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The Behavioral Response to Location Based Services: An Examination of the Influence of Social and Environmental Benefits, and Privacy

Pedro R. Palos-Sanchez *, José M. Hernandez-Mogollon and Ana M. Campon-Cerro

Department of Business Management and Sociology, Faculty of Business, Finances and Tourism, University of Extremadura, 10003 Caceres, Spain; jmherdez@unex.es (J.M.H.-M.); amcampon@unex.es (A.M.C.-C.)

* Correspondence: ppalos@unex.es; Tel.: +34-927-257-480; Fax: +34-927-257-481

Received: 25 September 2017; Accepted: 26 October 2017; Published: 31 October 2017

Abstract: Given the importance tourism has in many economies, this research was designed to study how the social and environmental benefits of Location Based Services (LBS) in the tourism sector influence user behavior and thus contribute to sustainable development. The objective has been to study LBS as a solution that makes the deployment of tourism activities easier, more useful and improves attitudes towards it, but in a context where trust in privacy and benefits-based sustainable social and environmental development are key. To achieve this, this research identifies what could be the influence factors in the adoption of mobile applications with Location Based Services from the point of view of the tourism sector, especially if the social and environmental benefits of LBS can help improve usage behavior. We investigated the technological acceptance of LBS in tourism, using Technology Acceptance Model (TAM) as a solid model to explain its adoption. Nine hypotheses were investigated by carrying out a survey of travelers (n = 277) during their visit to Seville (Spain). To test the conceptual model's hypotheses, the Partial Least Squares (PLS) technique was applied to estimate variance-based structural equations models (SEM).The results of this study indicated that tourists are willing to accept these LBS services within a particular adoption model, where trust in privacy and social and environmental benefits are paramount.

Keywords: location-based services (LBS); tourism; geolocation; geomarketing; technology adoption; PLS; sustainability

1. Introduction

At present, the need for users to be connected at all times to the Internet is becoming more and more usual. While we surf the Internet, our location is constantly available, whether we connect from a fixed IP address, which locates our access router, or we connect from a mobile device. This location represents a huge source of benefits for companies, since the location information of a user or consumer can increase their income. However, location information also plays an important role in the world of transport and logistics, for example location-based information can present a solution to a growing range of problems. Today, smartphones are the most commonly used devices to access the network on a daily basis [1]. Technological advances, such as Internet, smartphones or geolocation, have forced companies to develop special marketing techniques for each of the devices to market their products or services through different channels [2].

Thus, the adaptation of websites and web applications to mobile devices has increased the number of visits, and they are more accessible and usable. This adaptation is known as app (short for applications in English) or mobile application [3], since it is a computer application designed to be executed on smartphones, tablets and other mobile devices and that allows the user to perform any kind of task (professional, leisure, educational, access to services, etc.) reducing the effort or activity needed to do it [4].

Mobile marketing is also used in the tourism sector and is defined as any form of marketing that uses a mobile device as a channel to transmit information [5]. Mobile devices combine some special features of other tools such as computers, telephones, TV cameras, audios, video cameras, GPS, etc. [6].

This commercialization is therefore being favored by technological advances. At present, several cities have already rebelled against this current model of the tourism business, as is the case of the demands and demonstrations of citizen protest against the growth of tourism in some neighborhoods of the city of Barcelona [7] or in Madrid [8]. These protests have their origin in the overexploitation of the available tourist resources (illegal squares, small and large speculators and renters of rooms, low cost flights, global franchises or cruises) that causes social and environmental problems. There is an urgency to address the lack of effective urban management tools and the new conflicts in the coexistence and habitability with regard to increasing tourism in the city [8]. The consequences for the current inhabitants of any tourist city are the deterioration of their daily life, which worsens with the passage of time (increased cost of living, housing prices, less urban mobility, etc.). However, perhaps, technology can help organize a model for sustainable tourism and it is in this sense that we have set out to study LBS (Location Based Services) as a solution that allows the deployment of these activities in an easier, more useful way, but within a context where trust in privacy is key and the achievement of social and environmental benefits is simultaneous.

