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Uncovering the predictive power of neural networks in the adoption of beacon technology in the tourism sector

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ABSTRACT

This study examines the main factors influencing the adoption of location-based mobile services (LBS) powered by beacon technology in the tourism sector. Using logistic regression models and neural networks, specifically the multilayer perceptron (MLP), this research identifies eleven significant variables driving the adoption process. Among these, system quality, trust, perceived ease of use, perceived usefulness, and service quality stand out as the most influential factors. The MLP model demonstrated superior performance with a classification accuracy of 99.14% and an area under the curve (AUC) of 0.947, highlighting the exceptional predictive capability of non-parametric models over traditional logistic regression. These findings underscore the importance of system trust and reliability in driving users' adoption of beacon-based applications. Additionally, this study provides valuable insights for marketing professionals and tourism stakeholders, suggesting that enhancing user trust, improving system quality, and simplifying the user experience can positively impact LBS figures in the tourism sector. The results provide a solid foundation for leveraging advanced predictive models to improve the operational efficiency of digital solutions in tourism.

RESUMEN

Este estudio examina los principales factores que influyen en la adopción de servicios móviles basados en la localización (LBS) impulsados por la tecnología de balizas en el sector turístico. Utilizando modelos de regresión logística y redes neuronales, concretamente el perceptrón multicapa (MLP), esta investigación identifica once variables significativas que impulsan el proceso de adopción. Entre ellas, destacan como factores más influyentes la calidad del sistema, la confianza, la facilidad de uso percibida, la utilidad percibida y la calidad del servicio. El modelo MLP demostró un rendimiento superior con una precisión de clasificación del 99,14 % y un área bajo la curva (AUC) de 0,947, lo que pone de relieve la excepcional capacidad predictiva de los modelos no paramétricos frente a la regresión logística tradicional. Estos resultados subrayan la importancia de la confianza y la fiabilidad del sistema para impulsar la adopción por parte de los usuarios de aplicaciones basadas en balizas. Además, este estudio proporciona información valiosa para los profesionales del marketing y las partes interesadas del sector turístico, ya que sugiere que aumentar la confianza de los usuarios, mejorar la calidad del sistema y simplificar la experiencia del usuario puede tener un impacto positivo en las cifras de los servicios de localización en el sector turístico. Los resultados proporcionan una base sólida para aprovechar los modelos predictivos avanzados con el fin de mejorar la eficiencia operativa de las soluciones digitales en el turismo.

KEYWORDS

Mobile applications; beacon; adoption; usage intention; neural networks.

PALABRAS CLAVE

Aplicaciones móviles; baliza; adopción; intención de uso; redes neuronales.

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1. INTRODUCTION

In the last decade, location-based mobile services (LBS) have experienced significant growth due to their ability to offer personalized experiences across a wide variety of sectors, especially in tourism (Aggarwal et al., 2024). These services allow companies to provide real-time information and services based on users' exact locations, adding value for both consumers and businesses (Liang et al., 2017). According to MarketsandMarkets (2023), the global LBS market was valued at $45.4 billion in 2021, and it is projected to reach $402.4 billion by 2031, with a compound annual growth rate (CAGR) of 24.6% for the period 2022 to 2031. The LBS market growth is mainly driven by the increased adoption of social networks and the widespread use of smartphones, coupled with the general availability of GPS and advances in location-based technologies. Furthermore, the growing number of smartphone users and internet accessibility contribute positively to this expansion. However, high installation and maintenance costs, along with various operational challenges, remain obstacles to growth. Despite these barriers, the rising penetration of 3G and 4G networks, along with the sustained increase in internet users, is expected to provide new opportunities for the development of the LBS market in the coming years (Budi et al., 2021).

The adoption of LBS presents significant challenges, including user concerns regarding privacy and data security (Lin et al., 2023). According to the European Commission (2020), 73% of European users express some concern about the amount of data these applications collect, posing a barrier to mass adoption and a relevant issue for study in the field of marketing.

Beacon technology, as an advanced form of LBS, has gained popularity worldwide. It enables short-range communication with mobile devices using Bluetooth Low Energy (BLE) signals and provides a considerable advantage over other location systems, such as GPS, by operating more accurately indoors and without requiring an internet connection (Navío-Marco et al., 2018). Overall, the implementation of this technology has transformed various sectors, particularly in terms of improving decision-making and service personalization (Ozkan et al., 2024). In tourism, LBS has allowed tourists to receive real-time contextualized information on points of interest, routes, and personalized recommendations, significantly enhancing the user experience (Xiang and Fesenmaier, 2017).

Beacons have demonstrated a significant impact on tourism. Their strategic placement on physical objects at specific points allows for the provision of relevant, location-adapted information (Choi and Kim, 2017). This facilitates a more personalized and enriching experience for tourists. In other words, once a tourist downloads the application, they can use it throughout their visit, and at the end, the host company or institution can gather valuable information from the collected metrics, such as time spent in each area, zones visited, and time spent in front of each exhibit (Cerruela García et al., 2017). Currently, beacon technology is used in tourist destinations like Benidorm (Spain), museums like the Metropolitan Museum of Art in New York and the Guggenheim in Spain, airports such as Heathrow in London and Hong Kong International, and hotels like James Hotels in Chicago, Miami, and New York. These examples highlight the current relevance and future potential of this technology for

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stakeholders in the tourism sector worldwide (see Appendix Figure 1).

A key research gap is the lack of studies that integrate explanatory and predictive models to analyze the factors influencing LBS adoption. Although factors such as perceived usefulness and ease of use have been explored in previous studies (Venkatesh et al., 2012), few have applied predictive models like neural networks to improve the understanding of the determinants of this technology's adoption (Liébana-Cabanillas and Lara-Rubio, 2017). These models offer high predictive power and can help identify variables that facilitate or hinder the use of LBS-based applications (Migliore et al., 2022).

Therefore, the main objective of this study is to address this research gap by using explanatory and predictive methodology, such as logistic regression and neural networks. The application of these techniques will allow the detection of factors that influence the adoption of LBS through beacon technology in the tourism sector. This approach provides valuable information for tourism managers, technology companies, and public policy makers interested in improving the tourism experience through digitalization.

The remainder of this paper is structured as follows: Section 2 introduces the literature review, hypotheses, and research model employed; Section 3 describes the methodological approach; Section 4 presents and discusses the results and their implications; and finally, Section 5 summarizes the main conclusions, mentions some implications for managers, acknowledges the limitations of this study, and proposes avenues for future research.

2. LITERATURE REVIEW

Many theories and models on behavioral decisions and intention, primarily those originating from social psychology (Pavlou, 2002), have been developed to analyze individuals' reactions to innovations.

In terms of consumer behavior, our literature review focuses on models and theories that have received substantial support in marketing and information technology studies (Liébana-Cabanillas et al., 2024a; Tomić et al., 2023). We propose an aggregated model that includes the main variables, adapted for our research, used in studies on the adoption of mobile services supported by beacon applications (see Appendix Table 1). A Literature Review section should extend, not repeat, the background to the article already dealt with in the Introduction and lay the foundation for further work.

In this study, the variables defining the intention to use LBS are grouped as follows: behavioral, previous user experience with similar tools, and sociodemographic (see Appendix Table 2).

Specifically, the following variables were considered: 1) Innovativeness, identified as one of the most important determinants of new technology adoption (Okazaki et al., 2017). Furthermore, it is unaffected by environmental or internal influences (Agarwal and Prasad, 1998). Personal innovativeness toward information technologies (PIIT) can be defined as "an individual's willingness to try out any new information technology." 2) Simplicity, considered a fundamental concept in mobile device design, always aims to reduce complexity and facilitate use (Lee et al., 2015). 3) Interactivity, an essential feature of some technologies, generally has a positive effect on user attitudes and encourages the use of these technologies (Lee, 2005; Wu & Wu, 2006). 4) Habit is a repeated behavior pattern that

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occurs automatically, independent of conscious awareness (Triandis, 1977); it has a direct effect on the use of specific technologies, such as the technology considered in our research (Venkatesh et al., 2012). 5) Affinity refers to the presence of positive feelings toward an application, reflecting perceived value and ease of use (Stern et al., 2008). 6) Dependency is a relationship in which individuals' ability to achieve their goals depends, to a greater or lesser extent, on the information available in the environment (Ruiz Mafé and Sanz Blas, 2006). 7) Perceived usefulness is the degree of belief of the potential user that using a given resource will improve the utility obtained from a given situation (Davis et al., 1989). 8) Ease of use is the perception that using a given resource will not require undue effort (Davis et al., 1989). 9) Usefulness is the effort required to learn, use, and manage a technology/system (Flavián et al., 2006). 10) Perceived benefits increase the incentive to use a technology/system; in this case, these perceived benefits are functional, i.e., those derived from the use of the beacon application. Social benefits are those derived from contact with others, and hedonic benefits are those derived from entertainment (Parra-López et al., 2011). 11) Perceived value is the result of the consumer's comparison between perceived benefits and associated costs (Zeithaml, 1988). 12) Perceived enjoyment is an intrinsic motivation, associated with doing something because the action itself and/or its outcome is enjoyable; Venkatesh (2000) defined perceived enjoyment as the degree of fun or pleasure derived from using a technology. 13) Mehrabian and Russell (1974) describe three types of emotion (pleasure, arousal, and dominance) that reflect emotional responses to environmental stimuli. 14) Subjective norm has been described as the degree to which individuals perceive that important people to them believe they should behave in a particular way (Venkatesh and Bala, 2008). 15) Service quality is essential for promoting acceptance (Parasuraman et al., 1988), but defining this variable is often complicated by its multidimensional nature; in the present study, we follow the proposals of Ahn et al. (2007), for whom service quality basically means how well the provided service matches customer expectations; this variable is closely related to information quality (data format, completeness, timeliness, etc.) and system quality (interface design, functionality, response time, etc.). 16) Flow is the holistic sensation obtained with full involvement (Csikszentmihalyi, 2000), such that the experience is enhanced, thereby promoting further use of the service. The perceived fit between task and technology refers to the degree of match between the characteristics of a technology/system (the tools, applications, and support services required to carry out the involved tasks) and the requirements of the task itself (Huang et al., 2017). 17) Trust is defined as a psychological state in which the individual accepts their vulnerability, which is countered by positive expectations about others' intentions and behavior. 18) Perceived risk (general risk) is a multidimensional construct composed of various factors that together explain the total risk associated with adopting a new proposition (Featherman and Pavlou, 2003; Park and Tussyadiah, 2017; Ramos de Luna et al., 2023; Seow et al., 2017; Stone and Grønhaug, 1993). In our study, the main proposed dimensions are performance risk (the possibility that services do not work as designed), social risk (potential loss of status in one's social group as a result of using a particular service), psychological risk (the risk that choosing a particular service may have a negative influence on the tourist's peace of mind or self-perception), and time loss risk (time

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spent on actions that do not contribute anything positive).

