# New insights into consumers' intention to continue using chatbots in the tourism context

Several industries recognize the potential of Artificial Intelligence to complete tasks. However, there is limited research on chatbots, and a gap in the research on what factors contribute to consumers' intention to continue using them. This research aims to analyze the relationship of the TAM and ISS dimensions, continuing to use satisfaction and brand attachment as mediators, and using the need for interaction with the employee as a moderating dimension. The results indicated that the role of brand attachment increases the model's explanatory power, and the need for interaction with the employee positively favors the relationship between brand attachment and satisfaction.

## Introduction

Artificial Intelligence (AI) has been studied for decades and encompasses subfields such as natural language processing, machine learning, and robotics. Artificial Intelligence has gained economic and social relevance with advances in machine learning and big data (Przegalinska et al., 2019). Technological innovations transform industry structures, processes, and practices (Buhalis et al., 2019). AI is expected to take over several functions of the digital age, especially through text-based conversational agents. This role changes customer service, as these agents provide 24-hour service (Ashfaq et al. 2020). Chatbots can replace human agents to perform tasks like healthcare, financial, and customer service (Araujo, 2018). In addition, there is commercial interest in adopting chatbots due to the financial benefit. While there is some interest, consumers are skeptical of this technology, still preferring to interact with humans rather than chatbots (Roy & Naidoo, 2021). Roy & Naidoo note that addressing consumers' skepticism of chatbot technology is essential information for marketers.

Government agencies and leading global brands have adopted intelligent agents to increase operational efficiency and provide on-demand services. According to Escobar (2020), chatbots provide answers to peoples' questions worldwide. The author mentions that the larger the company, the more problems are eliminated with these innovative tools. However, for companies to better understand the benefits of this technology, they must gain a deep understanding of user behavior as it relates to how they use technology

(Seethamraju et al., 2018). Calvaresi et al. (2020) mention that chatbots help provide users with tips, information and essential support in the tourism industry. Meanwhile, Pereira, Limberger, and Ardigó (2021) claim that the online travel agency Booking.com answered about 30% of consumer queries using a chatbot, thus optimizing service and freeing up staff for other activities.

Adoption of chatbots has increased, as has interaction with chatbots; trends that are expected to continue to rise (Shumanov & Johnson, 2021). However, some consumers are uncomfortable with this technology. They believe chatbots are less informative and less empathetic, resulting in fewer purchases (Luo et al., 2019). This discomfort has drawn attention, since users' long-term viability and continuance behavior depends on their initial adoption decisions (Venkatesh et al., 2011). Although chatbots have already achieved a remarkable degree of automation and efficiency, a more sophisticated level of conversation has not yet been achieved. This lack of alignment between the user and the conversational assistant can cause distress and frustration. Thus, a greater understanding of a tourist and their interests is necessary for this tool to be more successful and model future interactions (Ibrahim et al., 2021).

The chatbot's initial adoption of technology does not necessarily imply its long-term commercial success or use (Yan, Filieri & Matthew, 2021). Yan, Filieri & Matthew note cite the game Pokémon Go as a recent example of technology adoption that witnessed a rapid adoption followed by a rapid disengagement. The authors recommend seeking to understand the factors that explain the intention to continue use (IS) in order to extend long-term use. It is clear that, while first use is crucial to the success of a new system, long-term viability is determined by continued use rather than initial adoption (Bhattacheriee, 2001; Li & Fang, 2019).

In general, two other theories, the technology acceptance model (TAM) and the information system success model (ISS), are customarily used as predictors of satisfaction and CI (Joo, So & Kim, 2018; Ambalov, 2018; Li & Fang, 2019; Ashfaq et al., 2020). Although both models can explain the relationship between satisfaction and intention to continue use, the existing empirical evidence on this relationship remains inconclusive. Some authors, such as Lee and Kwon (2011) and Ashfaq et al. (2020), recommend including consistent affective factors to explain long-term use. In this case, we adopt brand attachment, as this factor has, in the long run, strengthened the relationship between the company and the consumer (Ashfaq et al., 2020). Li and Fang (2019) stated a reciprocal path for brand attachment and satisfaction. Hew et al. (2017) stated that brand

attachment symbolizes consumers' affection for a brand. They indicate that the long-term relationship between the consumer and the brand ensures more meaningful consideration of using the brand's chatbot. For them, brand attachment may be a mediating variable in the relationship between satisfaction and the intention to continue use. Furthermore, we add the need for interaction with service employees as a moderating factor. In Ashfaq et al.'s (2020) study, adding this benefit to the user has improved the explanatory power of the intention to continue use of chatbots.

Our study's model aims to optimize user satisfaction with chatbots in the tourism sector, and to help them establish continuing relationships with users. Currently users have generally low satisfaction with chatbots, and low intention to continue to use them. Furthermore, understanding the role of brand attachment as an antecedent of the intention to continue using chatbots in tourism will contribute to the growing literature on this topic, and help interested professionals such as marketers and programmers adjust chatbot systems' design. Thus, our study aims to analyze the relationship of TAM and ISS dimensions to the intention to continue using chatbots, having satisfaction and brand attachment as mediators, and using the need for interaction with the employee as a moderating dimension.

## Literature review

### *Technology acceptance model and information system success model*

Technological innovations that include robotics and artificial intelligence (AI) have revolutionized the tourism industry (Buhalis & Moldavska, 2021). For Buhalis & Moldavska (2021), intelligent automation, embodied by AI, will likely help most operations across different tourism sectors. As customers spend more time in digital environments, brands shift to digital services (Chung et al., 2018). Service automation through chatbots in the tourism and hospitality sector has received positive feedback due to the benefits they provide, although they still face challenges more broadly (Buhalis and Cheng (2020). However, in addition to automating the service, the design of the tool and its functionality must be attractive to the end-user (Meuter et al., 2005; Sheehan et al., 2020). Thus, several researchers have tirelessly sought to create an ideal model to examine the adoption and continued intention to use technologies in various industries (Dieck and Jung 2018).

User acceptance of new technologies is a critical indicator of successfully implemented technology (Aldhaban 2012). According to Wu et al. (2011), the technology acceptance model (TAM) has been the predominant theory for examining technology acceptance since Davis' development in 1989. Over the years, TAM has been adopted in various studies, including consumer behavior in computer-mediated environments (Porter and Donthu, 2006), to explore the use of 3D virtual worlds (Saeed, Yang & Sinnappan, 2009), in mobile services (Gao, Rohm, Sultan and Huang, 2012), in tourism (Ayeh et al. 2013) and augmented reality (Wojciechowski and Cellary 2013). The application of technology acceptance models reveal several benefits, such as being better able to monitor behaviors, attitudes, and behavioral intention (Cheung, Wan & Chan, 2018). These conditions aim to explore compatibility issues that may restrict usage (Guardia et al., 2020).

