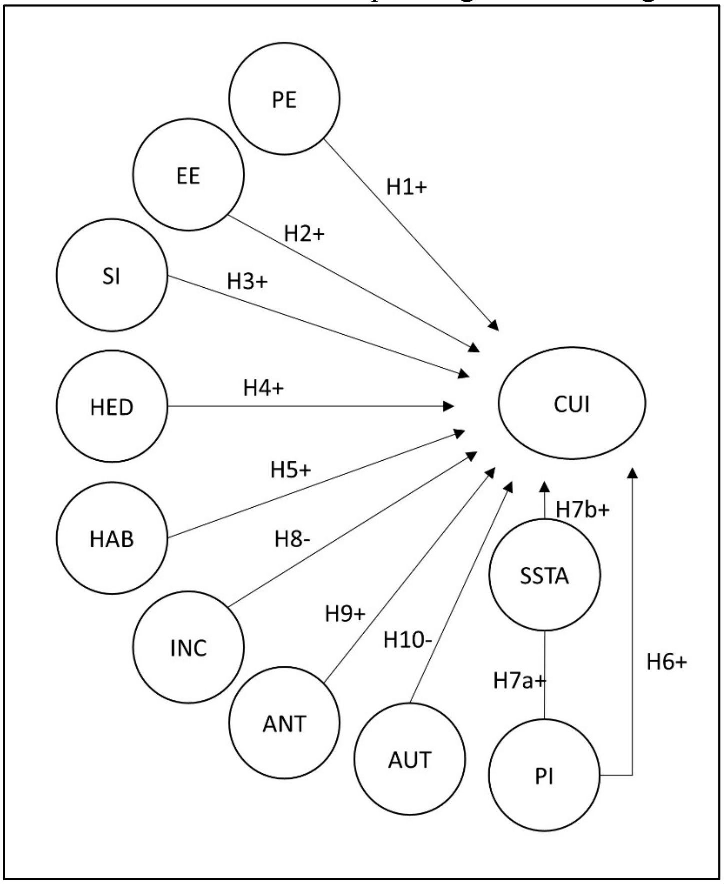
Automation. One of the most controversial issues in the current field of employment is technological unemployment. Pol and Reveley (2017: 170) stated that 'machines make cars, write articles, diagnose diseases, and are encroaching on all sorts of professions, including but not limited to, teaching, accounting, and law'. Although there are no conclusive results about the extent to which advances in IT are affecting employment, media and non-academic publications frequently warn that current technologies are replacing workers. In this vein, Akst (2013) introduced the term 'anxiety over automation' to reflect the fear of technology's power to displace people from jobs. In fact, a Pew Research Center (2018) study revealed that most people think that robots and computers will take over much of the work that individuals currently perform. Additionally, Patel, Devaraj, Hicks, & Wornell (2018) found that workers in occupations at high risk of automation reported greater job insecurity, which was associated with poorer health. Thus, consumers could have a negative attitude towards chatbots because they are carrying out services that have traditionally been performed by humans. This leads us to hypothesis 10.

H10: There is a negative relationship between the belief that technology will replace workers and chatbot usage intentions.

Hypothesized model

Figure 1 depicts the theoretical model. In this model, we can see how performance expectancy, social influence, hedonism, habit, anthropomorphism, and perceived innovativeness (directly and also through self-service attitudes) have a positive effect on chatbot usage intentions, while effort expectancy, chatbot-related inconveniences, and automation have a negative effect.

Figure 1. Theoretical model for explaining chatbots usage intention



NOTE: PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; HED: Hedonism; HAB: Habit; INC: Inconvenience; ANT: Anthropomorphism; AUT: Automation; PI: Perceived innovativeness; SSTA: Attitude towards SSTs; CUI: Chatbots usage intention

Methodology

Measures

Table 1 displays the constructs' measures and their source. Because there were no scales for the inconvenience and automation constructs, they were formulated from the theoretical concepts. The initial items were analyzed by three IT researchers in order to guarantee their validity. After considering their suggestions, the items were elaborated on. The other constructs' measures were based on existing scales that were adapted to mention chatbots. All items were measured by a 7-point Likert scale about the level of agreement.