In addition, a user's positive prior experience with a similar tool will decisively impact their future behavior (Fishbein and Ajzen, 1975). The variables we use, defined from tourists' experiences with systems similar to our proposal (prior knowledge, need, experience with information systems and tools, phone use during tourist visits, and tourist information systems), have been tested in various ways in many previous studies (Agapito and Guerreiro, 2023; Guillén et al., 2016; Lin, 2011; Molinillo et al., 2023; Yoon et al., 2018).

Finally, sociodemographic variables are also determinants in innovation adoption (Goldsmith and Horowitz, 2006). In this regard, gender, age, marital status, education, and income (Choi and Park, 2017; Grau-Berlanga et al., 2023; Kang et al., 2018; Kim et al., 2021; Raleting and Nel, 2011; Yoon et al., 2018) have been considered in the literature. Our analysis confirms that these variables have varying levels of influence on many of the relationships that determine technology adoption.

3. METHODOLOGY

3.1. Study fieldwork and data collection

This quantitative multi-stage sequential study was undertaken to determine the factors influencing tourists' adoption of LBS with beacon technology. Study data were collected using an online survey based on convenience sampling of smartphone users who had visited a tourist destination in the previous six months and who, during this trip, had used one or more apps to access information about the destination. The study participants were recruited through an email invitation sent to members of the two universities to which the authors, students, faculty and co-workers belonged. In the same email, using the snowball technique, the respondents were asked to forward the invitation to others who met the above conditions. The snowball technique is a non-probabilistic sampling method that is used to expand the range of participants (Chang and Chen, 2008; Murphy et al., 2016) when the target population size would otherwise be difficult to attain (as in the present case) (Murphy et al., 2016). The respondents to our email were assigned a date to attend the computer laboratory, where the necessary instructions were given. Each participant watched a video explaining the use of beacons in a museum and then completed an online questionnaire. Video screenshots are incorporated in Appendix Figure 2.

Before they entered the survey website, the users were expressly informed that they had to remember a promotional code that would appear at the end of the video, to ensure that they watched it in its entirety. Our analysis used data only from participants who correctly remembered the code. According to previous research, information that is processed, consciously or unconsciously, activates the memory. The process described, therefore, was expected to increase the reliability of the results obtained (Migliore et al., 2022; Wells, 1997). In accordance with Hu et al. (2010), the participants were monitored to ensure they followed the instructions. Any questionnaires completed in less than eight minutes were excluded from the analysis, as it would have been impossible to complete the task properly in that time.

The survey was conducted in November 2017 in a university computer room, under the supervision of two members of the research team and a graduate student. Of the 597 participants recruited, the final valid sample was composed of 542. In the Appendix Table 3 summarises the characteristics of the study sample.

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3.2. Development of the measurement scales

A set of measurement items was adapted to the specific context of the research; a total of 134 items, structured around 33 constructs, was obtained. Appendix Table 9 shows the complete list of items, which were measured by means of multi-item scales, of the constructs studied in this research. The participants' responses to the questionnaire items were measured on a 7-point Likert scale, ranging from 1 (= "strongly disagree") to 7 (= "strongly agree"). This is the normal method to measure variables that are not directly quantifiable or observed (Churchill and Iacobucci, 2002).

The questionnaire items were validated by a panel of ten academics and tourism professionals, who gave their opinions as to whether the items were appropriate for analysing tourists' intention to use beacon apps to access information based on their locations during a visit to the museum. A pilot test was then conducted with 45 individuals of different ages and genders who met the required conditions. The results of this pilot test were used to fine tune the final questionnaire.

The questionnaire was divided into three sections: 1) evaluation questions to confirm the participants' understanding of the subject; 2) questions related to the study's behavioural model; 3) sociodemographic questions to ensure the empirical results are not due to covariance with other variables. The design focused on the evaluation and refinement of the survey to check levels of acceptance, dimensionality, reliability and validity of the proposed scales. Finally, after the relevant tests had been conducted, and the scales and relationships had been verified, the proposed model was evaluated (see Table 4). To collect the data, the questionnaire was distributed online, using the Qualtrics questionnaire tool (www.qualtrics.com).

The questionnaire was originally in the English language; a back-translation technique was used to translate the items from English to Spanish (Brislin, 1970).

3.3. Research methodology and experimental design

3.3.1. Forecasting approach and accuracy

According to Blanco-Oliver et al. (2024), Morescalchi (2021), Olson et al. (2012), and Ravi Kumar and Ravi (2007) nonparametric techniques, especially MLP, usually provide better performance and greater precision than classical parametric techniques such as logistic regression (LR), due to their considerable learning capacity and computational complexity, when dealing with suitable samples, as in the case we describe. With parametric techniques, however, the researcher has greater freedom to create a model suited to the research objectives (Rodrigues and Stevenson, 2013), due to the greater flexibility and transparency of these techniques compared to the non-parametric approach. Nevertheless, these methods are not mutually exclusive, but enable the researcher to take advantage of the synergies they present and to mitigate the weaknesses of each one alone.

In our procedure, the first step is to use LR to predict and explain the use of LBS, generating the most parsimonious model possible, with a stepwise regression. The explanatory variables are introduced in the order described in previous research, after which we analyse the robustness of the model and determine the relationship between the independent variable and the intention to use LBS by examining the sign of each coefficient.

In the second stage of the process, we construct a multilayer perceptron (MLP) neural network and compare its performance with that of the classical parametric LR technique. A neural network is merely

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a limited implementation of an ordinary smoothing algorithm, i.e. a nonlinear and not necessarily additive extension to the LR model (Blanco et al., 2013; Cubiles-de-la-Vega et al., 2013; Solano-Sánchez et al., 2024). The statistical characteristics of the best prediction models obtained can then be described.

Receiver operating characteristic (ROC) analysis is a useful way to assess the accuracy of model predictions. This is done by plotting the sensitivity versus specificity of a classification model. In our case, the SPSS 23 statistical package was used to compute the area under a given ROC curve (AUC), which is an important statistic, representing the probability that the prediction is in the correct order when a test variable is observed.

The general predictive capacity of a model depends on the prior probabilities and the costs of any misclassification. According to West (2000), the relative importance of Type I and Type II errors is different, in the ratio 1:5. According to, in our model special attention is paid to the Type II errors, i.e. when an individual who adopts LBS is classified as one who does not (false negative). The following terminology can be applied: the prior probabilities of not adopting LBS using beacon technology are described as $\pi 1$; and the probability of doing so as $\pi 2$; P21 and P12 measure the probability of the occurrence of Type I and Type II errors, respectively; C21 and C12 are the misclassification costs of Type I and Type II errors, respectively. Then the formula for estimating the cost of the classification error is:

$$\text{Cost (error)} = C_{21}\,P_{21}\,\pi_1 + C_{12}\,P_{12}\,\pi_2$$

3.3.2. Logistic Regression Model

Logistic regression (LR) is an appropriate technique for our research aims for several reasons. First, because it has been used in previous studies to address commercial classification problems; second, because it is very appropriate for a sample with the characteristics we describe; and third, because it is a useful complement to other non-parametric techniques.

Therefore, we apply a LR model consisting of a dummy dependent variable which takes the value zero when the tourist does not adopt beacon technology and a value of one otherwise. Accordingly, the following LR formula is used:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k$$

where p is the probability of the beacon technology being adopted. This is calculated from the value of the independent variables, as follows:

$$p = \frac{e^Z}{1+e^Z} = \frac{1}{1+e^{-Z}}$$

where

$$Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k$$

In accordance with the characteristics of our sample, LR can be used for decision making and its performance compared with that of other techniques or models (whether parametric or non-parametric). To do so, we must first define the classification threshold that maximises the correct percentage of classification. In our case, this probability threshold, to classify the zeros and ones, is taken as 0.48, after determining the value that minimises the 10-fold validation error (Blanco et al., 2013).

One disadvantage of LR is that it requires a certain minimum amount of data (observations, characteristics or variables) to obtain stable results. Moreover, in some cases, the independent variables must be transformed in order to determine the complex, nonlinear relationships existing between them and the dependent variable. In our case, however, there are sufficient observations and

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characteristics, and so LR is less prone to the problem of overfitting.

3.3.3. Artificial Neural Networks Model

Artificial neural networks (ANNs) in general and the MLP architecture in particular are capable of replicating the neuronal activity of the human brain, and thus transform inputs into the desired results. In this context, the nodes or neurons are the processing elements, a priori simple. These are strongly interconnected and form a series of artificial intelligence networks with the capacity to solve complex classification problems (Bishop, 1995). MLP neural networks are commonly used in commercial studies (Zhang et al., 1998) because they enable the researcher to address more complex relationships, albeit at the possible cost of increased training and scoring time.