Given the importance of tourism in Spain, currently contributing 11.2% to GDP (Gross Domestic Product) with a contribution of €119.011 billion [9], research was designed to study the factors and their interrelationships, of an adoption model using LBS in the Spanish tourism sector. One of the reasons for this is that few empirical studies examine the effects of online localization on a variety of different tasks, and it has only recently begun to be considered [10] as a way of knowing the performance in different markets, as is the case of tourism. Very few studies consider LBS adoption including a variable related to Social and Environmental Benefits, which can contribute so much to Sustainable Development.

Knowing what conditions to include, by studying their influence factors, will improve the adoption and use of localization services. Therefore, this article has the main objective of identifying what could be the influence factors in the adoption of mobile applications with Location Based Services from the point of view of the tourism sector, especially if the social and environmental benefits of LBS can help improve usage behavior. To do so, Section 2 undertakes a thorough review of the adoption literature. Section 3 details the applied methodology, resulting in a survey of tourists. On the one hand, by reviewing the LBS adoption literature to locate the main factors influencing adoption and, on the other hand, with the survey, we have been able to construct an adoption model that addresses the influence of sustainable development of tourism using this technology. Section 4 details the characteristics of the sample and the questionnaire used. Section 5 presents the analysis of the results and Section 6 summarizes the conclusions.

2. Literature Review

2.1. LBS: Location Based Services

The concept of geolocation is the ability of a device to process information to determine its geographical position. Location Based Services started being integrated into the strategies of companies in 2009. From a commercial point of view, they are known as services based on location (LBS). Among the most well-known localization services are GPS navigation services. Typical LBS includes mobile navigation, location-based advertisements, emergency evacuation and check-in services of mobile social networks [11]. For any location request, there are at least two entities involved: one of the entities is always the object of location (that is, it is the entity on which location information is recorded) while the other is the recipient of the location, whose function is to send information according to their position [10]. Therefore, companies can motivate the user to reveal their location, even when they are aware of the risks involved in it, such as privacy [12]. The companies that use geolocation get, on the one hand new customers who, because of their proximity, are encouraged to use them and, on the other hand to increase the loyalty of current customers. Thus, geolocation is applied to marketing in two antagonistic but interrelated procedures. Companies that decide to include geolocation strategies, not only must register their geographical location, but also add information and content such as photographs, videos, documents, etc. and share that information using existing geolocation tools, such as QR codes, Bluetooth or other technologies. QR is a black squares arranged in a grid on a white background. This representation can be read with an imaging device such as a camera of a smartphone and interpreted, so that it gives us data such as access to a web site, personal identification data, etc. On the other hand, users, who increasingly use social networks to promote their socialization, can become customers if companies share information, promotions or offers when consumers are close to it [13].

A related term is geomarketing, which automatically relates the strategies of the company to the knowledge of the geographical location of places, objects or people, in real time, using technological tools and mechanisms such as Internet, browsers, mobile satellites, PDA, smartphones or tablets, among other devices [14]. This location is combined with coupons, offers, or simply through targeted advertising to people who use these devices in specific geographic areas. This is what is meant by using geomarketing strategies or location marketing.

2.2. Advantages and Disadvantages

Among the most important advantages of using geolocation is that companies can determine which products or promotions are best adapted to lifestyles and consumption patterns from a geographical perspective. It is also possible to delimit the zones of consumption, by spatial analysis of the competitors. Finally, geolocation analyzes and detects possible locations for different points of sale [15]. Another of the uses of geomarketing is to increase sales or solve logistics problems among suppliers, distribution centers and retail stores [16]. This last advantage can be usefully applied in the tourism sector.

Several studies highlight the benefits of LBS for companies. These benefits are the application of new promotional techniques, such as discounts, or reward opportunities for customers when they enter physical stores or when they scan the bar codes of their products using their mobile cameras [17]; the location of the nearest activity or service, such as banks, hotels, restaurants or pharmacies; receiving alerts such as notification of offers at a mall, or traffic jams in nearby streets; the search for friends or people with whom you have an appointment; and notification of the location in case of smartphone theft [18].

Other studies have focused on obtaining quantitative information on the behavior of users; increasing customer loyalty and improving customer relationships; the achievement of constant feedback and presence; and the ability to carry out more localized viral marketing campaigns [19]. This information collection has the disadvantage of loss of user privacy, which must be protected with legislation.

The European Union also provides a legal framework for data protection that may be applied for location-based services, and more particularly several European directives such as: (1) personal data: [20]; (2) personal data in electronic communications: [21]; and (3) data retention: [22]. However, the way of applying these legal provisions to different forms of LBS and data processing is unclear [23].