Table 1. Measures

Construct	Measurement	References
Performance expectancy (PE)	PE1 – I find chatbots to be useful PE2 – Using chatbots helps me accomplish things more quickly	Venkatesh et al. (2012)

	PE3 – Using chatbots improves information search PE4 – Chatbots help to solve doubts	
Effort expectancy (EE)	EE1 - Learning how to use chatbots is easy for me EE2 - I find chatbots easy to use EE3 - It is easy for me to become skillful at using chatbots	Venkatesh et al. (2012)
Social influence (SI)	SI1 – Many people who I know use chatbots SI2 – People who influence my behavior use chatbots SI3 – People whose opinions I value use chatbots	Venkatesh et al. (2012)
Hedonic motivations (HED)	HED1 - Using chatbots is fun HED2 – Using chatbots is enjoyable HED3 – Using chatbots is very entertaining	Venkatesh et al. (2012)
Habit (HAB)	HAB1 – The use of chatbots has become a habit for me HAB2 – Using chatbots has become natural to me HAB3 – I tend to use chatbots	Venkatesh et al. (2012)
Perceived innovativeness (PI)	PI1 – I find new tools easy to use PI2 – I am a person with technological skills, I like to be up to date with all the latest things PI3 – I am always seeking new ways and new tools	Parra-López et al. (2011)
Attitude towards SSTs (SSTA)	SSTA1 – I like receiving services through IT SSTA2 – I think it is all right to receive services through IT SSTA3 – I think receiving services through IT is good SSTA4 – Receiving services through IT is comfortable	Dabholkar & Bagozzi (2002)
Inconvenience (INC)	INC1 - I think that the use of chatbots is inefficient since the chatbots frequently do not understand what I am expressing INC2 – I think that expressing an idea to a chatbot is more complicated than doing so to a human INC3 - I think that using chatbots is impractical, since typing is required INC4 – I think that using chatbots is uncomfortable since I am required to express my ideas in a way that is understandable to the chatbot	Based on Hill et al. (2015), Robertson, McDonald, Leckie, & McQuilken (2016)
Anthropomorphism (ANT)	ANT1 – It is important that the conversation with a chatbot resembles one with a human being ANT2 – Conversations with chatbots should be natural ANT3 – Chatbots should seem as if they understand the person with whom they are interacting ANT4 – Conversation with a chatbot should not be artificial	Bartneck, Kulić, Croft, & Zoghbi (2009), Sheehan (2018)
Automation(AUT)	AUT1 – I think chatbots are going to replace workers AUT2 – Jobs that are currently performed by human beings will be performed by chatbots AUT3 – Firms will use more chatbots and less workers	Based on Freeman (2015)
Chatbot usage intention (CUI)	CUI1 – I intend to use or to continue using chatbots in the future CUI2 – When required, I will use chatbots CUI3 – I intend to use chatbots in the future CUI4 – I think that more and more people will use chatbots	Venkatesh et al. (2012), Parra-López et al. (2011)

Data gathering

The population of the study comprises individuals who regularly take vacation trips and have access to the Internet. A non-probabilistic sampling procedure was followed. Data were obtained from a sample of undergraduate students that belong to two Spanish universities and who met the two requisites of having traveled for vacations in the previous 12 months and having seen a chatbot while surfing the Internet.

Data were collected during March and April 2019, by means of an online self-administered questionnaire that respondents completed. 550 responses were received, out of which 74 were discarded for various reasons. Thus, the final sample comprised 476 responses.

Considering the statistical technique employed, the sample size was checked based on G*Power (Faul, Erdfelder, Buchner, & Lang, 2009). According to this, testing the proposed model required a minimum sample of 178 individuals for a statistical power of 0.95. Therefore, it can be safely concluded that the sample size used (476) was acceptable for the purposes of this study.

The final sample was balanced by gender (49% female and 51% male). Regarding age, 34% of respondents were between 18 and 19 years old, 26% between 20 and 21 and 40% over 21 years.

Data analysis

To analyze the proposed theoretical model and test the hypotheses, the Partial Least Squares technique (PLS-SEM) was used, with Smart PLS software v.3.2.8 (Ringle, Wende, & Becker, 2015). The measurement model was analyzed through the constructs' reliability and validity, and the structural model was analyzed through the R^2, trajectory coefficients, and confidence intervals.