As shown in Appendix Figure 3, the processing units are organised in layers. The MLP we propose normally has three components: an input layer, with units representing the input fields; one or more hidden layers; and an output layer, with one or more units representing the target field(s) (Rumelhart et al., 1986). The units connect with variable connection strengths (or weights). The input data is presented in the first layer, and the values are propagated from each neuron to any neuron in the next layer. Finally, a result is sent from the output layer.

According to the MLP universal approximation property, a single hidden layer network is sufficient to model any complex system to the desired level of precision (Zhang et al., 1998); Therefore, the model we present has only one hidden layer. Although no general rule exists to define the ideal number of hidden layer nodes (Gnana and Deepa, 2013), this parameter is crucial to optimal network performance. In consequence, the size of the hidden layer is normally established through experiment or by trial and error. In the present study, and in line with previous results, we tested a three-layer perceptron in which the output layer consisted of a node that gave an estimate of the probability of beacon technology being adopted.

The operational process for the MLP is represented mathematically as follows. Given a hidden layer of size H, where $\{v_{ih}, i = 0,1, 2, ..., p, h = 1,2, ..., H\}$ are the synaptic weights for the connections between the input of size p and the hidden layer, and where $\{w_h, h = 0,1, 2, ..., H\}$ are the synaptic weights for the connections between the hidden nodes and the output node, then the overall operation of the proposed architecture is expressed as:

$$\hat{y} = g\left(w_0 + \sum_{h=1}^{H} w_h\, g\left(v_{0h} + \sum_{h=1}^{H} v_{ih}\, x_j\right)\right)$$

In modelling the probability of beacon technology being adopted in the tourism industry, two programs are commonly used. The first is the R system, in which the nnet R (Liébana-Cabanillas and Lara-Rubio, 2017) function fits single-layer neural networks, using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) (Bishop, 1995) training algorithm, which minimises an error that allows a decay term λ and thus minimises problems of overfitting (Bishop, 1995). In the classification problem considered, we apply the conditional maximum likelihood (or entropy) criterion (Hastie et al., 2009). Thus, defining $W = (W_1, ..., W_M)$ as the vector of all the M coefficients of the network, and given n objectives $y_1, ..., y_n$, where $y_i = 1$ for the tourist who adopts beacon technology, and $y_i = 0$ otherwise, the equation applied with the BFGS method is:

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$$\underset{W}{\mathrm{Min}} \sum_{h=1}^{H} (y_i \, ln \, \hat{y}_i + (1 - y_i) \ln(1 - \hat{y}_i)) + \lambda \left(\sum_{i=1}^{M} W_i^2 \right)$$

After defining the size of the hidden layer (H) and that of the decay parameter (λ), we then performed a 10-fold cross-validated search for the size of the hidden layer and the decay parameter (λ), over a grid defined as {1,2, ..., 20} x {0,0,01, 0,05, 0.1, 0.2, ..., 1.5}. We also examined training without regularisation, where λ = 0.

Another instrument used to build MLPs is the Neural Network Toolbox (Cubiles-de-la-Vega et al., 2013) with MATLAB (2021). This commercial system offers a wide variety of learning rules. In the present case, we considered the following algorithms to train the MLP: the Levenberg-Marquardt and Scaled Conjugate Gradient algorithms and the quasi-Newton BFGS, gradient descent. These learning rules are applied in order to minimise the sum of square errors (SSE):

$$\underset{W}{\mathrm{Min}} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

One of the most commonly employed approaches in this context is k-fold cross-validation analysis. In this method, the initial dataset is randomly divided into k subsets of approximately equal size. Each of these subsets is then used alternately as the test set, while the remaining subsets are combined to form the training set. This process generates k different models, each trained on a distinct portion of the original dataset, ensuring that each subset serves as the test set exactly once. The overall accuracy of the models is obtained by computing the average accuracy across all k models. In this study, this technique was applied to determine the optimal size of the hidden layer (H) through a 10-fold cross-validation search over the range {1,2, …, 20}. Finally, following the recommendations of Hastie et al. (2001), the error function used was based on the conditional adjustment of maximum likelihood (entropy), which is appropriate for classification problems.

In this study, an MLP approach was used for three reasons: a) previous studies have used it as a complement, in most cases reporting that it performs better than parametric techniques; b) This technique can be applied to many different problems, providing good solutions in a short time, and without ignoring nonlinear relationships, as occurs with parametric techniques (Blanco et al., 2013; Cubiles-de-la-Vega et al., 2013; Liébana-Cabanillas and Lara-Rubio, 2017) c) nonparametric techniques have greater predictive power than their parametric equivalents.

The superiority of multilayer perceptron (MLP) neural networks over traditional parametric techniques, such as logistic regression, in credit risk assessment has been widely documented in the literature. Unlike logistic regression, which is based on linear relationships and strong distributional assumptions with subsequent activation of the logistic function, MLP models are capable of capturing complex and non-linear patterns in the data, which makes them especially suitable for tasks in which the interactions between variables are complex (Bishop, 1995). Several studies have shown that MLP-based models achieve greater predictive accuracy in estimating the risk of default compared to logistic regression and other parametric approaches (Baesens et al., 2003; Lessmann et al., 2015; West, 2000). Furthermore, recent research highlights that MLP models tend to be more robust when dealing with unbalanced data sets, a common

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problem in financial risk analysis, as they can learn latent structures in the data without relying on predefined statistical distributions (Zhang, 2010).

4. RESULTS

The analysis of the results obtained (see Appendix Table 5) indicated that a total of eleven variables were identified as significant in the logistic regression model for the adoption of beacon technology in the tourism sector. These include Habit, perceived usefulness, perceived ease of use, perceived benefits, functional benefits, perceived enjoyment, service quality, information quality, system quality, flow and trust. These findings are consistent with previous studies that have identified perceived usefulness and perceived ease of use as key determinants of new technology adoption (Davis, 1989; Venkatesh et al., 2012). Additionally, variables such as flow and trust also showed a positive association with the use of this technology.

On the other hand, it was observed that variables such as habit and functional benefits did not have a significant impact on the adoption of beacon technology, likely due to users' lack of familiarity and prior experience with this type of technology in tourism environments.

Although we did not find empirical evidence of a significant effect for the other variables used to explain the adoption of LBS in the tourism industry, MLP-type neural networks do identify the influence of these variables. However, the results regarding the weights of each variable obtained from the MLP, shown in Appendix Figure 4, which are based on the normalised importance of the variables, indicate that the variables found to be significant in the logistic regression model have greater weights, suggesting that these variables are more explanatory of the adoption of location-based mobile services supported by beacon technology.

The results of this analysis provided a correct classification percentage of 94.81%, with a sensitivity value of 92.76% and a specificity value of 96.29%, for an optimal cut-off point of 0.49, as shown in Appendix Table 6. This table also shows that the classification matrix values obtained by the neural network indicate a correct classification percentage of 99.14%, with sensitivity and specificity values of 98.60% and 99.51%, respectively.

According to these results, the neural network-based model (MLP) confirmed these findings and demonstrated a higher predictive performance compared to the logistic regression model. In addition to a higher correct classification rate, the MLP yielded an area under the curve (AUC) of 0.952 (see Appendix Table 7 and Figure 5), indicating that non-parametric models, such as neural networks, offer greater predictive ability for the adoption of emerging technologies in tourism. Neural networks were particularly effective in modelling non-linear relationships between independent variables and the adoption of beacon technology, allowing for the identification of complex patterns in user behaviour. Also, based on the results obtained for misclassification costs (Table 8), these results continue to suggest that the neural network performs better than a parametric LR model.

On the other hand, the cross-validation and independent tests in regard of the actual accuracy when predicting the adoption of mobile payment systems were found to be 92.89% and 95.20% for the logistic regression modeling and the neural network modelling respectively.

5. DISCUSSION AND CONCLUSIONS

The empirical results of this study confirm the theoretical superiority of non-linear and non-parametric adaptive learning properties in the

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development of predictive models for the adoption of location-based services (LBS) supported by beacon technology in the tourism sector. In this regard, we recommend that marketers and other stakeholders in this area consider using neural network-based models (MLPs) instead of traditional parametric models, as even small improvements in predictive capability can significantly impact the operational outcomes of beacon application deployment. Neural networks, by handling non-linear relationships and complex patterns of user behaviour, are better suited to predict the adoption of emerging technologies.

5.1. Implications for management

The implications of this study are wide-ranging for tourism managers and technology developers. First, the results suggest that variables such as trust and system quality are key factors in promoting LBS adoption in tourism. Therefore, companies should focus on ensuring that systems are reliable, secure, and easy to use, as well as implementing measures to foster users' trust in the collection and use of their personal data. Data security and transparency are essential, especially considering that a large majority of European users remain concerned about privacy in location-based applications (European Commission, 2020). Improving these aspects could facilitate greater adoption and, consequently, an increase in the competitiveness of technology and tourism companies committed to the digitisation of customer experience.

Secondly, a notable aspect of the results is that system quality and trust play a crucial role in the adoption of LBS technologies. These findings suggest that technology developers should focus on improving these aspects to increase user acceptance. Trust in technology, in particular, has been identified as a crucial factor in previous studies related to the adoption of mobile services (Kim et al., 2008), which is consistent with the findings of this study.

Finally, the superior predictive capability of MLP models highlights the importance of adopting advanced analytical approaches to predict user behaviour. Companies using non-parametric predictive models will be able to more accurately anticipate adoption patterns, enabling them to design more effective and personalised marketing strategies. This data-driven approach offers a competitive advantage in the digitised tourism market, where consumers expect experiences tailored to their preferences and behaviours.