2.3. LBS and Social Networks

The development of geolocation has been strongly driven by the improvement in mobile devices and the increased popularity of social networks [19]. The extreme increase in the number of mobile device users has led to a shift in location-based information sharing [24]. The integration of location-based services (LBS) into social networks and mobile technologies has stimulated the emergence of a variety of new services [25,26]. Thus, a new variant emerges, social geolocation, which began to be used as a result of the union of social networks and the GPS function of mobile devices, which allows the user to communicate and share the place in which they are [19], as well as location-related information, such as photographs or activities [27].

These new social networks are known as Location Based Social Networks (LBSNS) because of the importance of location in their functions. In recent years, the number of LBSNS has rapidly increased worldwide [27]. At present, companies are recommended to get involved in this trend and become visible to consumers, as, in addition to having their space on the network, it is necessary to interact directly with customers. To this end, many social networks and map applications emerge, and focus their functions on geolocation. Some examples are Facebook Places, with which users can publish their current location, recommend places and events, and evaluate them [14], Google Maps and Earth to view and use content such as maps with data, images, business listings, traffic, reviews and other data. Foursquare is a social geolocation network where users are rewarded if they register places where they are with other people or discover new ones, and finally, Swarm, used to search for and meet with friends [19].

These geolocalized social networks or LBSNS represent examples of the business potential that sociability and geolocation can reach. The study of its future growth and sustainability is a new source of research, which has shown that one of the factors for success is the dependence on the continual contribution of users [28,29].

2.4. Tourist Recommendation Systems

One of the main functions provided by a smartphone is to provide the ability to locate the user at all times. Over time, LBS applications or apps have been diversifying. Applying LBS to e-commerce has provided users with better quality of service [30], since the positioning provided by the smartphone suggests new additional services to the user, giving way to m-commerce or mobile commerce. In the Table 1, You can see research articles about LBS and LBSNS.

Table 1. Research articles about location-Based Services (LBS) and Location based Services Networks Social (LBSNS).

Reference	Research
[31]	Middleware for LBS
[18]	Implementation of LBS in Androids using GPS and web services
[32]	Examining the use of LBS from the perspectives of the unifying theory of acceptance, use of technology and risk of privacy
[5]	Development of mobile marketing in Croatian tourism using LBS
[17]	Use of mobile in stores: Download and intention to use location-based commercial apps (LB) via mobile
[12]	Disclosure of location in LBSNS apps: The role of incentives in sharing behavior
[33]	The disclosure of location information in LBSNS: Calculation of privacy, benefit structure and gender differences
[24]	Motivations, privacy, concerns, and participation of the mobile phone for information exchange LB with check-in on Facebook
[34]	Mobile recommender systems in tourism

This new mode of e-commerce, thanks to the location, provides a better personalization of the service. That means customer loyalty is improved and they can be informed on promotions and discounts. However, the acquisition of tourist activity packs or offers seems to be even more attractive, where the purchase is related not only to the level of need or desire, but also to the current location [35]. Therefore, the main trend is to combine LBS and electronic maps to allow the user to have a clear concept of travel time and distance. The application of this concept to a tourism recommendation system can provide personalized data and better planning of both travel [36] and purchase decisions.

A tourist recommendation system works by combining tourist location with recommendations that best meet their needs by LBS. It is more flexible to use and its operation is more immediate, so the overall efficiency is enhanced. Borras et al. [37] analyzed the tourism recommendation systems from 2008 to 2013, finding the main functionalities provided by different authors: the offer of destination/tourist packs, suggest attractions, trip planner and social aspects. Thus, the main function of most tourism recommendation systems is to recommend and value attractions (see examples in Table 2). However, planning is its main function and LBS can play an important role in this. Some recommendation systems work in permanent connection with social networks. However, currently, few of tourist recommendation systems studied offered information about tourist destinations and tourist packages.

In addition to offering personalized recommendations through sophisticated user modification methodologies, they can also take advantage of the use of context-based tourist attraction recommendations [38].

Table 2. Examples of tourist recommendation systems. Based in [33].