Results

Descriptive analysis

Table 2 shows the results of the descriptive analysis of the constructs of the proposed model. It can be observed that while there is a foreseeable intention to use chatbots, it is not extremely high: the mean of the chatbot usage intention in the constructs are between 4.72 and 5.05, in a 1 to 7 scale.

The items of constructs Anthropomorphism, Perceived innovativeness, Self-service attitude, and Effort Expectancy receive the most agreement from the interviewees, with scores averaging 5.5 points. For their part, items of constructs Hedonism, Automation and Inconvenience are in the middle of the scale, with scores slightly above the midpoint 4. The items of constructs receiving the lowest agreement were Habit (less than 3) and Social Influence (slightly above 3). At the time of the survey, the use of chatbots was not a habit of those answering neither in acquaintances nor in social referents.

Table 2. Descriptive Analysis.

	Constructs and associated Items	Mean	Standard Deviation
CUI	**Chatbots Usage Intention**		
CUI1	I intend to use or to continue using chatbots in the future	4.72	1.432
CUI2	When required, I will use chatbots	5.05	1.330
CUI3	I intend to use chatbots in the future	4.76	1.427
CUI4	I think that more and more people will use chatbots	4.97	1.341
PE	**Performance Expectancy**		
PE1	I find chatbots to be useful	5.04	1.288
PE2	Using chatbots helps me accomplish things more quickly	4.78	1.232
PE3	Using chatbots improves information search	4.90	1.145
PE4	Chatbots help solving doubts	5.05	1.274
EE	**Effort Expectancy**		
EE1	Learning how to use chatbots is easy for me	5.44	1.232
EE2	I find chatbots easy to use	5.31	1.229
EE3	It is easy for me to become skillful at using chatbots	5.46	1.202
SI	**Social Influence**		
SI1	Many who I know use chatbots	3.25	1.513
SI2	People who influence my behavior use chatbots	3.42	1.428
SI3	People whose opinions I value use chatbots	3.60	1.374
HED	**Hedonism**		
HED1	Using chatbots is fun	4.06	1.325
HED2	Using chatbots is enjoyable	4.16	1.272
HED3	Using chatbots is very entertaining	4.23	1.326
HAB	**Habit**		
HAB1	The use of chatbots has become a habit for me	2.49	1.121

HAB2	Using chatbots has become natural to me	2.90	1.342
HAB3	I tend to use chatbots	2.80	1.221
INC	**Inconvenience**		
INC1	I think that the use of chatbots is inefficient since the chatbots frequently do not understand what I am expressing	4.62	1.308
INC2	I think that expressing an idea to a chatbot is more complicated than doing so to a human (dropped)	5,11	1.400
INC3	I think that using chatbots is impractical, since typing is required	3.12	1.333
INC4	I think that using chatbots is uncomfortable, since I am required to express my ideas in a way that is understandable to the chatbot	4.59	1.436
ANT	**Anthropomorphism**		
ANT1	It is important that the conversation with a chatbot resembles one with a human being	5.63	1.348
ANT2	Conversations with chatbots should be natural	5.50	1.338
ANT3	Chatbots should seem as if they understand the person with whom they are interacting	5.54	1.285
ANT4	Conversation with a chatbot should not be artificial	5.56	1.339
AUT	**Automation**		
AUT1	I think that chatbots are going to replace workers	4.17	1.676
AUT2	Jobs that are currently performed by human beings will be performed by chatbots	4.60	1.519
AUT3	Firms will use more chatbots and less workers	4.57	1.528
PI	**Perceived innovativeness**		
PI1	I find new tools easy to use	5.63	1.137
PI2	I am a person with technological skills, I like to be up to date with all the latest things.	5.47	1.332
PI3	I am always seeking new ways and new tools	5.31	1.264
SSTA	**Self-service technologies attitude**		
SSTA1	I like receiving services through IT	5.42	1.312
SSTA2	I think it is all right to receiving services through IT	5.71	1.170
SSTA3	I think receiving services through IT is good	5.67	1.169
SSTA4	Receiving services through IT is comfortable	5.66	1.189

Evaluation of the measurement model

The individual reliability of the indicators of the constructs, formulated in Reflective Mode A, is evaluated by examining the loads (λ) of the indicators with their respective construct. As indicated in Table 3, all the item loads in the final measurement model were greater than 0.707 (Carmines & Zeller, 1979). Only one indicator that was part of the Inconvenience construct did not fulfil this requirement, and it was consequently dropped.