5.2. Social implications

The implementation of beacon technology in the tourism sector presents significant social implications, particularly in terms of accessibility, inclusivity, and community benefits. By enhancing real-time, location-based interactions, beacons create a more engaging, seamless, and inclusive experience for diverse groups of tourists, including individuals with disabilities, elderly visitors, and international travelers.

One of the most relevant contributions of beacon technology is its potential to improve accessibility in tourism spaces. For individuals with visual, auditory, or mobility impairments, beacon-based systems can provide real-time audio descriptions, interactive maps, and step-by-step navigation that enable independent movement through museums, historical sites, and urban environments. By offering contextualized, on-demand information, beacons facilitate access to cultural and historical knowledge without requiring physical interaction with fixed information points. Furthermore, multilingual support within beacon-enabled applications enhances the experience for international visitors by

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eliminating language barriers and fostering a more inclusive tourism environment.

Beyond individual accessibility, beacon technology promotes inclusive tourism by tailoring experiences to diverse visitors' needs. Through personalized recommendations, beacons adapt to tourist preferences, ensuring that information, services, and promotions align with their interests and requirements. For instance, families traveling with children can receive notifications about kid-friendly activities, while tourists with specific dietary restrictions can be directed to appropriate dining options. This customized approach enhances user satisfaction and encourages more equitable participation in tourism services.

At a community level, the widespread adoption of beacon technology in tourism brings substantial benefits for local businesses and public institutions. By providing real-time visitor analytics, beacons allow local stakeholders to optimize resource allocation, improve visitor flow management, and enhance economic opportunities for small businesses. Retail shops, restaurants, and cultural institutions can leverage beacon-generated insights to tailor their offerings, ensuring that visitors receive timely and relevant recommendations that drive local economic growth. Additionally, by fostering sustainable tourism practices, beacon technology helps destinations reduce overcrowding, protect fragile heritage sites, and promote responsible visitor behavior through real-time alerts and guidance.

5.3. Limitations and future research

Despite the significant contributions of this study, it is important to highlight some limitations. First, the composition of the study sample was restricted to mobile users in Spain, which limits the generalisability of the results. In future research, it would be useful to extend this analysis to other countries and cultures to determine whether geographical and social differences affect the factors that influence LBS adoption.

Secondly, the study employed a cross-sectional design, which prevented us from analysing the evolution of user behaviour over the long term. To verify the strength of the identified relationships and observe their development over time, longitudinal studies are needed. This would make it possible to assess the persistence of the observed effects and changes in user behaviour in relation to the adoption of beacon technology.

Thirdly, although the study included a video demonstrating how beacon applications work, the research could be enriched by incorporating real data obtained during tourist visits. The use of such data could provide a more accurate representation of how users interact with these apps in tourist environments, allowing their effectiveness to be compared with other technologies, such as NFC or augmented reality.

This study opens up new opportunities for further research in additional ways. Firstly, it would be relevant to incorporate real data from users who utilise beacon apps during their tourist visits, providing a more accurate and contextualised analysis of the interaction between the user and the technology. Furthermore, a comparative analysis between different location-based technologies, such as NFC and augmented reality, could identify which offers the greatest advantages in terms of adoption, user satisfaction, and operational effectiveness.

Another important line of research would be to assess the cultural effect on the adoption of these technologies. A comparative analysis between tourists from different cultural backgrounds could reveal how factors such as social norms and risk perception influence the adoption of location-based

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applications. Such cross-cultural research would be especially valuable for international tourist destinations, where visitors come from different parts of the world with varied technological expectations.

Finally, it is suggested to conduct studies in different geographical and social contexts to assess whether the results obtained in Spain can be replicated in other countries. This would provide a more global and comprehensive view of the factors influencing the adoption of LBS in tourism.

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APPENDIX

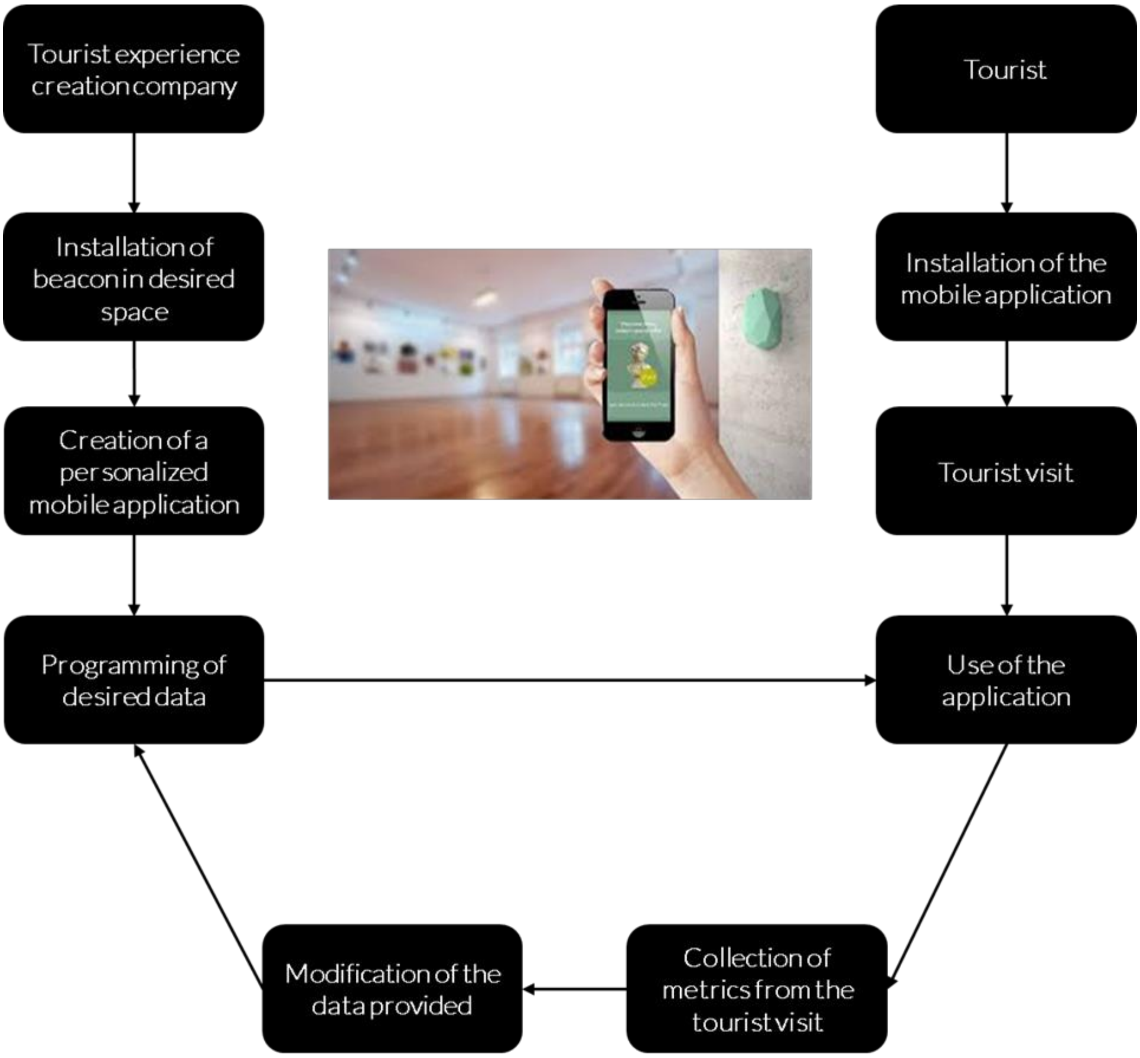

Figure 1. Beacon technology procedure in the tourism sector[1].

[1] Source: Own elaboration.

Author(s)	Mobile Service	Objective	Theoretical Framework Used	Main Findings
Adeline et al. (2023)	Mobile advertising in retail	New consumer expectations in mobile advertising	Consumer expectations theories	Consumers expect advertising to offer more personalized and interactive experiences
Al-Qudah et al. (2024)	Mobile payment adoption	Factors that affect the adoption of these tools by users, and how mobile payments can be key tools for helping companies on their journey to digital transformation	Not determined	Mobile user skillfulness is the primary factor influencing the intention to use the payment system, followed by perceived usefulness and convenience. While perceived risk has a negative impact, its effect is weak due to the high Cybersecurity Index in the UAE.
Barfi et al. (2024)	Electronic library and support services for distance education	Perspectives on the acceptance of electronic library and support services for distance education	Technology adoption models	Ease of use and perceived usefulness drive the initial acceptance of the electronic library
Li et al. (2024)	Mobile technologies in hospitality and tourism	Meta-analysis and SEM on consumer intention to use mobile technologies	Technology acceptance model and structural equations	Positive intention to use mobile technologies in hospitality is driven by ease of use and usefulness
Liébana-Cabanillas et al. (2024b)	Biometric m-payment systems	Effect of key antecedents in UTAUT2 model and perceived risk on the intention to use a mobile payment system featuring biometric identification.	UTAUT2 extended with perceived risk. SEM + ANN	The most significant variables affecting use intention were performance expectancy, effort expectancy, facilitating conditions, hedonic motivation and risk.
Lin et al. (2023)	Mobile health applications	Study privacy, security, and resilience in mobile health applications	Not determined	Privacy and security concerns are key to the adoption of mobile applications
Lucas et al. (2023)	From e-commerce to m-commerce	Analyze user experience with different e-commerce and m-commerce platforms	User experience models and platform comparison	User experience significantly impacts the transition from e-commerce to m-commerce
Parayil Iqbal et al. (2023)	Mobile banking (m-banking) in Islamic banking	Trust with the Unified Theory of Acceptance and Use of	UTAUT extended with trust integration	Trust significantly enhances the adoption of mobile banking among Islamic banking users

		Technology (UTAUT) for m-banking adoption in Islamic banking		
Park and Le (2023)	Ridesharing mobile app	Develop a continuity model for ridesharing apps, moderated by brand awareness	Continuity model with brand awareness moderation	Brand awareness positively moderates the intention to continue using the app
Pick-Soon et al. (2025)	Mobile payment	Investigate the key determinants predicting users' behavioural intention in adopting mobile payment (m-payment) in the new normal era.	MTAM extended with attitudes, perceived trust, perceived risk and personal innovativeness with government support functioning as a moderator.	Mobile usefulness and personal innovativeness significantly predicted user BI to use m-payment. Based on the moderation analysis, government support strengthened attitude-based impacts on behavioural intention towards m-payment adoption.
Ramos de Luna et al. (2023)	Mobile payments at point of sale	Explore determinants of intention to adopt mobile payments	Behavioral intention models	Security and ease of use are key determinants for adopting mobile payments

Table 1. Studies on the adoption of mobile services[2].