Reference	Research
[39]	Turist @ system based on multi-agent technology to improve the sending of personalized recommendations of tourist attraction offers
[40]	Web services ITravel recommendation system on a peer-to-peer mobile device, where users discuss revisions of travel plans
[41]	SoLoMo system using the nearest k-neighbors algorithm to consider both geographic distance and social distance based on its recommendations
[42]	Designed an algorithm that requires time, user preferences and the most appropriate factors to recommend Itineraries
[43]	SocoTraveler Model to take advantage of the individual travel history and the social influence of co-travelers. Analyze personal interests.
[44]	PlanTour system to provide tourist services: gathering information generated by the human being on social networking sites in the travel application "minube"
[45]	Adapt the TF-IDF (Term Frequency-Inverse Document Frequency) to filter the content and construct based in the location and the recommendation

Some statistical data, compiled from eMarketer Market Research [46], indicate that nine out of ten US smartphone owners use location services on their phones, according to data from Pew Research Center. However, there is significant room for growth. eMarketer estimates the number of smartphone users increased by 8.7% in 2016, and the number of those who use location-based services is expected to rise at a nearly equal pace. However, privacy is a major barrier. In the European Union, almost half (46%) of all internet users refused to allow the use of personal information for advertising and two fifths (40%) limited access to their profile or content on social networking sites. In addition, more than one third (37%) of Internet users read privacy policy statements when providing personal information, while just under one third (31%) restricted access to their geographical location [47].

3. Research Model and Hypotheses Development

To carry out this study, appropriate research methodologies have been selected. To do so, a thorough bibliographic review has been carried out on the subject of this research to build the theoretical understanding about the adoption of LBS and the most relevant influence factors in this study. Journals, research theses, official policies and standards, as well as books related to this research topic, are the main sources of literature. In addition, the review of the literature has allowed us to develop a solid basis for implementing a subsequent questionnaire. This was how the survey was presented to tourists, and which allowed us to collect research data.

3.1. Internal Variable: Information Technology Model for Adoption and Use

The existing literature presented several models of adoption for information technologies that help to understand the adoption of these. For this, they present a set of factors, among which one can establish dependency relations. The relationships between the factors, and how they influence one another, help to explain the behavior of the users. The adoption rate of LBS applications is below the expected rate [10,48]. Researchers try to find the causes and reasons for this low adoption [49]. This slow adoption of LBS has been mainly explained by three causes: (1) mobile phone providers have taken longer, and at a higher cost than expected, to implement more precise location techniques; (2) there has sometimes been a latency of responding to applications by providing the user's location; and (3) the users' concern for privacy issues.

Several models try to explain the behavior of the intention of use to adopt technologies and systems of information. Some of these models include the Technology Acceptance Model (TAM) [50], Theory of Planned Behavior (TPB) [51], and Diffusion of Innovation Theory [52]. Later, [53] introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which is based on a combination of several models [54].

A special adaptation of the Reasoned Action Theory (TRA) [55] has been introduced by [56] in the form of a Technology Acceptance Model (TAM). According to TRA, the behavior of an individual is determined by the individual's intention to perform that behavior. Such intention is the result of a joint function and/or influence of the subjective norms and of the attitude of the individual towards the participation in that specific behavior. TAM postulates that the use of a technology (i.e., actual adoption of technology) can be predicted as the behavior in the individual's intention to use technology (BIU). The individual's intention to use may be determined by his or her attitude towards the use of that technology. Thus, based on the original TAM model, the following hypotheses are formulated:

Hypothesis 1 (H1). *The attitude of the users to the services based on location positively influences the intention to use them.*

The TAM model establishes a direct link between the perceived utility and the intention of use behavior. The model also postulates that the perceived utility of technology is directly influenced by the ease of use of that technology.

Hypothesis 2 (H2). *The perceived utility of location-based services positively influences the intention to use them.*

Thus, both attitude (A) and intention are postulated as the main predictors of technology acceptance. It is assumed that attitude acts as a mediator between behavioral intention and two influential beliefs: the ease of use of technology (PEOU) and its perceived utility (PU).

Hypothesis 3 (H3). *The perceived utility of location-based services positively influences the attitude of users to such services.*

Hypothesis 4 (H4). *The perceived ease of use of location-based services has a positive impact on the attitude of users towards the use of these services.*

Hypothesis 5 (H5). *The ease of use perceived for location-based services has a positive impact on the expected utility of such services.*

The choice of TAM to understand the processes of adoption and use of ICT is justified by its robustness and wide acceptance in a lot of previous research. In general, there is an important body of research, based on the Reasoned Action Theory and the Davis Technology Adoption Model [56], formed by the relationships between factors that influence individual attitudes toward technology and relationships between these attitudes, the intentions of using technology and actual use.