In Table 3, the reliability of the constructs is analyzed and it is observed that all the values of the Cronbach's Alpha and composite reliability (Dijkstra & Henseler, 2015) are above the minimum cut-off point of 0.70 (Fornell & Larcker, 1981). Table 3 also indicates that all latent variables reached convergent validity, since their AVE measures exceeded 0.5 (Fornell & Larcker, 1981).

Table 3. Assessment Results of the Measurement Model.

Construct and associated items	Loading	Cronbach's alpha	rho_A	Composite reliability	AVE
Chatbots Usage Intention		**0.904**	**0.905**	**0.933**	**0.776**
CUI1	0.902				
CUI2	0.870				
CUI3	0.898				
CUI4	0.853				
Performance Expectancy		**0.797**	**0,800**	**0.868**	**0.622**
PE1	0.785				
PE2	0.769				
PE3	0.786				
PE4	0.813				
Effort Expectancy		**0.808**	**0.841**	**0.884**	**0.718**
EE1	0.874				
EE2	0.868				
EE3	0.798				
Social Influence		**0.819**	**0.829**	**0.892**	**0.733**
SI1	0.858				
SI2	0.841				
SI3	0.869				
Hedonism		**0.890**	**0.893**	**0.931**	**0.819**
HED1	0.910				
HED2	0.908				
HED3	0.897				
Habit		**0.921**	**0.935**	**0.949**	**0.862**
HAB1	0.907				
HAB2	0.943				
HAB3	0.935				
Inconvenience		**0.711**	**0.719**	**0.838**	**0.634**
INC1	0.839				
INC3	0.751				
INC4	0.795				
Anthropomorphism		**0.848**	**0.859**	**0.897**	**0.685**
ANT1	0.845				
ANT2	0.828				
ANT3	0.825				
ANT4	0,811				
Automation		**0.871**	**0.892**	**0.920**	**0.793**
AUT1	0.913				
AUT2	0.868				
AUT3	0.891				
Perceived innovativeness		**0.807**	**0.807**	**0.886**	**0.722**
PI1	0.822				
PI2	0.858				
PI3	0,868				
Self-service attitude		**0.874**	**0.876**	**0.914**	**0.726**
SSA1	0.866				
SSA2	0.871				
SSA3	0.832				
SSA4	0,838				

Note: See Table 2 for the names of the items; AVE: Average Variance Extracted

Discriminant validity was evaluated using the recommended approach of Fornell and Larcker (1981) and also by examining the Hetero Trait-Mono Trait ratio (HTMT) of the correlations, which is considered to be a stricter criterion (Henseler, Ringle, & Sarstedt, 2015). The results of Table 4 indicate that the constructs examined: i) exceeded the requirements of Fornell and Larcker (1981) since all the correlations were lower than the square of the AVEs, and ii) fulfilled the requirement of the HTMT of the correlations, since they were all below the threshold of 0.85 (Kline, 2011). Therefore, the measurement model was considered satisfactory and provided sufficient evidence in terms of reliability and convergent and discriminant validity.

Table 4. Result of discriminant validity.

Constructs	ANT	AUT	CUI	EE	HAB	HED	PI	PE	SSA	SI	UNC
Fornell–Larcker											
ANT	**0.827**										
AUT	0.215	**0.891**									
CUI	0.218	0.176	**0.881**								
EE	0.303	0.078	0.360	**0.847**							
HAB	0.041	0.060	0.419	0.264	**0.929**						
HED	0.094	0.080	0.397	0.214	0.260	**0.905**					
PI	0.291	0.019	0.288	0.383	0.240	0.131	**0.850**				
PE	0.161	0.062	0.584	0.525	0.350	0.429	0.186	**0.788**			
SSA	0.313	0.029	0.394	0.420	0.206	0.170	0.682	0.310	**0.852**		
SI	0.020	0.046	0.390	0.241	0.432	0.331	0.037	0.392	0.080	**0.856**	
UNC	0.051	0.111	-0.355	-0.229	-0.239	-0.164	-0.073	-0.409	-0.156	-0.247	**0.796**
HTMT											
ANT											
AUT	0.253										
CUI	0.244	0.196									
EE	0.352	0.104	0.408								
HAB	0.078	0.064	0.455	0.289							
HED	0.102	0.091	0.441	0.241	0.288						
PI	0.354	0.065	0.338	0.475	0.275	0.156					
PE	0.189	0.078	0.685	0.638	0.401	0.507	0.232				
SSA	0.360	0.081	0.444	0.488	0.229	0.193	0.809	0.371			
SI	0.067	0.069	0.448	0.272	0.493	0.385	0.065	0.481	0.091		
UNC	0.131	0.143	0.441	0.294	0.291	0.199	0.118	0.541	0.203	0.323	