[2] Source: Own elaboration.

Behavioural variables	
Innovativeness	Subjective norm
Simplicity	Service quality
Interactivity	Information quality
Habit	System quality
Affinity	Flow
Dependency	Perceived task-technology fit
Perceived usefulness	Task characteristic
Perceived ease of use	Technology characteristic
Usability	Trust
Perceived benefits	Performance risk
Perceived value	Social risk
Functional benefits	Psychological risk
Social benefits	Overall risk
Hedonic benefits	Time loss risk
Perceived enjoyment	Arousal
Perceived dominance	Pleasure
User´s experience	
Previous knowledge	
Necessity	
Experience with information systems and tools	
Telephone use during tourist visits	
Tourist information systems	
Socio-demographic variables	
Age	
Gender	
Marital status	
Education	
Income	

Table 2. Variables analyzed[3].

[3] Source: Own elaboration.

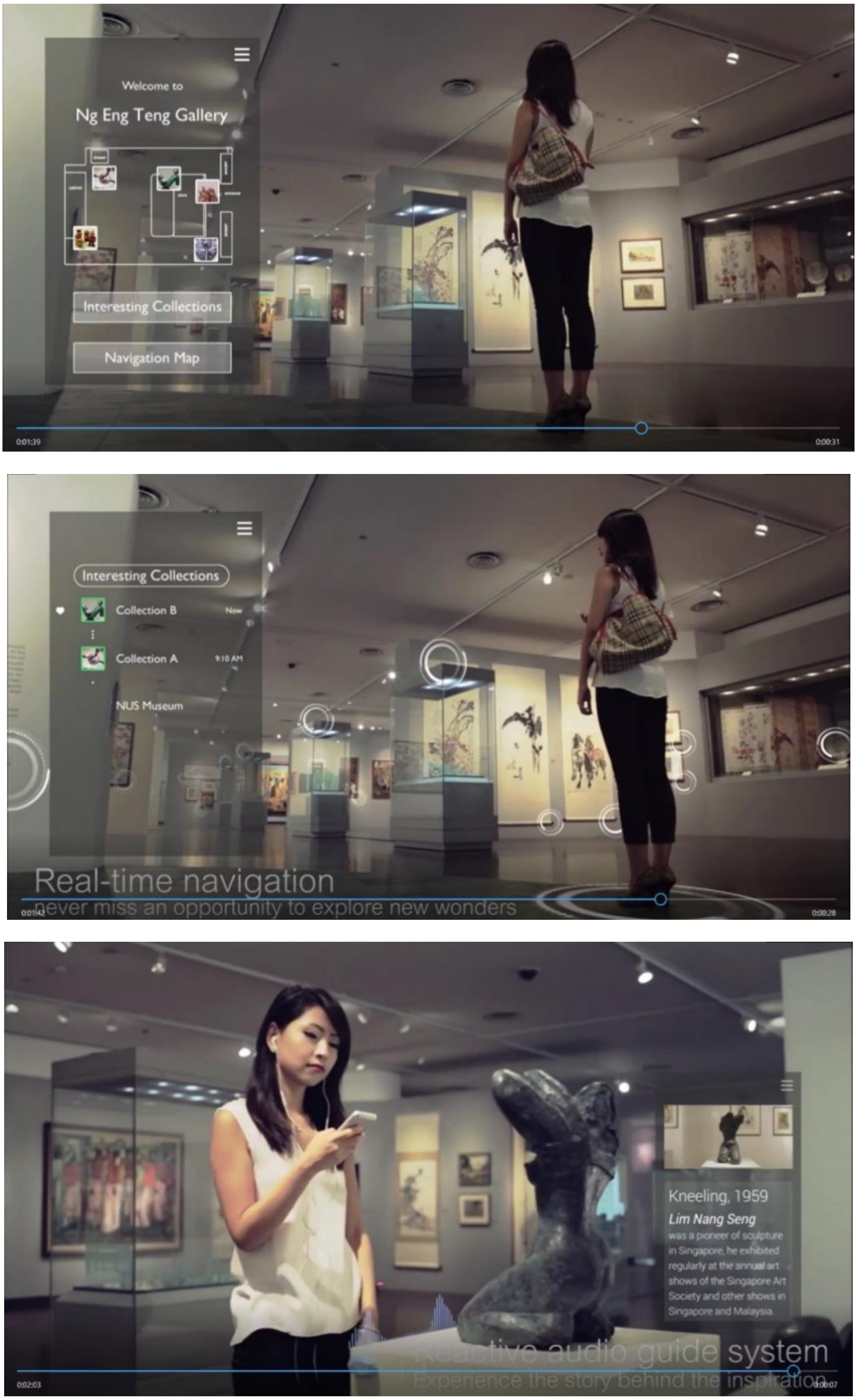

Figure 2. Screenshot of the experimental scenario video.

Characteristics	n	%
Age		
18-25	104	19.2
26-35	255	47.04
36-45	158	29.15
46-65	25	4.61
Gender		
Male	233	42.99
Female	309	57.01
Marital Status		
Single	489	90.22
Married	53	9.78
Academic qualifications		
High school award/certificate, Diploma or similar	167	30.81
Undergraduate/postgraduate teaching degree	293	54.06
Postgraduate research degree	82	15.13
Income (euros/month)		
<1,100	173	31.92
1,100 – 1,800	159	29.34
1,800 – 2,700	129	23.80
>2,700	81	14.94

Table 3. Sample characteristics[4].

[4] Source: Own elaboration.

Variable	N	Mín.	Máx.	Mean	Standar desviatio
KNOW	694	0	1	0,37	0,484
UTILITY	694	0	1	0,95	0,216
EXP_SIM	694	0	1	0,47	0,499
EXP_SYS	694	0	1	0,99	0,076
EXP_SYS_A	694	0	1	0.72	0.448
EXP_SYS_B	694	0	1	0,10	0,296
EXP_SYS_C	694	0	1	0,44	0,497
EXP_SYS_D	694	0	1	0,98	0,125
EXP_SYS_E	694	0	1	0,82	0,387
EXP_SYS_F	694	0	1	0,30	0,458
INN1	694	1	7	3,82	1,823
INN2	694	1	7	4,84	1,788
SI1	694	1	7	4,38	1,714
SI2	694	1	7	4,76	1,665
SI3	694	1	7	4,33	1,569
SI4	694	1	7	4,32	1,680
IN1	694	1	7	4,67	1,690
IN2	694	1	7	4,51	1,753
IN3	694	1	7	4,98	1,578
IN4	694	1	7	4,82	1,735
IN5	694	1	7	4,89	1,595
HT1	694	1	7	6,03	1,449
HT2	694	1	7	4,61	1,639
HT3	694	1	7	4,89	1,670
HT4	694	1	7	5,86	1,625
AF1	694	1	7	5,37	1,608
AF2	694	1	7	5,34	1,631
AF3	694	1	7	4,82	1,738
AF4	694	1	7	4,56	1,987
AF5	694	1	7	3,90	1,926
DP1	694	1	7	3,50	1,885
DP2	694	1	7	4,24	1,911
DP3	694	1	7	3,24	1,824
DP4	694	1	7	3,36	1,765
DP5	694	1	7	3,30	1,869
DP6	694	1	7	3,35	1,696
UP1	694	1	7	4,20	1,631
UP2	694	1	7	4,28	1,645
UP3	694	1	7	4,51	1,668
UP4	694	1	7	5,02	1,600
FUP1	694	1	7	4,99	1,621
FUP2	694	1	7	4,77	1,656
FUP3	694	1	7	4,86	1,639
FUP4	694	1	7	4,99	1,567
FUP5	694	1	7	4,92	1,687
US1	694	1	7	4,83	1,682
US2	694	1	7	4,84	1,676
US3	694	1	7	4,20	1,715
US4	694	1	7	4,70	1,659
IU1	694	1	7	4,40	1,682
IU2	694	1	7	4,77	1,599
IU3	694	1	7	4,72	1,632
IU4	694	1	7	4,75	1,612
IU5	694	1	7	4,86	1,608
BP1	694	1	7	6,17	1,281
BP2	694	1	7	4,81	1,670
BP3	694	1	7	4,87	1,504