Advancing their studies, Delone and Mclean (2003) proposed the information systems success model (ISS). This model comprises the following variables: "system quality, information quality, information system usage, user satisfaction, individual impact, and organization impact" (p. 87). The model has been well accepted to explain technology use behaviors. The authors found that the technical level of communication systems needs to be accurate and efficient. The sophistication of the semantic level will drive the success of the information in conveying its intended meaning. The effectiveness level is the effect that this information has on the recipient. Information quality measures semantic success, and system quality measures technical success. For this research, we used the dimensions of information quality (IQ) and service quality (SQ) since previous studies have pointed out that both are crucial determinants of the success of any Information System Platform (Ashfaq et al., 2020). According to the authors, if a chatbot has these components well established, it will encourage the user to continue using the chatbot in the future. In the tourism industry, these dimensions are particularly important since the first interactions with a chatbot, in general, involve users searching for tips, information, questions regarding check-in and requests for essential services (Hosseini, 2020). The combination of TAM and ISS was previously tested to explain the intention to continue using chatbots. However, several questions remained open (Ashfaq et al., 2020), such as whether or not adding an affective factor could imply a better fit for the model (Ashfaq et al., 20210), particularly in the tourism sector (Pereira et al., 2021).

**Hypothesis Development**

### Predictors of Chatbot satisfaction

Chatbots are robots designed to talk to humans using natural language (Brennann, 2006). They act as virtual agents for businesses, helping to solve problems, support marketing, and provide valuable information (Chung et al. 2018). The use of chatbot technology is not new; however, some resistance from consumers is still present, due to a lack of personalization and uncertainty about the efficiency of this technology (Ashfaq et al., 2020). As a result, human-chatbot interactions still have barriers to overcome. Although consumers are generally likely to use a chatbot for their travel planning, satisfaction with this service may affect usage (Pillai & Sivathanu, 2020). Some authors report privacy issues (Pagallo 2013; Zamora 2017), difficulty in obtaining information (Colace et al. 2017), and feelings of discomfort (Luo et al. 2019) in using chatbots. Emerging research shows the diverse contexts of chatbot applications. Studies have addressed satisfaction as a strong determinant in consumers' relationships with their intention to continue using chatbots (Ramkissoon and Mavondo, 2015; Chung et al., 2018; Li et al., 2019; Ashfaq et al., 2020).

### Information Quality, Service Quality and Satisfaction

Although in most cases, the use of chatbots in tourism aims to satisfy any user who interacts with them (Calvaresi et al., 2021), developing a program to inform tourists, suppliers and stakeholders has become a priority requirement when building a text-based virtual communication service (Ivanov & Webster, 2017). In this case, the information system success model (ISS) is widely accepted to explain post-use behavior (Ashfaq et al., 2020). ISS was developed by DeLone and McLean (1992) and adapted DeLone and McLean (2003). Initially, the authors proposed six dimensions: system quality, information quality (IQ), Information System use, user satisfaction, individual impact, and organizational impact. In the adaptation of the model (DeLone and McLean 2003), the service dimension quality (SQ) was inserted. In the literature review by Ashfaq et al. (2020), IQ and SQ were identified as crucial determinants for the success of information system platforms.

Information quality concerns evaluating the information system's performance in providing information based on the user's experience in using the system (McKinney, Yoon & Zahedi 2002). For a better evaluation, information should be personalized, complete, relevant, easy to use and conveying safety (DeLone and McLean 2003;

Veeramooto et al. 2018). This is especially the case in tourism and hospitality, as an information-dependent market (Buhalis, 2019). Users interact with chatbots in order to gain information about products, offers or even instructions for use. This information should be easy to understand and well-formatted (Ashfaq et al., 2020). For the authors, if information is not easy to understand, this can be detrimental to the user experience. This type of experience influences the perception that the business cannot provide quality service and impacts customers' level of satisfaction. When the interaction between user and chatbot meets these expectations, the likely result is that they will be satisfied. This in turn promotes loyalty, positive word of mouth, good purchase intentions, and ultimately profits for the company (Chung et al. 2020). The relationship between IQ and continuity of use (CI) has been tested and validated in several studies (Chiu et al. 2007; DeLone and McLean 2003; Yang et al. 2017; Zheng et al. 2013; Ashfaq et al. 2020). In the context of tourism research, a chatbot can offer a better tourism experience by providing necessary and quality information (Lombardi, Pascale & Santaniello, 2019). Informed by the literature, the following hypothesis is proposed:

**H1a -** Information quality has a significant positive influence on user satisfaction.

The ISS model states that service quality is fundamental to user satisfaction (DeLone and McLean, 2003; Ashfaq et al., 2020). SQ reflects reliability, responsiveness, assurance, and personalization (Gao et al., 2015). According to Gao et al., if SQ is not sufficient, chatbots will not be able to gain users' trust, which may affect the experience, thus reducing their perception of enjoyment, and sense of control over shopping. Information quality contributes positively to service quality. Many researchers have established a link between service quality and customer satisfaction (Cronin et al., 2000; Park et al., 2013). If the SQ of a chatbot is designed to focus on understanding users' concerns by solving their problems quickly and effectively, the SQ can increase the satisfaction level. According to Buhalis and Chen (2020), in the hospitality industry, the personalization of amenities and smart room services can be provided via chatbots. The researchers claim that another way to provide quality service is to train the chatbot with emotion-based mechanisms to further personalize them. According to Hu et al. (2018), training the chatbot to learn the styles that characterize different brands, and behaving accordingly, can also indicate better service quality in the tourism industry. However, with an inadequate interface and non-individualized attention, slow systems tend to reduce users' trust and influence their satisfaction level (Ashfaq et al., 2020). According

to Kim et al. (2011), if service quality is adequate, it will influence loyalty, causing an effect on continuance intention. Consequently, the following hypothesis is developed:

**H1b -** Service quality has a significant positive influence on user satisfaction.

### *Perceived enjoyment, perceived ease of use, perceived usefulness, and satisfaction*

TAM was proposed by Davis (1989) to assess the individual acceptance of information technology, claiming that perceived usefulness and perceived ease of use determine an individual's attitude toward using information technology. TAM has its origins in the Theory of Reasoned Action (TAR) (Fishbein and Ajzen, 1975) and incorporates the attitudes and beliefs of users who intend to adopt new technology (Dieck and Jung, 2018). TRA examines the mutual relationship between individual behavior, behavioral intention, attitudes, and subjective norms. Davis (1989) applied the core concept of TRA to explain users' acceptance of new technological knowledge (Wu et al., 2020). Because Davis (1989) understood that TRA could not reasonably interpret people's behavioral predictions using information technology, he removed "subjective norms". Instead, he developed two variables, "perceived usefulness of technology" (PU) and "perceived technological ease of use "(PEOU) to shape the "technology acceptance model". Perceived enjoyment is another essential determinant of primary relevance to technology acceptance behavior (Davis et al. 1992).