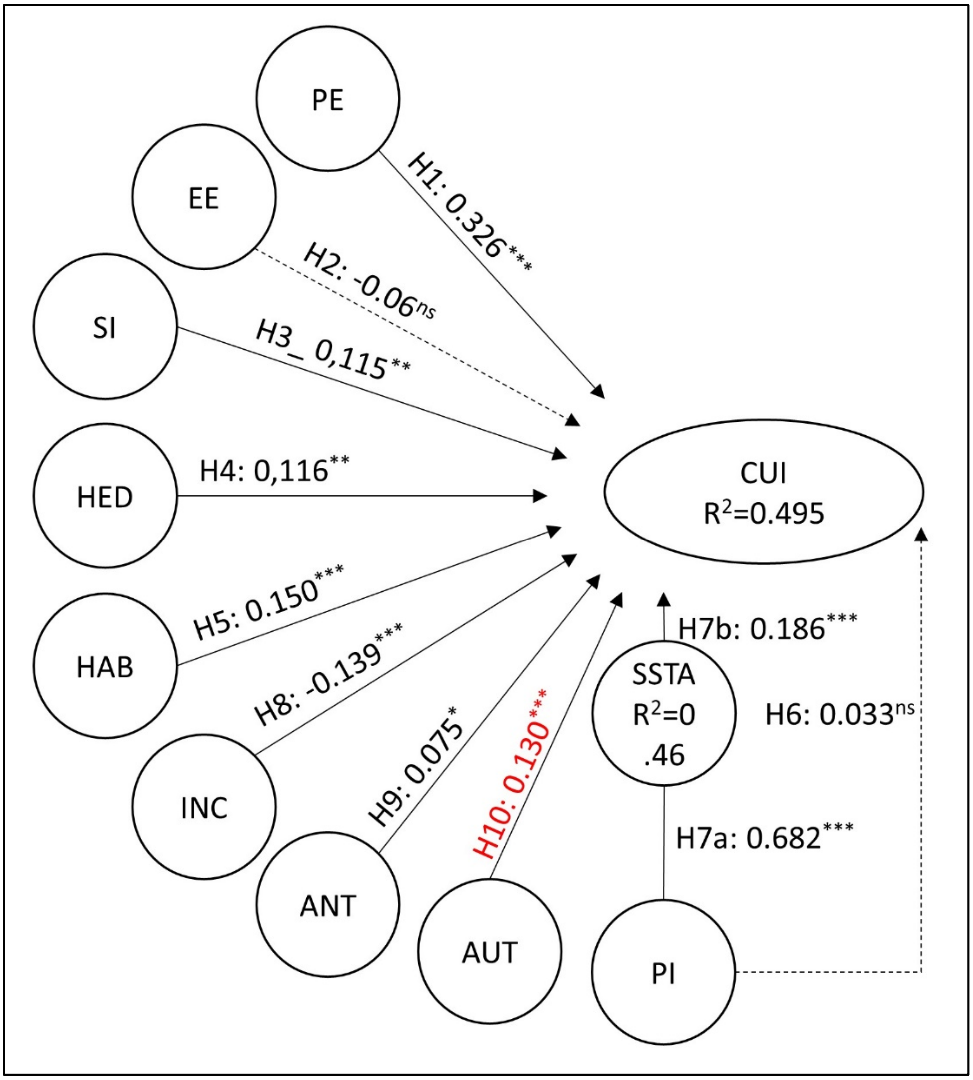
Note: The square root of AVEs are shown diagonally in bold; see Table 2 for the names of the items.

Assessment of the structural model

It has been verified that there is no evidence of multicollinearity between the antecedent variables of each of the endogenous constructs, since all the VIF (Variance Inflation Factor) values were less than 5.