Variable	N	Mín.	Máx.	Mean	Standar desviatio
BP4	694	1	7	4,49	1,642
BP5	694	1	7	4,87	1,570
VAL1	694	1	7	4,85	1,534
VAL2	694	1	7	4,71	1,501
VAL3	694	1	7	4,66	1,597
VAL4	694	1	7	4,66	1,579
BF1	694	1	7	5,07	1,429
BF2	694	1	7	4,78	1,594
BF3	694	1	7	5,16	1,478
BS1	694	1	7	4,27	1,653
BS2	694	1	7	4,20	1,664
BS3	694	1	7	3,69	1,603
BH1	694	1	7	4,52	1,607
BH2	694	1	7	4,17	1,686
DP1	694	1	7	4,53	1,573
DP2	694	1	7	3,74	1,698
DP3	694	1	7	4,20	1,627
DP4	694	1	7	4,74	1,607
DP5	694	1	7	3,57	1,769
DOP1	694	1	7	3,91	1,661
DOP2	694	1	7	4,26	1,642
DOP3	694	1	7	4,44	1,629
DOP4	694	1	7	4,54	1,580
NS1	694	1	7	4,72	1,530
NS2	694	1	7	4,33	1,616
NS3	694	1	7	3,98	1,741
NS4	694	1	7	4,70	1,496
CSE1	694	1	7	4,67	1,508
CSE2	694	1	7	4,57	1,496
CSE3	694	1	7	4,64	1,504
CSE4	694	1	7	4,37	1,561
CSE5	694	1	7	4,34	1,521
CI1	694	1	7	4,63	1,511
CI2	694	1	7	4,51	1,560
CI3	694	1	7	4,56	1,521
CI4	694	1	7	4,86	1,478
CI5	694	1	7	4,60	1,450
CI6	694	1	7	4,86	1,435
CS1	694	1	7	4,61	1,428
CS2	694	1	7	4,84	1,426
CS3	694	1	7	4,84	1,451
CS4	694	1	7	4,57	1,525
CS5	694	1	7	4,71	1,600
CS6	694	1	7	4,81	1,520
CS7	694	1	7	4,41	1,400
CS8	694	1	7	4,89	1,376
F1	694	1	7	4,02	1,589
F2	694	1	7	4,34	1,515
F3	694	1	7	4,62	1,604
APTT1	694	1	7	4,14	1,564
APTT2	694	1	7	4,53	1,542
APTT3	694	1	7	4,37	1,562
CT1	694	1	7	4,73	1,437
CT2	694	1	7	4,56	1,586
CTE1	694	1	7	4,50	1,646
CTE2	694	1	7	4,57	1,470
CTE3	694	1	7	4,38	1,604
CO1	694	1	7	4,34	1,529
CO2	694	1	7	4,56	1,512

Variable	N	Mín.	Máx.	Mean	Standar desviatio
CO3	694	1	7	4,46	1,437
CO4	694	1	7	4,70	1,445
CO5	694	1	7	4,67	1,550
RRE1	694	1	7	4,26	1,724
RRE2	694	1	7	4,51	1,755
RRE3	694	1	7	3,93	1,739
RSO1	694	1	7	2,83	1,774
RSO2	694	1	7	2,73	1,731
RSO3	694	1	7	2,84	1,703
RSO4	694	1	7	2,87	1,817
RPS1	694	1	7	2,76	1,840
RPS2	694	1	7	2,93	1,801
RPS3	694	1	7	2,99	1,674
RG1	694	1	7	3,09	1,777
RG2	694	1	7	2,88	1,710
RG3	694	1	7	2,86	1,705
RG4	694	1	7	2,99	1,807
RPT1	694	1	7	3,16	1,666
RPT2	694	1	7	3,10	1,747
RPT3	694	1	7	3,31	1,663
RPT4	694	1	7	3,97	1,833
EX1	694	1	7	3,77	1,497
EX2	694	1	7	3,26	1,491
PL1	694	1	7	4,44	1,437
PL2	694	1	7	4,36	1,500
PL3	694	1	7	4,69	1,527
PL4	694	1	7	4,61	1,569
EDAD	694	18	50	25,41	6,942
GENDER	694	0	1	0,58	0,494
CIVIL_STATUS	694	0	1	0,10	0,296
STUDY	694	0	2	0,52	0,600
INCOME	694	0	3	1,19	1,041
TOURIST_USE	694	0	1	0,82	0,385
INTENSITY_USE	694	1	5	3,38	1,247
INTENSITY_USE_A	694	1	5	2,72	1,354
GUIDE_ROLE	694	1	5	2,84	1,307
TOURISM_OFFICE	694	1	5	2,70	1,213
WEB_USE	694	1	5	4,14	0,894
TRIPADVISOR	694	1	5	3,45	1,334

Table 4. Descriptive statistics of participant characteristics (sample)[5].

[5] Source: Own elaboration.

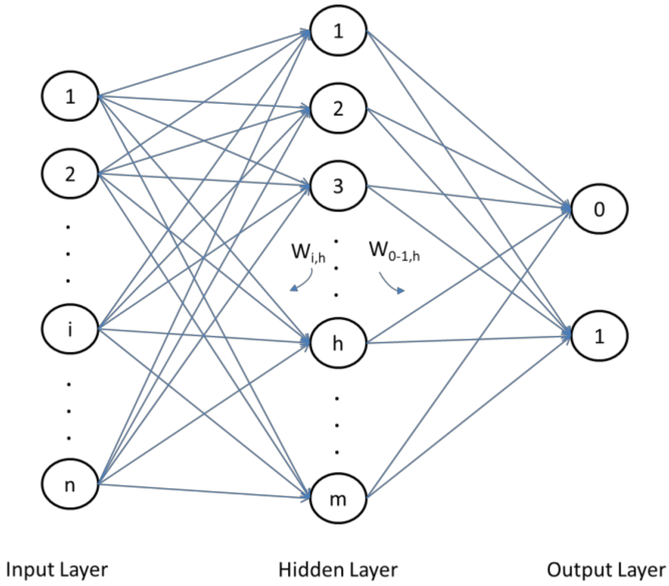

Figure 3. Three-layer MLP[6].

[6] Source: Own elaboration.

Variable	Coef. (β)	Std. Err.	Exp (β)
HT4			
HT4(1)	0.401	3.548	1.493
HT4(2)	-1.737	3.215	0.176
HT4(3)	11.232	8.411	75542.081
HT4(4)	-1.354	2.492	0.258
HT4(5)	-3.510	0.388	0.030
HT4(6)	-1.444	1.964	0.236
PU4			
PU4(1)	4.768	7.137	117.632
PU4(2)	4.794	3.805	120.825
PU4(3)	0.744	2.610	2.104
PU4(4)	0.516	2.229	1.676
PU4(5)	1.288	1.594	3.626
PU4(6)	-0.507	1.538	0.602
PEOU1			
PEOU1(1)	0.263	8.024	1.300
PEOU1(2)	7.209	8.813	1351.923
PEOU1(3)	-1.484	2.386	0.227
PEOU1(4)	4.757	1.596	116.429
PEOU1(5)	5.117	2.949	166.783
PEOU1(6)	3.868	2.379	47.867
PB3			
PB3(1)	-3.986	11.264	0.019
PB3(2)	-13.481	7.251	0.000
PB3(3)	-7.942	6.588	0.000
PB3(4)	-5.271	3.653	0.005
PB3(5)	-6.093	2.762	0.002
PB3(6)	-5.048	1.500	0.006
FB3			
FB3(1)	-8.845	6.632	0.000
FB3(2)	-10.682	12.277	0.000
FB3(3)	-0.874	4.219	0.417
FB3(4)	-2.266	2.952	0.104
FB3(5)	2.624	3.099	13.793
FB3(6)	0.796	1.175	2.217
PE1			
PE1(1)	6.425	3.704	617.136
PE1(2)	6.307	3.636	548.425
PE1(3)	3.783	1.797	43.935
PE1(4)	5.149	2.344	172.238
PE1(5)	4.496	1.873	89.636
PE1(6)	2.789	2.150	16.258
SSQ4			
SSQ4(1)	18.141	9.601	75587754.077
SSQ4(2)	0.832	3.838	2.299
SSQ4(3)	-1.223	3.306	0.294
SSQ4(4)	-1.633	3.225	0.195
SSQ4(5)	0.848	2.484	2.335
SSQ4(6)	1.549	2.582	4.705
IQ6			
IQ6(1)	-12.564	6.936	0.000
IQ6(2)	1.881	4.840	6.562
IQ6(3)	9.068	4.120	8669.287
IQ6(4)	0.082	1.801	1.086
IQ6(5)	-2.267	1.674	0.104
IQ6(6)	-0.469	1.177	0.626
SQ7			

SQ7(1)	-0.249	7.239	0.780
SQ7(2)	-0.854	2.985	0.426
SQ7(3)	-1.396	4.508	0.248
SQ7(4)	0.256	2.907	1.291
SQ7(5)	0.339	2.713	1.404
SQ7(6)	2.016	4.141	7.507
F1			
F1(1)	0.793	4.790	2.211
F1(2)	-2.113	3.564	0.121
F1(3)	1.678	2.565	5.354
F1(4)	0.328	1.372	1.388
F1(5)	0.661	2.816	1.937
F1(6)	-1.680	1.916	0.186
TR4			
TR4(1)	5.794	5.267	328.163
TR4(2)	1.392	4.079	4.021
TR4(3)	-0.577	3.759	0.562
TR4(4)	-0.738	2.533	0.478
TR4(5)	1.033	2.308	2.810
TR4(6)	-1.732	2.316	0.177
TOURIST_USE (1)	-5.084	1.817	0.006
Constant	2.444	1.182	11.514

Table 5. Variables included in the final logistic regression model[7].

[7] Source: Own elaboration.