In general, ease of use refers to the degree to which a person believes that using a particular system would be effortless; already perceived usefulness is related to the degree to which a person believes that using the system, in our case, the chatbot, would improve his or her job performance; and perceived pleasure reflects the extent to which an activity is perceived to be enjoyable in itself, apart from any performance consequences (Davis, 1989; Yan, Filieri & Matthew, 2021). In the case of tourism, the number of users who use the chatbot tool for their travel planning is gradually increasing (Pillai & Sivathanu, 2020). Pillai & Sivathanu found that the chatbot is helping travel agencies to accurately and efficiently complete travel-related tasks. For businesses, this tool primarily holds economic value, as it allows the company to have fewer human travel assistants. In addition to satisfying company profits, businesses have claimed that users are satisfied with gaining easily accessible information, and are surprised to see accurate travel options provided by an artificial intelligence-based system. According to businesses, in general, the feedback on chatbots often includes ease of use, indicated a building of trust,

usefulness for planning trips, developing travel itineraries, and being pleasant to talk to (Pillai & Sivathanu, 2020).

Regarding chatbots, the research results of Rese et al. (2020) pointed out that both utilitarian factors and perceived enjoyment positively influenced chatbot acceptance. In the research of Pereira, Limberger, and Ardigó (2021), in addition to pleasure and perceived usefulness, ease of use is positively related to tourist satisfaction when using chatbots. According to the authors, most tourists claim that the chatbot increases productivity since it reduces time they spend on tasks. They also find chatbots easy to use as they generally have a clear and understandable interaction, resulting in a fun and pleasant conversation. According to Ashfaq et al. (2020), users' pleasant experiences when using a chatbot will result in them feeling more satisfied, and willing to continue using the system. Informed by the literature, we build the following hypothesis:

**H1c –** The perceived utility has a significant positive influence on user satisfaction.

**H1d** – Ease of use has a significant positive influence on user satisfaction.

**H1e** - Perceived enjoyment has a significant positive influence on user satisfaction.

### *Satisfaction, brand attachment, and intention to continue*

When an experience exceeds expectations, this results in satisfaction (Oliver, 1980). Following this rational logic of the expectation-confirmation paradigm, satisfaction can be explained as the result when the affective and cognitive evaluation of users (in this case) results in the perceived performance of the chatbot exceeding the expected performance. In general, studies point out that the dimensions of perceived usefulness, ease of use, system quality, information quality, and perceived enjoyment are crucial factors in achieving satisfaction in using chatbots in the tourism industry (Pereira, Limberger & Ardigó, 2021). Furthermore, these studies demonstrate how chatbot user satisfaction affects the intention to continue use (Ashfaq et al., 2020) and purchase (Pereira, Limberger & Ardigó, 2021), as they have enough positive attributes to meet user expectations.

The literature has pointed out that satisfaction is a mediator between TAM and ISS dimensions with continuance intention (Veeramootoo et al., 2018; Yan, Filieri & Gorton, 2021), which leads to a favorable brand attitude (Bozbay et al., 2018). It has also been identified that satisfaction leads to stronger brand attachment (Danniswara et al.,

2020). For Danniswara et al. (2020), the consequences of satisfaction with technologies indicate the importance of brand attachment and behavioral intentions. The marketing literature finds that satisfaction is a crucial element for the long-term ambitions of a service, as it is an indicator that leads to loyalty (Oliver, 1999). Although well established, some studies have pointed out divergence in this relationship (Ghorbanzadeh & Rahehagh, 2021). According to Bahri-Ammari et al. (2016), the effect of satisfaction on long-term loyalty is implicitly considered in the development of brand attachment. For Oliver (1999), consumer satisfaction is crucial as it can evolve into brand attachment.

The attachment theory is based on the concept of brand attachment (Thomson et al. 2005). Attachment theory (Bowlby 1980; Bowlby 1979; Bowlby 1969) was used to understand deep and lasting emotional connections between humans and objects. According to Pedeliento et al. (2016), the basic tenet of this theory is that individuals are naturally motivated to seek closeness/attachment to a specific figure, to acquire protection from physical and psychological threats and to gain affection. Following this logic, Thomson et al. (2005) stated that emotional attachment is a basic need. They defined brand or product attachment as the relationship between a person and a brand, characterized by a feeling of deep connection, involving affection, passion, and feelings about the brand and their relationship with it.

Recently, there has been a growing interest from EI users in the online community. One of the factors has been that most of these systems require feedback on usability-related issues and feature requests from users. Such feedback can contribute to product quality and marketing, and innovation. As a result, some researchers have begun to explore factors that lead users to engage in such activities and have found that attachment has been a key motivator for these IS (Choi, 2014). By assuming that the outcome of brand attachment is the individual's willingness to maintain proximity to the attachment figure (Pedeliento et al. 2016), several studies have appropriated this construct to explain loyalty-related phenomena, such as those related to repurchase intention (Lin et al. 2011), consumer-brand relationship (Japutra et al. 2018), and intention to continue using mobile apps (Li and Fang 2019).