The results of the analysis are shown in Figure 2.

Figure 2. Results of Analysis for Chatbots Usage Intention



NOTE: See Figure 1 for the names of the constructs, *p<0.05; **p<0.01; ***p: 0.00.

The path coefficients (standardized regression coefficients) indicate the estimates of the relationships of the structural model, that is, the hypothesized relationships between the constructs.

The evaluation of the significance of the effects was done by bootstrapping (Hair, Ringle, & Sarstedt, 2011). Since the hypotheses specified the direction of the variables' relationship, a 1-tail Student's t-distribution with n-1 degrees of freedom was used, where n was the number of subsamples. 5000 samples were made (Streukens & Leroi-Werelds, 2016) with a number of cases equal to the number of observations in the original sample. For the assessment of the significance of the relationships, confidence intervals were analyzed in addition to bootstrapping (Henseler, Ringle, & Sinkovics, 2009).

Table 5. Results of Hypothesis Testing.

		Path Coeff.	Sig.	T Statistics	Confidence Intervals	Confidence Intervals Bias	Supporte d
Hypothesis 1	PE → CUI	0.326	***	6.559	[0.244; 0.408]	[0.244; 0.41]	Yes/Yes
Hypothesis 2	EE → CUI	-0.060	ns	1.211	[-0.139; 0.023]	[-0.142; 0.021]	No/No
Hypothesis 3	SI → CUI	0.115	**	2.778	[0.049; 0.186]	[0.044; 0.182]	Yes/Yes
Hypothesis 4	HED → CUI	0.116	**	2.955	[0.048; 0.178]	[0.053; 0.183]	Yes/Yes
Hypothesis 5	HAB → CUI	0.150	***	4.055	[0.091; 0.212]	[0.091; 0.212]	Yes/Yes
Hypothesis 6	PI → CUI	0.033	ns	0.630	[-0.052; 0.119]	[-0.054; 0.117]	No/No
Hypothesis 7a	PI → SSA	0.682	***	19.231	[0.621; 0.739]	[0.613; 0.733]	Yes/Yes
Hypothesis 7b	SSA → CUI	0.186	***	3.523	[0.096; 0.269]	[0.1; 0.272]	Yes/Yes
Hypothesis 8	UNC → CUI	-0.139	***	3.756	[-0.2; -0.079]	[-0.194; -0.074]	Yes/Yes
Hypothesis 9	ANT → CUI	0.075	*	1.934	[0.016; 0.142]	[0.009; 0.136]	Yes/Yes
Hypothesis 10	AUT → CUI	0.130	***	3.638	[0.071; 0.189]	[0.071; 0.188]	Yes/Yes

n = 5000 subsamples: * $p < .05$; ** $p < .01$; ***$p < .001$; ns: non-significant (one-tailed t Student)
$t(0.05; 4999) = 1.645$; $t(0.01; 4999) = 2.327$; $t(0.001; 4999) = 3.092$
Confident Intervals [5%-95%]

As can be observed in both Table 5 and Figure 2, Performance Expectancy (PE) has the largest effect on Chatbots Usage Intention (CUI) (H1: $\beta = 0.326$, $p < 0.001$). Habit (HAB) also has a high effect on CUI (H5: $\beta = 0.150$, $p < 0.001$), and the same can be said for Hedonism (HED) (H4: $\beta = 0.116$, $p < 0.01$) and Social Influence (SI) (H3: $\beta = 0.115$, $p < 0.01$). Additionally, and as hypothesized, there is a high negative relationship between Inconvenience (INC) and CUI (H8: $\beta = -0.139$, $p < 0.001$).

The relationship between CUI and Anthropomorphism (ANT) is significant but weak (H9: $\beta = 0.075$, $p < 0.05$). Perceived Innovativeness (PI) does not have a direct relationship with CUI (H6: ns), but it has an indirect relationship through Self-Service Technologies Attitude (SSTA) (H7a: $\beta = 0.682$, $p < 0.001$, H7b: $\beta = 0.186$, $p < 0.001$). The relationship between Effort Expectancy (EE) and CUI was not confirmed (H2: ns).

The proposed negative relationship between Automation (AUT) (i.e, loss of jobs due to chatbots) with CUI was not confirmed. Moreover, a contrary relationship was observed, that is, a direct positive and significant relationship (H10: $\beta = 0.130$, $p < 0.001$).