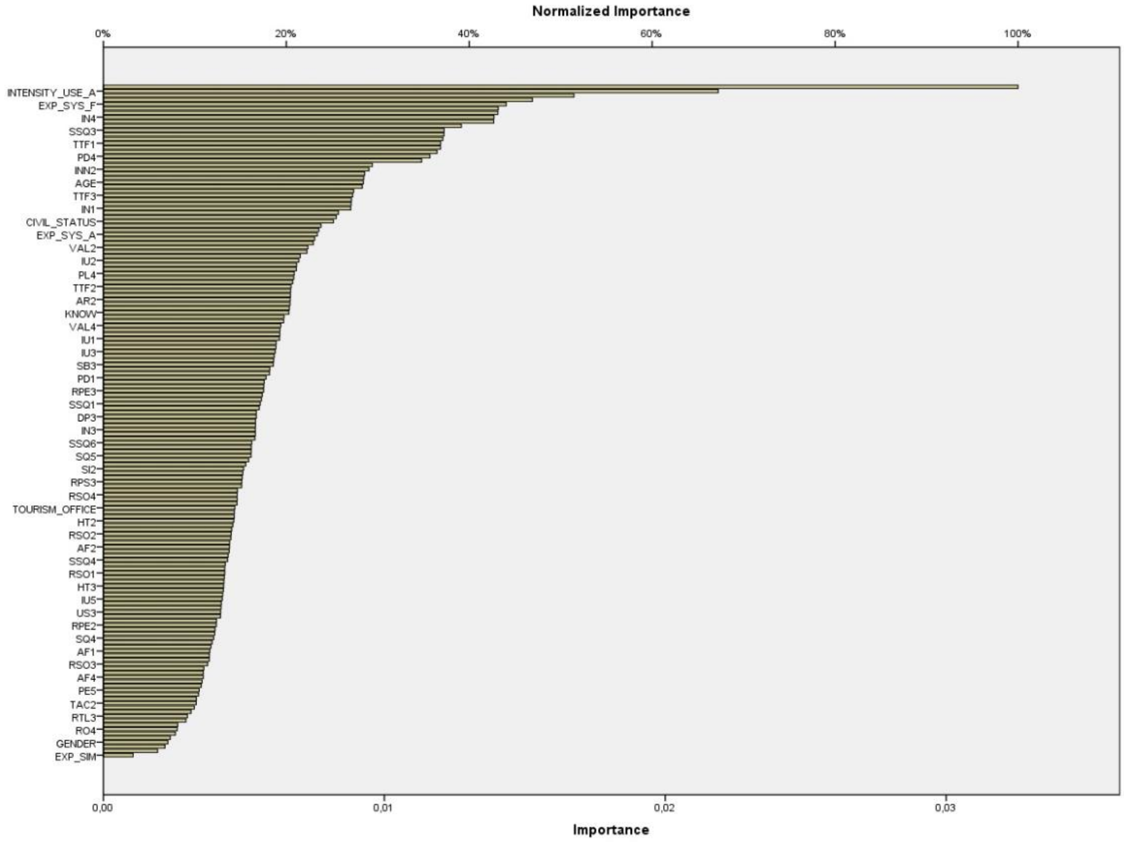

Figure 4. Weights and relative importance of the variables in the neural network model[8].

[8] Source: Own elaboration.

Logistic Regression			
Observ.	**Prediction**		
	0	1	Correct Classification
0	269	15	94.72%
1	21	389	94.88%
Sens	92.76%		94.81%
Spec		96.29%	
Neural Network			
Observ.	**Prediction**		
	0	1	Correct Classification
0	282	2	99.30%
1	4	406	99.02%
Sens	98.60%		99.14%
Spec		99.51%	

Table 6. Classification matrix[9].

[9] Source: Own elaboration.

	Training sample (80%)				Test sample (20%)			
Statistical technique	**AUC**	**Test accuracy**	**Type I**	**Type II**	**AUC**	**Test accuracy**	**Type I**	**Type II**
LR	0.917	92.51%	17.23%	22.49%	0,901	91.92%	17.46%	22.89%
MLP	0.952	94.89%	14.88%	16.55%	0,947	94.27%	15.37%	17.01%

Table 7. AUC, Type I errors and Type II errors[10].

[10] Source: Own elaboration.

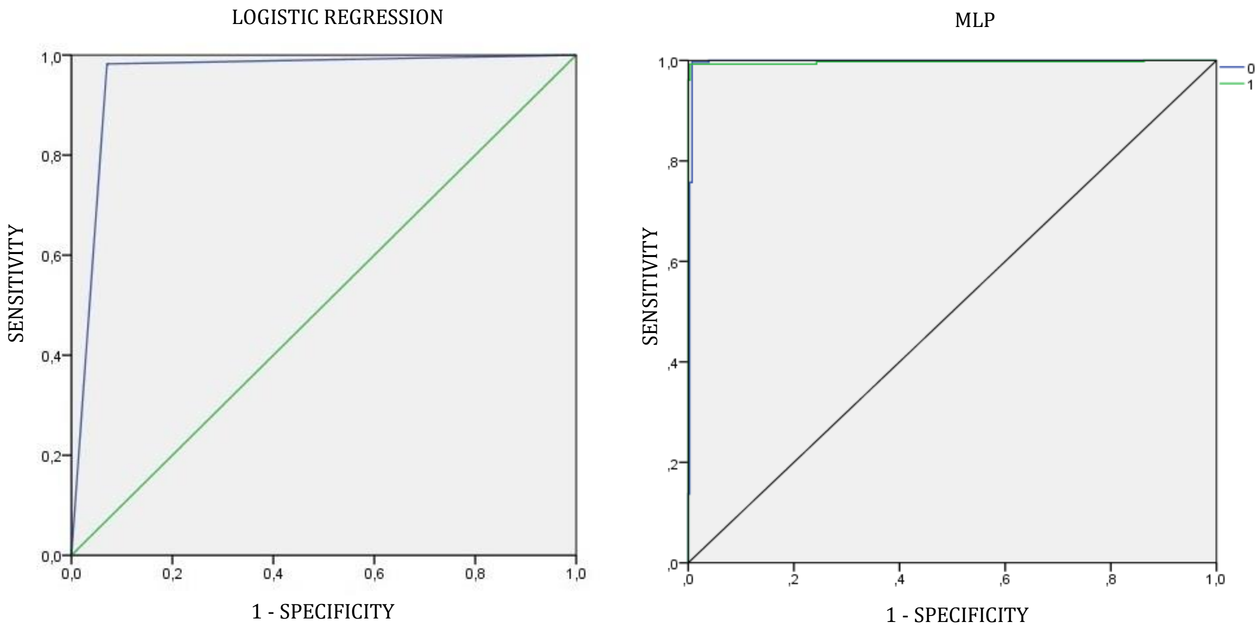

Figure 5. ROC Curve[11].

[11] Source: Own elaboration.

Statistical Technique	Misclassification cost (Training sample)	Misclassification cost (Test sample)
LR	0,6788	0,6860
MLP	0,5698	0,5763

Table 8. Costs of misclassification[12].

[12] Source: Own elaboration.

Construct	Item	Source
Innovativeness (INN)	INN1. If I heard about a new information technology, I would look for ways to experiment with it. INN2. Among my peers I am usually the first to explore new information technologies	Agarwal and Prasad (1998) Herrero-Crespo and Rodriguez del Bosque (2008)
Simplicity (SI)	SI1. Using the beacon application in my trips and tourist visits involves few operations. Sl2. Using the beacon application in my trips and tourist visits I can carry out different transactions. Sl3. Using the beacon application in my trips and tourist visits I can carry out different transactions without complications. SI4. Using the beacon application in my trips and tourist visits I can carry out different transactions without difficulty.	Lee et al. (2015)
Interactivity (IN)	IN1. I can effectively control the use of the beacon application during my visits to the museum (perceived control). IN2. During my visits to the museum, while using the beacon application, there are no operational delays. (e.g., information loading time, saving time) (perceived responsiveness). IN3. Using the beacon application during my visits to the museum provides me with relevant information (perceived responsiveness). IN4. The beacon application provides me with a useful interactive experience (due to the icons, images and pictures) (nonverbal information). IN5. Overall, I can adapt the beacon application during my visit to the museum for my own use (perceived personalisation).	Lee et al. (2015)

Construct	Item	Source
Habit (HT)	HT1. The use of mobile phones has become a habit for me. HT2. I am addicted to using the mobile phone. HT3. I must use the mobile phone. HT4. Using the mobile phone has become natural to me.	Venkatesh et al. (2012)
Affinity (AF)	AF1. Using the mobile phone is one of my main daily activities AF2. If my mobile phone is inoperable, I really miss it. AF3. My mobile phone is important in my life. AF4. I cannot go for several days without using my mobile phone. AF5. I would be lost without my mobile phone.	Aldás-Manzano et al. (2009)
Dependency (DP)	I rely on my mobile phone: DP1. to make decisions. DP2. to understand and interact with others. DP3. to set personal goals. DP4. to understand society. DP5. to relax and enjoy my life. DP6. to understand the mobile phone's role in society.	Grant (1996) Li (2014)
Perceived usefulness (PU)	PU1. Using the beacon application in my trips and tourist visits improves my productivity / performance. PU2 Using the beacon application improves my effectiveness on my trips and tourist visits.	Davis et al. (1989) Tan et al. (2012, 2014)

Construct	Item	Source
	PU3. Using the beacon application helps me in my trips and tourist visits. PU4. In general, using the beacon application is advantageous.	
Perceived ease of use (PEOU)	PEOU1. The beacon application is easy to use. PEOU2. The beacon application is understandable and clear. PEOU3. Using the beacon application requires minimum effort. PEOU4. It is easy to learn to use the beacon application. PEOU5. It is easy to become proficient in the use of the beacon application.	Zhang et al. (2012) Chong (2013) Shih and Chen (2013)
Usability (US)	US1. It is easy to understand the use of the beacon application in my trips and tourist visits. US2. Using the beacon application in my trips and tourist visits it is easy to get the information I need for my tourist experiences. US3. The use of the beacon application in my trips and tourist visits makes me feel that I control the situation. US4 Obtaining information through the beacon application in my trips and tourist visits is quick.	Flavián et al. (2006) Venkatesh et al. (2014) Lee et al. (2015)
Perceived benefits (PB)	PB1. The price of the beacon application in my trips and tourist visits is reasonable. PB2. The time it takes to perform procedures with the beacon application in my trips and tourist visits is very reasonable. PB3. The effort involved in using this application in my trips and tourist visits is worth the trouble. PB4. The beacon application is excellent for my trips and tourist visits. PB5. I obtain value from using the beacon application in my trips and tourist visits.	Kim et al. (2008) Lin and Wang (2006) Mathwick et al. (2001) Luo et al. (2014)