Brand attachment, as mentioned, can lead to loyalty in the context of IS (Barreda et al., 2013). The authors identified that brand attachment would make consumers more willing to repurchase from the website and to recommend it to others. This factor may drive consumers' emotional attachment to the brand (Theng et al., 2013). Furthermore, businesses often put significant time and effort into cultivating a high degree of brand

attachment (Smaoui and Temessek Behi 2011). Li and Fang (2019) identified that brand attachment positively influences continuous usage intention. Other studies have also identified the influence of brand attachment on the intention to continue use (Lam and Shankar 2014; Matzler et al. 2015; Shukla et al. 2016; Hew et al. 2019). Thus, we hypothesize that:

**H2a** – Satisfaction positively influences brand attachment.

**H2b** – Satisfaction positively influences the intention to continue using.

**H3** – Brand attachment positively influences the intention to continue to use.

### *The role of moderating the need for interaction with the service employee*

The need for interaction with a service employee (NFI-SE) was defined by Dabholkar (1996) as the importance of human interaction with the customer in service encounters. Before Dabholkar's (1996) study, Langeard et al. (1981) already brought essential insights into this factor. They suggested that the need for the human touch to provide a particular service is crucial for specific consumers. To quantify this need, they used two items: the first is human contact, and the second is dependency on interacting with others. When testing in a self-service survey, they observed that both constructs affected the selection of the self-service option. As a result, Dabholkar (1996) expanded the Langeard et al. (1981) study by combining the two items: the authors brought together human contact and dependence on others through presenting the option of interacting with a service employee. The results pointed out a relevant factor for technology-based self-service. They stated that if a consumer has a high need for interaction, they will avoid self-service, whereas if the consumer presents with a low need for interaction, they will seek self-service.

Advancing this need for personal contact and interaction, Dabholkar & Bagozzi (2002) used the NFI-SE as a possible dimension capable of moderating relationships using self-service machines. The authors' idea was that users with a greater need for contact would tend to avoid the machines since they might not be compatible with their expectations; they might make consumers anxious to have contact with employees, and to avoid the machines. In addition, these authors suggested that to get these high contact consumers to use these machines, they would have to be easy to use, reliable, and a lot more fun, which could positively affect satisfaction. These attributes would be more

relevant for this type of consumer than consumers who have a low need for interaction, so they thought that NFI-SE would be able to moderate this relationship.

Advancing this theme, and already using a chatbot, Ashfaq et al. (2020) appropriated the studies of Langeard et al. (1981), Dabholkar (1996),) and Dabholkar & Bagozzi (2002) and brought the perspective that NFI-SE would be able to moderate ease of use, perceived usefulness and perceived pleasure. For the authors, users with higher NFI-SE prefer human-human interaction as they find it more convenient to deal with an employee. They claim that if these users perceive a chatbot to be too simple, they may associate it with a lack of human interaction and touch. Thus, ease of use would moderate negatively on satisfaction. In this case, to raise satisfaction, more humanized, valuable and interesting features would be crucial to raising satisfaction for these users. They also argued that NFI-SE would moderate perceived usefulness and perceived pleasure as users with higher NFI-SE would have a very low expectation of using chatbots. Therefore raising perceived usefulness, such as providing relevant information and personalized recommendations, and raising enjoyment, such as providing ways for the user to feel more comfortable and enjoy the service, would lead to higher satisfaction.

In our study, we believe NFI-SE could moderate information quality and service quality. We start from the logic that service quality depends on quick responses in an individualized way, whereas information quality is crucial to measure the quality of a system. In this case, when the quality of information is low and if a chatbot system is not well-designed or does not understand the user's concerns, it can negatively affect satisfaction. Moreover, we also understand that they will be able to moderate the relationship between satisfaction and brand attachment. According to the research of Chan and Tung (2019), who investigated the effects of robot services in hospitality on guests, the positive experience with the robot service reflected positively on the brand. However, Ivanov et al. (2020) indicated that guests considered human employees more valuable for their social skills and for tasks involving emotional intelligence.

Choi et al. (2020) identified that the quality of service provided by humans results in more positive relationships than those provided by robotic services. This information makes us believe that a consumer with a higher NFI-SE will need more satisfaction to have an affective bond with the brand than a lower NFI-SE consumer. Thus we hypothesize that:

**H4a** - The relationship between ease of use and satisfaction will be moderated by the NFI-SE.

**H4b** - The relationship between perceived usefulness and satisfaction will be moderated by the NFI-SE.

**H4c** - The relationship between perceived pleasure and satisfaction will be moderated by the NFI-SE.

**H4d** - The relationship between information quality and satisfaction will be moderated by the NFI-SE.

**H4e** - The relationship between service quality and satisfaction will be moderated by the NFI-SE.

**H5** - The relationship between satisfaction and brand attachment will be moderated by NFI-SE.


**Research Method**

This study was designed to analyze the interrelationships between service quality, information quality, perceived utility, and perceived pleasure in the intention of continuous use. We also aim to explore the role of brand attachment in moderating these relationships. To fulfill this objective, we defined consumers who used a chatbot when planning their trips as the population of interest. The target sample was defined as tourists who used a chatbot one year before the questionnaire was completed. Initially we considered a shorter time period, but we extended the eligible time period due to the Covid-19 pandemic and the widespread impact this had on people's ability to travel. The questionnaire was delivered in English on the Mechanical Turk platform. Two questions were inserted to verify whether the user was responding to the survey. The first queried whether the interviewee had used a chatbot during the past year. The second was a control variable. The sample, collected in August 2020, included 531 respondents from various countries, most of whom lived in the United States and India. After eliminating searches with errors or missing values, 448 responses were used for the analyzes.

*Research instrument*

The scales related to perceived utility (PU), perceived enjoyment (PE), quality of service (QS), quality of information (IQ), Ease of Use (PEOU), need for interaction with a service employee (NFI-SE), and intention to continue (CI) were adapted from Ashfaq et al. (2020). The satisfaction (SAT) was adapted from Chung et al. (2020), and brand

attachment was adapted (BA) from Li et al. (2019). To maintain the previous research pattern, we used a five-point Likert scale (where 1 = strongly disagree; 5 = strongly agree) for all constructs.