The coefficient of determination (R^2) represents a measure of predictive power that indicates the amount of variance in a construct, that is explained by the predictor variables of that endogenous construct in the model. The proposed model explains 49.5% of the variance in the CUI and 46.4% of the variance in SSTA.

Discussion and implications

Performance expectancy is a key requirement for chatbot usage intention. As some of the previous studies (e.g. Phocuswright, 2018) found, tourists use chatbots to obtain information, solve doubts, and find objects or locations. Thus, it is logical that the best explanation for future usage intentions is the fact that the chatbot performs adequately and is able to answer the user's requirements. This coincides with previous research which shows that usefulness and performance are the main drivers of user adoption of technologies, in both mandatory and voluntary settings (Morosan & DeFranco, 2016). In this sense, while at present chatbot use is mostly voluntary, it is conceivable that in the near future many organizations will use chatbots as the starting point for customer support.

In the same vein, we believe that it is logical for habit to explain usage intention. Chatbots are currently a new technology that are starting to be massively adopted by tourist companies. However, these companies should take into consideration that tourists still have to get used to them and have to get into the habit of opening the chatbot, instead of sending an email or calling the company.

The impacts of hedonism and social influence deserve extended comments. Hedonism was found to have a positive and significant impact on chatbot usage intentions. Although performance expectancy is the key consideration, the positive impact of hedonism demonstrates that when users open a chatbot, they also expect to enjoy the conversation. It must be taken into account that users often ask computer-assisted systems questions that they would never ask a human, and that many chatbots have been programmed to be playful and engage in humorous conversations (Bilton, 2015; Woods, 2018). That is, apart from specific questions, knowing that the dialogue is taking place with a computer may cause users to ask non-related questions (e.g. ‘Siri, tell me a joke’, ‘Siri, will you marry me?’) (Bilton, 2015). In addition, if the interaction process with a chatbot is enjoyable, the emotion reinforces many of the tourists’ pleasurable objectives aimed at this interaction (e.g. booking a room and/or planning a trip for holidays).

On the other hand, social influence also explains chatbot usage intention. This refers to two cases: people who the user knows in general, and people who have an influence on the person. Specifically, the examples of those who are social referents indicate a way in which firms could promote chatbot usage, if they are interested in doing so. Tourists frequently browse the Internet when planning their holidays, so if they watch videos of famous people having successful interactions with chatbots, their usage intention could increase.

Both these perspectives (the hedonic and social influence) should be specially taken into account if, in the future, chatbot usage becomes mandatory in certain scenarios.

Regarding the inconveniences in and difficulties of using chatbots, a significant and negative relationship was found. This is, users reported that communication with chatbots is uncomfortable, since the relationship cannot be based on natural language. The expectation that effort must be expanded to express questions and requirements in a way that chatbots can understand, negatively influences the intention to use chatbots. It seems as if we still have a long way to go until general-purpose chatbots can pass the Turing Test. In this same vein, and as expected, the fact that a chatbot behaves like a human and is able to have natural conversations had a positive impact on the usage intentions.

Additionally, we found that the individual’s perceived innovativeness is not related to usage intention, at least not directly. However, there is a relationship in the sense that those who are more innovative will have a more favorable attitude towards SSTs. In turn, those with this positive attitude will tend to use chatbots more frequently. Many tourists are used to interacting with SSTs (e.g. hotel check-ins either online or through a kiosk, receiving boarding passes online, booking a room online, or buying tickets online), so tourists companies are in a favorable position to implement chatbots.

The relationship between effort expectancy and usage intention was not confirmed. This result was logical to us. The concept of effort expectancy was derived from the UTAUT2 model. However, this concept was tested with technologies that have a certain learning curve. We believe that this is not the case with chatbots. In most cases, using a chatbot should simply mean opening the chatbot, typing questions, and trying to have a natural conversation with the system.