This allows researchers to apply scales that have already been developed and empirically validated on many occasions.

Due to its predictive power, TAM has been widely applied, empirically validated, and expanded in many studies related to users' acceptance of information technology (see, for example, [57–59]). In this way, research has been done on adoption of mobile telecommunication services [60], mobile cloud computing [61,62], and LBS [32,33,36,63,64]. Of all the well-known adoption models, we especially highlight published research papers where TAM is applied to LBS [10,36,49,65,66] or to mobile devices [67].

However, TAM is a general model that only provides information on the acceptance and use of technology and does not specify the determinants of perceived utility (PU) and perceived ease of use (PEOU) as important determinants in this model.

Therefore, more information is needed, which are specific factors that can affect the usefulness of a particular technology and the ease of use from an individual perspective. [58] suggested that the user's behavioral beliefs included in the TAM could be affected by external variables. These variables influence the behavior of intention-of-use (BIU) through perceived utility and perceived ease of use [57]. As such, this research uses LBS Privacy and Social and Environmental Benefits as external factors that affect the perceived utility and perceived ease of use in TAM. The rest of the research hypotheses, presented in the following sections, are completely coherent with the TAM formulation and do not alter, in any way, the reasoned theory of TAM on TRA.

These external factors are a consequence of the references initially selected in the literature reviews.

3.2. External Variables: Confidence in Privacy of LBS

The literature review indicates that previous work has included Privacy as an antecedent variable of users' behavior in the intention to use information systems, such as e-commerce [27,68,69], and social networking sites [28]. Privacy has been defined from different perspectives. One of them is the concern for privacy of information or CFIP [70], where they define up to fifteen elements that provide an instrument to measure privacy concerns. This model has been applied in studies on LBS adoption and has been shown to influence confidence and perceived risk [11,71]. Both have shown as determinants in the intention to use [49].

However, we have formulated this construct based on other studies that have proposed privacy from the perspective of the information that Internet has of the users (IUIPC). This variable [71] has three dimensions: collect, control and awareness. The difference between the CFIP and IUIPC model seems to be that the former was designed for an off-line context, while the latter studies the privacy of Internet users, since LBS is an online service [49].

In the field of LBS, several investigations recently acknowledge the need for LBS to have more privacy and to investigate possible solutions [72–74]. This indicates that this variable must be present in the model.

Privacy could be defined as "the degree to which an individual is concerned about the collection, improper access, errors, and secondary use of their personal location information" [64,75]. Our hypothesis formulation has been partially based on the IUIPC model [71], but with a different approach. We have taken into account the relationship between Privacy and Trust, investigated in other fields such as e-Commerce [76,77] and formulated in the positive sense is:

Hypothesis 6 (H6). *The trust in the privacy of the users of the location-based services has a positive impact on the perceived utility of those services.*

Hypothesis 7 (H7). *Confidence in the privacy of users of location-based services has a positive impact on the perceived ease of use of those services.*

3.3. External Variables: Social and Environmental Benefits

The last variable included as external to the proposed model has been called Social and Environmental Benefits. This variable has been selected based on other similar applications considered as external in TAM models of technology adoption, such as Corporate Social Responsibility or CSR, which has been related to consumer satisfaction in TAM adoption models [60]. The CSR variable arises to counteract the exclusively economic view of business objectives: maximizing the company's profitability for shareholders and integrating environmental or social concerns in business operations [78].

As for the adoption of LBS systems, authors mention social and environmental benefits (e.g., [65,79,80]), tourism [36,63], overall benefit perceptions of the system or financial gains for consumers [80] or effect of perceived value [81].

This construct was reflected in items that mainly value that LBS supports tourism activities and cultural events, in the sense that they are facilitators when locating them or acquiring tickets.

It was also reflected in the sending of personal ads that help to respect the environment, such as the location of recycling points, trash delivery, especially vulnerable areas or protection of endangered species.

Likewise, another item studied reflected the sensitivity towards the local market and stores. In Europe, as a consequence of globalization, cities are experiencing the gradual disappearance of local and traditional commerce [82], in contrast to large and multinational companies. Therefore, we think that it is worth assessing if LBS can help the tourist to buy in these stores through the location of small stores in the tourist areas. An assessment was made of whether the practice of sending geolocalized discount tickets could express that LBS brings a social benefit.