**Figure 1 – Theoretical model**
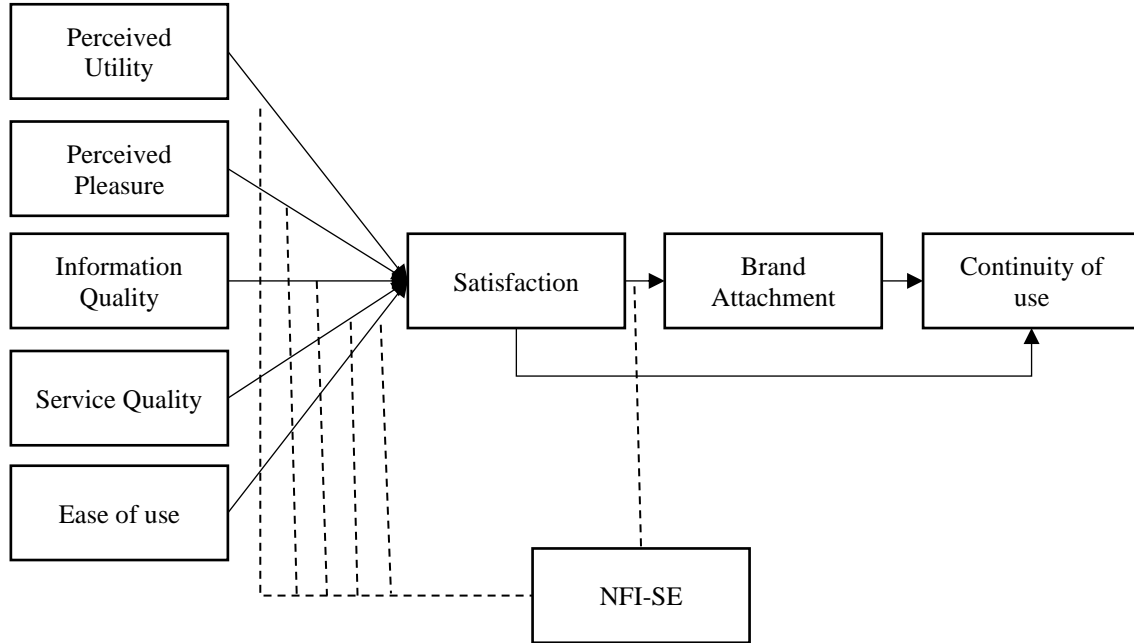


### Analysis method

First, compliance with the conditions was verified to ensure the validity of the proposed model. Among the main premises, it is worth mentioning that the Kolmogorov-Smirnov test suggests the variables' non-normality. This indicates that structural equation modeling is based on variance (PLS-SEM). When there is a problem concerning the normal distribution, PLS-SEM is recognized as a good methodological option for theory tests (Sarstedt et al., 2011). The G * Power 3.1 software was also used to estimate the appropriate sample size (Ringle et al., 2014). According to the parameters (effect size $f^2$ = 0.15, power = 0.95, number of predictors = 5), it was indicated that the minimum sample size was calculated as 138, which means that the current sample size (n = 448) is adequate.

## Results

### Descriptive statistics

In terms of demographic data among the chatbot users in the sample for this study, 60.9% were male and 39.1% female, with the most frequent age group (21-38) at 70.3%, followed by customers 39-58 by 23.4%. Regarding degree of education attained, 64.1%

had an undergraduate degree, and 27.7% had a Master's degree. The average monthly family income was US $1001.00 to US $2000.00 (15.4%), US $2001.00 to US $3000.00 (21.4%) and US $3001.00 to US $4000.00. When asked where they had used the chatbot, 65% of participants had used one on hotel websites, 39.5% when using online travel agencies, and 35.9% when visiting airline websites.

**Table 1** Socio-Demographic Profile

| Variable | | Frequency | % |
|---|---|---|---|
| Gender | Male | 273 | 60,9 |
| | Female | 175 | 39,1 |
| Age | 18-20 | 12 | 2,7 |
| | 21-38 | 315 | 70,3 |
| | 39-58 | 105 | 23,4 |
| | 59 and older | 16 | 3 |
| Education | High school | 19 | 4,2 |
| | Incomplete higher | 13 | 2,9 |
| | Graduated | 287 | 64,1 |
| | Master's degree | 124 | 27,7 |
| | Doctorate degree | 5 | 1,1 |

### *Measurement model*

To evaluate and validate the proposed questionnaire before testing the relationships (Hair et al. 2016), we ran some tests. We applied the Cronbach's Alpha test to assess the reliability and internal consistency of the factors. The indicators' external load values must be greater than 0.708 (Hair et al., 2016). As shown in Table 2, all values were adequate above 0.708. For internal consistency, Cronbach's alpha (α) was calculated. All latent constructs had values above the acceptable minimum of 0.700 (Hair et al. 2016). Following preliminary tests, we calculated the average extracted variance (AVE) (Hair et al. 2016). All constructs showed values above the suggested limit of 0.50. Furthermore, finally, the Stone-Geisser $Q^2$ values were obtained through the blindfolding technique for satisfaction and the intention to continue. Both were higher than zero, providing support for the model's predictive validity (Hair et al., 2014).

**Table 2** Measurement Model.

| Items | Factors | Cronbach | Rho_A | R.C. | AV. | Q² |
|---|---|---|---|---|---|---|
| Brand attachment | | 0.805 | 0.806 | 0.885 | 0.720 | 0.273 |
| BA1 | 0.869 | | | | | |
| BA2 | 0.817 | | | | | |
| BA3 | 0.859 | | | | | |
| Intention to continue use | | 0.735 | 0.736 | 0.850 | 0.654 | 0.474 |
| CI1 | 0.781 | | | | | |
| CI2 | 0.793 | | | | | |
| CI3 | 0.850 | | | | | |
| Need for interaction | | 0.702 | 0.713 | 0.826 | 0.612 | |
| NISE1 | 0.822 | | | | | |
| NISE2 | 0.757 | | | | | |
| NISE3 | 0.786 | | | | | |
| Ease of use | | 0.705 | 0.724 | 0.816 | 0.597 | |
| PEOU1 | 0.823 | | | | | |
| PEOU3 | 0.737 | | | | | |
| PEOU4 | 0.755 | | | | | |
| Perceived enjoyment | | 0.818 | 0.818 | 0.892 | 0.733 | |
| PE1 | 0.864 | | | | | |
| PE2 | 0.839 | | | | | |
| PE3 | 0.866 | | | | | |
| Perceived usefulness | | 0.748 | 0.749 | 0.856 | 0.665 | |
| PU1 | 0.783 | | | | | |
| PU2 | 0.729 | | | | | |
| PU4 | 0.833 | | | | | |
| Information quality | | 0.769 | 0.770 | 0.867 | 0.684 | |
| QI3 | 0.835 | | | | | |
| QI5 | 0.821 | | | | | |
| QI7 | 0.825 | | | | | |
| Service quality | | 0.753 | 0.755 | 0.859 | 0.670 | |
| QS2 | 0.840 | | | | | |
| QS4 | 0.801 | | | | | |
| QS6 | 0.813 | | | | | |
| Satisfaction | | 0.755 | 0.764 | 0.860 | 0.673 | 0.393 |
| SAT1 | 0.859 | | | | | |
| SAT3 | 0.750 | | | | | |
| SAT5 | 0.847 | | | | | |

*Structural Model Assessment*

The results of the reliability and validity of the measurement model allowed us to continue the analysis in PLS-SEM. We then used bootstrapping and vantages. According to Hair et al. (2016), the number of bootstrap samples should be larger than the number of valid observations in the original dataset. In our case, we used 5,000 samples. The $R^2$

for satisfaction was 0.601, for brand attachment was 0.387, and for intention to continue to use, it was 0.746, suggesting average variance explained by the predictive constructs of the model. Next, we evaluated the effect size ($f^2$).