Lastly, a rather surprising result was that not only was the proposed negative relationship between automation (given the possibility of loss of jobs due to chatbots) and chatbot usage intention not confirmed, but a contrary relationship was observed, that is, a direct positive and significant relationship. From our perspective and from the literature review, it was clear that when people see that a technology removes jobs, there may be a certain reluctance to use it. However, in this case it was found that not only did this effect not occur, but the relation was inverted. We believe a possible explanation could that many of this study's subjects were young undergraduates, who may not have been concerned with job losses and other type of problems related to implementations of IT. In addition, for tourists the objective of their interaction with a chatbot would be to enjoy an experience (e.g. a hotel stay or a visit to a destination), which could offset any kind of fear about automation. Inconsistencies between attitudes and behavior have been found in several areas such as green purchase behavior (Joshi & Rahman, 2015).

Contributions to the literature

This research has made several contributions to the literature. First, we have demonstrated the factors that explain the intentions to use chatbots, which up to this point had not been studied. Second, we based our research on the well-known UTAUT2 model, spreading its applicability.

We then extended this model by including five constructs that are relevant in the case of chatbots: anthropomorphism, automation, perceived innovativeness, attitude towards SSTs, and inconvenience. The high R^2 of the model supported the constructs' in explaining chatbot usage intention. We also believe that the five additional constructs could be useful in other attempts to explain SSTs usage intention.

Lastly, our study also contributes to the literature regarding chatbot design, adding to the previous research such as the study by Ciechanowski, Przegalinska, Magnuski, and Gloor (2019). While these authors showed that users prefer and feel more comfortable with simple chatbots, we add the need to take into account a hedonic perspective.

Implications for managers

From our perspective, our study's implications for managers are straightforward: people use chatbots mainly because they expect that the chatbots will perform properly. Thus, the design process must take into account their capacity to provide meaningful answers and solve the users' problems. In this sense, it is recommended that initial deployments of chatbot are minimally functional, otherwise there is a risk that future users would not want to use chatbots if their initial interactions were not fulfilling. Initial failed attempts can clearly generate unfavorable expectations about chatbots' usefulness.

Additionally, there seems to be a certain social influence, and thus finding people who can use chatbots without much effort and explain how they communicate their questions, can have a significant and positive effect on the usage intentions of tourists. Finally, although enjoyment and hedonic perspectives are not the main reasons for people to use chatbots, they are still relevant and should be taken into consideration. Therefore, gamification techniques have been proposed to improve tourists' interaction with technology (Yung & Khoo-Lattimore, 2017).

Conclusions

This research focused on analyzing the impact of the key constructs that explain the intentions to use chatbots in the process of organizing and taking vacation trips. To that end, an online questionnaire was developed and 476 valid responses from undergraduates were received.

The main reason for people to use chatbots is that chatbots are expected that to perform correctly and help users to organize their trips. Explanations of chatbot usage intention include habits of using chatbots, the expectation of fun when using the chatbot, and social influence. Possible inconveniences associated with the process of using chatbots (e.g. having to express ideas in a way that the bot will understand them) were found to have a negative impact. The fact that a chatbot communicates like a person was found to have an impact, although it was weak.

The user's innovativeness was not found to have a direct effect. However, an indirect effect was found because more innovative users will tend to use more SSTs, which means that they will also use more chatbots.

The expectation of the effort related to using chatbots (learning how to use them, and requiring specific skills to do so) was not found to be a significant predictor. This is natural because using chatbots is simple and does not require any specific skills.

We were surprised to find that there was no relationship between the fact that chatbots could mean a loss of jobs and the willingness to use them. Although there are similar inconsistencies that could be explained by contextual factors (e.g. respondents could think that automation is an unavoidable issue), we believe that this is a matter that should be further researched with other technologies (e.g. self-checkout kiosks).

Limitations and implications for future research

There is one significant limitation regarding the sample: the geographical context comprised two universities in Spain. In the same way, a limitation of the study is the fact that respondents were self-selected; these problems are difficult to avoid in online studies since the respondents cannot be 'forced', to fill out a survey questionnaire and the characteristics of the individuals have not been documented (Hwang & Fesenmaier, 2003). Thus, this study was not able to address the question of whether respondents and non-respondents differ in important ways.

Moreover, there is a series of variables whose analysis may be more complex than they first appear to be. We believe that this is the case with automation. The questions that were derived from the literature are oriented to the fact that chatbots are going to replace humans. However, we were not able to analyze if users thought that automation was positive or negative, from a general perspective.

We understand that it could be valuable to conduct a series of studies similar to this one, in which the population is segmented, so as to consider other type of tourists who are less used to the Internet than those studied in this research.

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