Construct	Item	Source
Perceived value (VAL)	VAL1. The effort I made in using the beacon application during my visit to the museum was worthwhile. VAL2. The risks I ran in using the beacon application during my visit to the museum were worthwhile. VAL3. Overall, the use of the beacon application during my visit to the museum delivered good value. VAL4. The cost of using the beacon application during my visit to the museum was worthwhile.	Kim et al. (2012)
Functional benefits (FB)	FB1. The use of the beacon application during my trips and tourist visits allows me to have updated information about places and activities of tourist interest. FB2. The use of the beacon application during my trips and tourist visits allows me to save costs and get the most out of the resources invested in the trip. FB3. The use of the beacon application during my trips and tourist visits gives me the possibility to receive information about places and activities of tourist interest.	Wang and Fesenmaier (2004) Goldsmith and Horowitz (2006) Parra-López et al. (2011)
Social benefits (SB)	SB1. Using the beacon application during my trips and tourist visits allows me to be in contact with other people who share my interests. SB2 Using the beacon application I have more chance of interacting with similarly-motivated tourists, which I find of interest. SB3. Using the beacon application during my trips and tourist visits gives me a strong feeling of belonging to a group.	Wang and Fesenmaier (2004) Parra-López et al. (2011)
Hedonic benefits (HB)	HB1. Using the beacon application in my trips and tourist visits is pleasant and fun. HB2. I am proud to use the beacon application in my tourist experiences.	Wang and Fesenmaier (2004) Parra-López et al.[55]
Perceived enjoyment (PE)	PE1. Using the beacon application during my trips and tourist visits is pleasant. PE2. Using the beacon application during my trips and tourist visits gives me pleasure.	Wang et al. (2015)

Construct	Item	Source
	PE3. Using the beacon application during my trips and tourist visits is fun. PE4. Using the beacon application during my trips and tourist visits is interesting. PE5. Using the beacon application during my trips and tourist visits is exciting.	
Perceived dominance (PD)	PD1. I feel in control during the experience of using the beacon application in my trips and tourist visits. PD2. I feel autonomous during the experience of using the beacon application in my trips and tourist visits. PD3. By using the beacon application in my trips and tourist visits I can decide the type of experience I want to have. PD4. By using the beacon application in my trips and tourist visits I can control my information searches.	Hsieh et al. (2014) Loureiro (2015) Mazaheri et al. (2011)
Subjective norm (SN)	SN1. The people whose opinion I value would approve my use of the beacon application during my trips and tourist visits. SN2. Most people I know think it is right that I use the beacon application during my trips and tourist visits. SN3. People expect me to use the beacon application during my trips and tourist visits. SN4. The people closest to me would agree that I should use the beacon application during my trips and tourist visits.	Herrero et al. (2005) Taylor and Todd (1995) Agarwal et al. (1998)
Service quality (SSQ)	SSQ1. The beacon application responds quickly to my needs during my trips and tourist visits. SSQ2. The beacon application meets my expectations during my trips and tourist visits. SSQ3. The beacon application gives me confidence and reduces my uncertainty during my trips and tourist visits. SSQ4. The beacon application understands and adapts to my needs. SSQ5. The beacon application gives me a professional and competitive image during my trips and tourist visits.	Ahn et al. (2007)

Construct	Item	Source
Information quality (IQ)	IQ1. Using the beacon application during my trips and tourist visits provides the precise information I need for my tourist experiences.	Brown and Jayakody (2008) Lee and Chen (2014) Kim et al. (2008)
	IQ2. Using the beacon application during my trips and tourist visits provides me with enough information to fulfill the objectives of my tourism experiences.	
	IQ3. The beacon application provides detailed information during my trips and tourist visits.	
	IQ4. The beacon application provides clear information during my trips and tourist visits.	
	IQ5. The information provided by the beacon application during my trips and tourist visits is useful in addressing my questions and problems.	
	IQ6. The beacon application provides updated information during my trips and tourist visits.	
System quality (SQ)	SQ1. The beacon application has an appropriate design for the use that I give it during my trips and tourist visits.	Ahn et al.(2007)
	SQ2. The beacon application allows easy navigation through information during my trips and tourist visits.	
	SQ3. The beacon application processes information rapidly during my trips and tourist visits.	
	SQ4. The beacon application keeps personal information secure during my trips and tourist visits.	
	SQ5. I can use the beacon application whenever I want during my trips and tourist visits.	
	SQ6. The beacon application provides adequate functionality during my trips and tourist visits.	
	SQ7. The beacon application allows me to perform transactions without errors during my trips and tourist visits.	
	SQ8. The beacon application creates an audiovisual experience during my trips and tourist visits.	
Flow (F)	F1. Using the beacon application during my trips and tourist visits I feel that I control the situation.	Trevino and Webster (1992)
	F2. When using the beacon application during my trips and tourist visits my focus is on using its services.	

Construct	Item	Source
	F3. Using the beacon application during my trips and tourist visits arouses my curiosity.	Wang (2015)
Perceived technology-task fit (TTF)	TTF1. The use of the beacon application in my trips and tourist visits is sufficient for my needs. TTF2. The use of the beacon application in my trips and tourist visits is appropriate TTF3. In general, the functions of the beacon application fully meet my needs during my trips and tourist visits.	Lin and Huang (2008) Zhou et al. (2010)
Task characteristic (TAC)	TAC1. Using the beacon application during my trips and tourist visits allows me to have information when I need it. TAC2. Using the beacon application during my trips and tourist visits allows me to manage information at any time and place.	Zhou et al. (2010)
Technology characteristic (TEC)	TEC1. Using the beacon application in my trips and tourist visits provides me with ubiquitous services during my tourism experiences. TEC2. Using the beacon application in my trips and tourist visits provides real-time services during my tourist experiences. TEC3. Using the beacon application in my trips and tourist visits provides me with secure services during my tourist experiences.	Zhou et al. (2010)
Trust (TR)	TR1. I believe that the beacon application will keep its promises and commitments during my trips and tourist visits. TR2. I can trust the beacon application for my trips and tourist visits. TR3. I would rate the beacon application for my trips and tourist visits as honest. TR4. I think that the beacon application is responsible in my trips and tourist visits. TR5. In general, the beacon application is reliable in my trips and tourist visits.	Pavlou (2002) Liébana-Cabanillas et al. (2014)

Construct	Item	Source
Performance risk (RPE)	RPE1. I worry about whether the beacon application will really perform as it is supposed to during my visits to the museum. RPE2. If I were to use the beacon application during my visit to the museum, I might become concerned that it would not provide the level of benefits that I expect. RPE3. The thought of using the beacon application during my visit to the museum causes me to be concerned as to how dependable and reliable the beacon application really is.	Stone and Grønhaug (1993)
Social risk (RSO)	RSO1. Using the beacon application during my visit to the museum could worsen the image other people have of me. RSO2. Using the beacon application during my visit to the museum would negatively affect the opinion that my friends or relatives have about me. RSO3. Using the beacon application during my visit to the museum makes some people whose opinion I value think that I am not behaving correctly. RSO4. Using the beacon application during my visit to the museum would make my friends and relatives think that I am unwise.	Curras-Pérez et al. (2013) Featherman and Pavlou (2003) Herrero-Crespo et al. (2009)
Psychological risk (RPS)	RPS1. Using the beacon application during my trips and tourist visits causes me anxiety. RPS2. Using the beacon application during my trips and tourist visits could cause me to experience unnecessary tension. RPS3. Using the beacon application during my trips and tourist visits does not fit well with my self-image.	Herrero-Crespo et al. (2009)
Overall risk (RO)	RO1. Using the beacon application during my trips and tourist visits is risky. RO2. Using the beacon application during my trips and tourist visits is dangerous. RO3. Using the beacon application adds uncertainty to my trips and tourist visits.	Featherman and Pavlou (2003)

Construct	Item	Source
	RO4. Using the beacon application during my trips and tourist visits involves a combination of risks.	
Time loss risk (RTL)	RTL1. If you start using the beacon application during your trips and tourist visits, what is the chance that it will waste your time? RTL2. Using the beacon application during my trips and tourist visits is not convenient due to the loss of time involved in resolving its systematic errors. RTL3. Using the beacon application during my trips and tourist visits would entail a possible loss of time learning how to operate the system. RTL4. Using the beacon application during my trips and tourist visits is the right choice taking into account the associated time savings.	Featherman and Pavlou (2003) Kim et al.(2015)
Arousal (AR)	Using the beacon application during my trips and tourist visits makes me feel: AR1. Relaxed-stimulated. AR2. Calm-excited.	Mazaheri et al.(2011)
Pleasure (PL)	Using the beacon application during my trips and tourist visits makes me feel: PL1 Unhappy-happy PL2 Irritated-pleased. PL3. Dissatisfied-satisfied PL4. Disappointed-excited	Mazaheri et al.(2011)
Intention to use (IU)	IU1. I intend to use the beacon application during a visit to the museum in the near future. IU2. I believe my interest in using the beacon application during my visits to the museum will increase in the future.	Zarmpou et al. (2012)

Construct	Item	Source
	IU3. I intend to use the beacon application as much as possible during my visit to the museum.	Zhang et al. (2012)
	IU4. I would recommend others to use the beacon application during their visits to the museum.	Alkhunaizan and Love (2012)
	IU5. I would encourage my friends and relatives to use the beacon application during their visits to the museum.	

Table 9: Construct measurement[13].

[13] Source: Own elaboration.