Satisfaction was affected by information quality (0.078) and perceived usefulness (0.071). Furthermore, the brand attachment was affected by the need for interaction with a service employee (0.139) and satisfaction (0.161). Finally, the intention to continue using chatbots was affected by brand attachment (0.151), ease of use (0,028), perceived enjoyment (0.056), perceived usefulness (0.088), and satisfaction (0.030). All f two effect sizes were more significant than the minimum cut-off value of 0.02 (Cohen, 1988). We then analyzed the Stone²-Geisser $Q^2$ to assess the magnitude of all $R^2$ values. All values of the endogenous variables were adequate (Cabelo et al., 2016).

We also verified the discriminant validity following the Fornell-Larcker criteria presented in Table 3. The matrix was presented properly. However, the Heterotrait-Monotrait Ratio (HTMT) matrix (Appendix) initially presented inconsistencies, so we checked the cross-loading table and eliminated the items that presented high correlations with the items of the opposite construct (PU3, IQ1, SAT1, and SAT3). Some values remained above 0.85 but within the limit of 0.9 recommended by Henseler et al (2015).

**Table 3** – Discriminating Validity

|  | BA | PEOU | IQ | CI | NFI-SE | PE | PU | SAT | SQ |
|---|---|---|---|---|---|---|---|---|---|
| BA | 0.849 |  |  |  |  |  |  |  |  |
| PEOU | 0.514 | 0.773 |  |  |  |  |  |  |  |
| IQ | 0.516 | 0.689 | 0.827 |  |  |  |  |  |  |
| CI | 0.739 | 0.685 | 0.640 | 0.809 |  |  |  |  |  |
| NFI-SE | 0.537 | 0.554 | 0.585 | 0.536 | 0.783 |  |  |  |  |
| PE | 0.746 | 0.610 | 0.541 | 0.750 | 0.492 | 0.856 |  |  |  |
| PU | 0.578 | 0.731 | 0.681 | 0.750 | 0.565 | 0.649 | 0.816 |  |  |
| SAT | 0.549 | 0.663 | 0.679 | 0.684 | 0.526 | 0.590 | 0.706 | 0.820 |  |
| SQ | 0.620 | 0.665 | 0.571 | 0.692 | 0.513 | 0.702 | 0.654 | 0.597 | 0.818 |

We checked the model fit using the standardized root mean square residual Razi (SRMR). According to Henseler et al. (2016), the SRMR value should be less than 0.08. The fit of our model was 0.066, suggesting an adequate fit. We then checked the variance inflation factor (VIF), which is used to analyse whether the model has multicollinearity or not (Hair et al., 2017). All the values (also in the supplementary material) were below the value of 5.0, indicating that the model is free of multicollinearity.

*Model Analysis*

After verifying the methodology for the analyses, following the same route taken by Ashfaq et al. (2020), we tested five different models. For the analyses, a bootstrapping approach was applied to a total of 5000 subsamples in all models. To expand further on the five models: in Model 1, we added information and service quality, brand attachment, satisfaction, perceived usefulness, and intention to continue using it. In Model 2, we added ease of use; in Model 3, we added perceived pleasure; in Model 4, we added the need for interaction with the service employee; in Model 5, we tested whether the need for interaction with the service employee would work as a moderator variable. Model 5 explained 62.2% of satisfaction, 40.1% of brand attachment, and 74.6% of intention to continue using, and presented itself as the best model tested. However, Model 3 was considered the best for this work since it presented the same explanatory power of the intention to continue use as Model 5.

This result is slightly better than the findings by Ashfaq et al. (2020), which presented an explanatory power of 72.2%. Although they are different objects of research and the explanatory power of each is roughly equivalent, the brand attachment dimension shows the potential to improve the intention to continue use. Another factor that differs our study from Ashfaq et al. (2020) is the NFI-SE moderator test. The study by Ashfaq et al. (2020) verified that this dimension could moderate the predictive dimensions (TAM and ISS) with satisfaction. In fact, the author found moderation in perceived usefulness and ease of use, which was not identified in our study. However, we can observe that the NFI-SE has the power to moderate the relationship between satisfaction and brand attachment.

**Table 4** – Models Analysis

| Path | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|------|---------|---------|---------|---------|---------|
| BA → CI | 0.420*** | 0.405*** | 0.302*** | 0.302*** | 0.302*** |
| IQ → SAT | 0.332*** | 0.289*** | 0.284*** | 0.271*** | 0.108*** |
| PU → CI | 0.373*** | 0.291*** | 0.255*** | 0.255*** | 0.255*** |
| PU → SAT | 0.373*** | 0.321*** | 0.292*** | 0.286*** | 0.242*** |
| SAT → BA | 0.551*** | 0.550*** | 0.551*** | 0.369*** | 0.402*** |
| SAT → CI | 0.191*** | 0.145*** | 0.131** | 0.132** | 0.132** |
| SQ → SAT | 0.163*** | 0.125** | 0.075 | 0.070 | 0.068 |
| PEOU → CI | | 0.168** | 0.134** | 0.134** | 0.134** |
| PEOU → SAT | | 0.146** | 0.134* | 0.130* | 0108 |
| PE → CI | | | 0.200*** | 0.200*** | 0.200*** |
| PE → SAT | | | 0.112* | 0.108* | 0.121* |

| | | | |
|---|---|---|---|
| NFI-SE → BA | | 0.343*** | 0.370*** |
| NFI-SE → SAT | | 0.045 | 0.022 |
| NFI-SE x IQ → SAT | | | -0.035 |
| NFI-SE x PE → SAT | | | -0.001 |
| NFI-SE x PEOU → SAT | | | -0.105 |
| NFI-SE x PU → SAT | | | 0.045 |
| NFI-SE x SQ → SAT | | | -0.016 |
| NFI-SE x SAT → BA | | | 0.079** |

In Table 5 we show all the R² of the five models tested.