Finally, tourists we asked to value if the localization services contributed to saving energy. Certainly, LBS contribute to saving fuel in vehicles and means of transportation thanks to geolocation [80].

More specifically, based on research that has formulated items related to this variable [35,83–85], we formulate these hypotheses:

Hypothesis 8 (H8). *The social and environmental benefit perceived by users of location-based services has a positive impact on the perceived utility of those services.*

Hypothesis 9 (H9). *The social and environmental benefits perceived by users of location-based services have a positive impact on the perceived ease of use of those services.*

Finally, based on research and these hypotheses, You can see the Figure 1 and the proposed model.

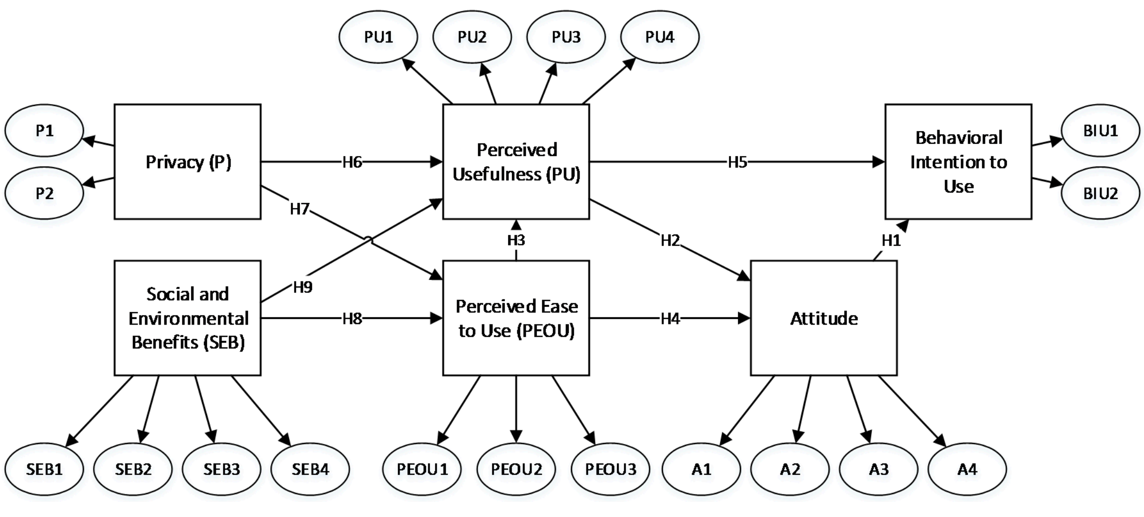

Figure 1. Proposed model.

4. Research Data

4.1. Measurement

The resulting typical factors from the comprehensive literature review of adoption of LBS are represented in Figure 1, and are classified in constructs and items. These factors have been used as constructs to develop the final questionnaire for the collection of data on the views of LBS users. Their adequacy was refined and adjusted by performing a pilot survey with a limited number of tourists, to understand if the factors were well chosen.

Finally, those questions that were ambiguous or could lead to error were removed. As for the importance of these factors, we must indicate that the reliability of the collected data is checked using the statistical software tool (IBM SPSS). The next step was to calculate the values for the mean and standard deviation for each factor, which allows us to identify critical factors. The following *t*-test and one-dimensional variance analyses are carried out to check whether there is consistency in the opinions of the different groups of tourists who took part in the process of questionnaire survey.

After data collection, the Harman single factor test was used as a common method bias post control measure [86]. The test detected no single factor that could explain most of the total variance, which suggests that bias is very unlikely.

As an effective rating method, the five-point Likert scale method is used to indicate the degree of significance of the factors [87]. All factors or constructs were measured using a five-point Likert scale from 1 (“strongly disagree”) to 5 (“strongly agree”). Using online mailing and contacting individuals allowed for multi-channeled distribution, so that enough effective responses are received. Online mailings are sent to travel agencies and individual contacts are made in the Tourism Consortium of Seville (Spain) and in various tourist offices of the capital, where tourists come to ask questions related to visits to places and monuments in the city. Convenience sampling is adopted through individual contacts in order to increase the number of respondents [88].