**Table 5** - Explanatory power of each model.

| R² | SAT | BA | CI |
|---|---|---|---|
| Model 1 | 0.587 | 0.303 | 0.721 |
| Model 2 | 0.594 | 0.303 | 0.732 |
| Model 3 | 0.600 | 0.303 | 0.746 |
| Model 4 | 0.601 | 0.387 | 0.742 |
| Model 5 | 0.622 | 0.401 | 0.746 |

For a better understanding, we examined the hypothesis test of the complete model.

**Table 6** - Direct relationships

| | Original Sample | Sample Mean | Standard Deviation | T Statistics | P Values | |
|---|---|---|---|---|---|---|
| BA → CI | 0.302 | 0.303 | 0.042 | 7.203 | 0.000 | Supported |
| IQ → SAT | 0.271 | 0.270 | 0.062 | 4.372 | 0.000 | Supported |
| NFI-SE → BA | 0.343 | 0.349 | 0.068 | 5.029 | 0.000 | Supported |
| NFI-SE → SAT | 0.045 | 0.046 | 0.052 | 0.857 | 0.392 | Rejected |
| PE → CI | 0.200 | 0.198 | 0.046 | 4.367 | 0.000 | Supported |
| PE → SAT | 0.108 | 0.109 | 0.055 | 1.967 | 0.049 | Supported |
| PEOU → CI | 0.134 | 0.134 | 0.046 | 2.915 | 0.004 | Supported |
| PEOU → SAT | 0.130 | 0.133 | 0.066 | 1.980 | 0.048 | Supported |
| PU → CI | 0.255 | 0.255 | 0.051 | 5.006 | 0.000 | Supported |
| PU → SAT | 0.286 | 0.283 | 0.064 | 4.432 | 0.000 | Supported |
| SAT → BA | 0.369 | 0.365 | 0.062 | 5.950 | 0.000 | Supported |
| SAT → CI | 0.132 | 0.130 | 0.043 | 3.091 | 0.002 | Supported |
| SQ → SAT | 0.070 | 0.068 | 0.072 | 0.974 | 0.330 | Rejected |

We can observe the analysis of relationships in this study as shown in Table 6. Information quality ($\beta = 0.271$, p <0.000), ease of use ($\beta = 0.130$, p <0.048), perceived usefulness ($\beta = 0.286$, p <0.000) and perceived enjoyment ($\beta = 0.108$, p <0.049) were presented as predictive dimensions of satisfaction. Satisfaction ($\beta = 0.369$, p <0.000) was presented as a dimension capable of influencing brand attachment. Perceived usefulness

(β = 0.255, p <0.000), ease of use (β = 0.134, p <0.004), perceived enjoyment (β = 0.200, p <0.000), satisfaction (β = 0.132, p <0.002) and attachment the brand (β = 0.302, p < 0.000) were able to influence the intention to continue use. Finally, the need for interaction with the service employee (β =0.343, p <0.000) was supported by brand attachment, but rejected (β = 0.045, p <0.392) with satisfaction. The relationship between service quality and satisfaction (β =0.070, p <0.330) was also rejected.

**Table 7** – Moderation of the need for interaction with service employee

| | Original Sample | Sample Mean | Standard Deviation | T Statistics | P Values | |
|---|---|---|---|---|---|---|
| Moderating IQ→SAT | -0.035 | -0.030 | 0.053 | 0.650 | 0.516 | Rejected |
| Moderating PE →SAT | -0.001 | 0.005 | 0.051 | 0.025 | 0.980 | Rejected |
| Moderating PEOU → SAT | -0.105 | -0.105 | 0.058 | 1.807 | 0.071 | Rejected |
| Moderating PU →SAT | 0.045 | 0.044 | 0.052 | 0.861 | 0.389 | Rejected |
| Moderating SAT →BA | 0.079 | 0.082 | 0.031 | 2.510 | 0.012 | Suported |
| Moderating SQ → SAT | -0.016 | -0.026 | 0.073 | 0.219 | 0.826 | Rejected |

As a result of 5,000 iterations, a moderating effect was identified in the relationship between satisfaction and brand attachment (β = 0.079, p <0.012). In this study, we did not identify a moderating effect of NFI-SE on service quality, information quality, perceived pleasure, ease of use, and perceived usefulness. This differs from the study by Ashfaq et al. (2020), which found a negative effect between ease of use and satisfaction, and a positive effect on perceived usefulness and satisfaction. However, despite this difference, we realized that this benefit could improve brand attachment's explanatory power – a quality desired by businesses. In this way, despite not moderating the predictors with satisfaction, satisfaction has stands out as a benefit, and a crucial measure of the chatbot's performance.

**Analysis**

The first point showed the interrelationships between the TAM and ISS dimensions in satisfaction and the intention to continue use. Structural equation modeling revealed that information quality (H1a), perceived usefulness (H1c), ease of use (H1d), and perceived pleasure (H1e) have a positive influence on satisfaction. When comparing standardized coefficients, information quality has a more significant positive effect on satisfaction. Satisfaction showed a positive relationship with brand attachment (H2a) and intention to continue use (H2b). In addition, brand attachment positively influenced the intention to continue use (H3).

We also analyzed the moderating role of the need for interaction with the service worker (NFI-SE). In this case, the NFI-SE presented itself as a moderator of the relationship between satisfaction and brand attachment (H5). Moderation in the relationships PEOU (H4a), PU (H4b), PE (H4c), IQ (H4d), and QS (H4e) with satisfaction were refuted.

*Theoretical Implications*

This investigation makes several theoretical contributions. Chatbot literature is still in its infancy and will benefit from further research. Researchers commonly perform surveys in order to discover clues regarding users' intention to continue using chatbots (Li & Fang, 2019; Rese, Ganster & Baier, 2020; Kasilingam, 2020), including the application of brand attachment in the use of chatbots (Ashfaq et al., 2020), as well as the application of ISS and TAM in the chatbot (Ashfaq, 2020). Previous research has investigated the role of ISS in satisfaction in the context of mobile applications (Li & Fang, 2019) and the use of TAM to explain the intention to use airline ticket booking apps (Suki & Suki, 2017). The overlap of ISS and TAM as predictors of satisfaction in the context of AI-powered service agents has also been explored (Ashfaq et al., 2020), and researchers have also used satisfaction to predict intention to continue use (Li & Fang, 2019; Ashfaq et al., 2020). The results of this investigation expand on the previous literature, by conducting empirical research to examine ISS and TAM as predictors of continuity and the intention to continue using chatbots in the tourism sector.

This study contributes to the ISS model literature, showing that service quality (Models 1 and 2) and information quality positively influence satisfaction. Our results contribute to those identified by Ashfaq et al. (2020) and Pereira, Limberger & Ardigó (2021). For chatbot users in tourism-related services, it is expected that a chatbot has a modern, visually pleasing interface and that the way the chatbot communicates meets the user's needs. The chatbot must also provide the right solution, an immediate response, and individual attention. As presented in the statistical data, the dimension that held the greatest weight for users was regarding the quality of the information. They expect information provided to be sufficient, quick, useful, clear, accurate, up-to-date, and reliable. Regarding the technology acceptance model (TAM), perceived usefulness, perceived pleasure, and ease of use significantly influence satisfaction. These results contribute to Ashfaq et al. (2020) and Pereira, Limberger & Ardigó (2021). We have

identified that, in general, the user expects the chatbot to solve a problem quickly and conveniently, to be easy to use, and to be thoughtful and pleasant.

Furthermore, our study focused on brand attachment. Although it has been extensively researched in the marketing and consumer behavior literature, Park et al. (2019) claim that there is a negligible amount of research in tourism literature, mainly related to text-based conversational agents (Ashfaq et al., 2020). In this study, brand attachment mediates the relationship between satisfaction and the intention to continue use. In general, the brand attachment theory states that individuals are motivated to seek closeness to acquire protection against possible inconveniences, and to gain affection (Pedeliento et al., 2016). Our study points to the existence of this positive relationship between both dimensions. This is quite important because, as pointed out in the literature review, brand attachment can lead to loyalty, which is an attribute of long-term use. In this way, even though it is a mechanized response, assigning a characteristic to the chatbot system will incentivize the user interact with the chatbot more often, and thus allow the human personnel to perform other activities.

In addition, we added the moderator role of the need for interaction with the service employee. As shown in Table 5, Model 5 presented the best explanatory power, which was when moderation was inserted. This theme is particularly relevant since brand attachment was not included in the studies by Ashfaq et al. (2020) and Pereira, Limberger & Ardigó (2021). Although the results indicate divergence between the studies, and one of these reasons may have been the object of study, we advanced by showing that the NFI-SE can moderate the relationship between satisfaction and brand attachment. Providing this benefit will incentivize the consumer to continue to use the chatbot. However, it will also strengthen the chances of acquiring a loyal customer.

### *Practical Implications*

This study provides some interesting practical implications for companies that have adopted the chatbot as a tool to interact with consumers. However, although they are away of technological developments, most companies in the tourism sector are adapting slowly to new technologies, especially when it comes to chatbots. Our study presents important insights that contribute to the adoption of technologies by consumers and a more effective result for companies, especially concerning the intention to continue using them.

First, perceived usefulness was the dimension most likely to evoke positive responses with satisfaction. One of the main focuses of chatbots should be usability, convenience, and productivity. According to our questionnaire, consumers seek to reduce bureaucracy and obtain quick answers. Therefore, when utilising this type of technology, businesses must ensure that chatbots correctly present this information. The second most relevant aspect of our study is the quality of the information. The consumer seeks reliable, up-to-date, accurate, and precise information. Businesses must be aware of this. In addition, the quality of service was relevant. Businesses must be concerned with the interface's appearance, aiming to provide a modern and visually appealing look to users.

Satisfaction significantly increases the intention to continue using the app. Businesses can seek feedback on interactions with chatbots to improve and strengthen communication and relationships with consumers. In addition, the attachment to the brand was an important indicator of the continued use of chatbots. Adding affective factors into a chatbot design will increase this behavioral intent. Furthermore, inserting an escape mechanism, that is, a mechanism that enables human-human interaction, will not only increase user satisfaction (especially those with a greater need for contact), but will also increase brand attachment. This mechanism can even impact the customer's long-term relationship with the company.

Understanding the mechanisms that predict the intention to continue using chatbots helps the company manage strategies, attract more consumers, optimize their relationships, and provide personalized attention 24 hours a day. The chatbot must ensure a hassle-free, useful, and enjoyable experience (Ashfaq et al., 2020). Ensuring these factors are met will increase consumer satisfaction as well as the intention to continue using this technology.

**Limitations and Future Research**

This study was designed to identify the impact of TAM and ISS on satisfaction, brand attachment, and intention to continue using the need to interact with a service worker as a moderator. While this study provides significant implications, there are limitations. Firstly, this study adopted the non-probability sampling technique to extract samples from multiple countries, with some more heavily represented than others, so generalization should be made with caution. We encourage future studies to increase the extent of sample representativeness, including studies that can do a multigroup analysis, as different cultures can provide additional answers. We recommend that in future studies

using chatbots, the anthropomorphism dimension is included to see if it has an impact on the continuity of use, and whether the social presence of the interface is a dimension capable of influencing satisfaction. We also recommend that studies aim to identify factors that influence the decision to disclose information to chatbots, and follow the advice given by chatbots. We recommend the propensity to trustworthiness and the chatbot morality as mediating dimensions. Lastly, we recommend studies that aim to identify ways to generate empathy in human-chatbot conversations since, in this study, it was found that it can affect the end user's satisfaction.

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## Appendix

|  | BA | PEOU | IQ | CI | NFI-SE | PE | PU | SAT | SQ |
|---|---|---|---|---|---|---|---|---|---|
| Brand attachment |  |  |  |  |  |  |  |  |  |
| Ease of use | 0.739 |  |  |  |  |  |  |  |  |
| Information quality | 0.655 | 0.858 |  |  |  |  |  |  |  |
| Intention to continue | 0.879 | 0.876 | 0.812 |  |  |  |  |  |  |
| NFI-SE | 0.887 | 0.755 | 0.740 | 0.771 |  |  |  |  |  |
| Perceived enjoyment | 0.896 | 0.886 | 0.717 | 0.890 | 0.781 |  |  |  |  |
| Perceived usefulness | 0.628 | 0.837 | 0.886 | 0.834 | 0.780 | 0.670 |  |  |  |
| Satisfaction | 0.702 | 0.820 | 0.890 | 0.801 | 0.701 | 0.751 | 0.874 |  |  |
| Service quality | 0.798 | 0.891 | 0.750 | 0.890 | 0.739 | 0.854 | 0.722 | 0.792 |  |