4.2. Data Collection

The survey was carried out between June 2017 and September 2017. In total, 400 questionnaires were sent out, and 277 responses were received. This makes for a 69.25% effective response rate. Overall, 58.12% of respondents were found to hold a bachelor’s degree or above, and 69.67% have more than five years work experience. You can see other demographic characteristics of the Respondents Attributes in the Table 3.

Table 3. Demographic Characteristics of the Respondents Attributes.

Classifications Variable		Frequency	Percentage
Gender	Male	151	54.5%
	Female	126	46.5%
Age	20–29	79	28.5%
	30–39	141	50.9%
	Over 40	57	20.7%
Job	Student	38	10%
	Employed	239	90%
Type of smartphone	iPhone (Apple)	133	48.0%
	Galaxy (Samsung)	121	43.7%
	Others	23	8.3%
Main purpose of using LBS	e-Commerce	41	14.8%
	Location-based social network [LBSN]	84	30.3%
	Cultural or environmental contents search	79	28.5%
	Others Information search	56	20.2%
	Others reasons	17	6.2%

The collected data are analyzed using statistical techniques to understand the relative importance between the factors and the agreement of the respondents’ perceptions about the relationship.

As previously mentioned, the use of the Partial Least Squares technique was used to contrast the hypotheses associated with the conceptual model of the present investigation.

PLS is a specially recommended method for exploratory research and allows the modeling of latent constructs with both formative and reflective indicators. In addition, PLS is more appropriate when the objective is to predict and investigate relatively new phenomena [89], as is the case with LBS.

5. Data Analysis

5.1. Social and Environmental Benefits Analysis

The results obtained and presented in Table 4 reflect that the means of each variable are very different, with variables centered or close to opinion 3 ("Neither agree nor disagree") and others in 4 ("agree") of the Likert scale. In addition, different values for the standard deviation are obtained. This statistic is a measure of dispersion, which tells us how far the values can move away from the average (mean). We found the lowest (σ SEB1 = 0.884) and the highest (σ SEB4 = 1.419). These values give us an idea of which variables have the greatest diversity of opinions among tourists. Thus, SEB1 ("The location based services I currently use support tourism activities and cultural events") is the variable that reaches the closest response to agreement with the proposed statement ($\bar{x}$ SEB1 = 4.217). Thus, the ease of finding these activities or the ability to acquire tickets has a behavior above "agree". However, the variable SEB4 ("The location based services I currently use saves energy") behaves very differently. SEB4 gets the lowest mean ($\bar{x}$ SEB4 = 2.911) so that the majority of respondents maintain a neutral position in this respect, so the men remains neutral ("Neither agree nor disagree") for this statement: "LBS contribute to saving fuel for vehicles and means of transport thanks to geolocation".

In Table 4, we can see that the variable SEB2 ("The location based services send personal advertisements that help to respect the environment") gets a mean that seems to be located neutrally and which is close to value 3 = "Neither agree nor disagree" ($\bar{x}$ SEB2 = 3.033) and SEB3 ("The location based services send location sensitive discount tickets from local stores in the visited city") has a result approaching agreement (4 = "agree"), although it is closer to 3 ($\bar{x}$ SEB3 = 3.367). Both are very similar averages.

Therefore, it seems that the sending of personal advertisements by using LBS, which helps to respect the environment, the location of recycling points, garbage collection points, particularly vulnerable areas or the protection of endangered species, do not seem to be valued as they have values close to 3 ("Neither agree nor disagree"). Likewise occurs with the sensitivity to the local markets and stores, where similar values are obtained. The sample mean, for its proximity to response 3 ("Neither agree nor disagree"), does not reflect any opinion close to agreement or disagreement, i.e., LBS may not help with the sending of geolocalized discount tickets and therefore there is no consensus as to whether LBS provides a social benefit in this regard. The sample does not value in any way that LBS, by sending geolocalized discount tickets, could help to bring a social benefit. More information about the rest of variables in the Appendix A.

Table 4. Average and standard deviation of the social and environmental benefits (SEB) items.

	Item Social and Environmental Benefits	Average ($\bar{x}$)	Standard Deviation (σ)
SEB1	The location based services I currently use support tourism activities and cultural events	4.217	0.884
SEB2	The location based services send personal advertisements that help to respect the environment	3.033	1.370
SEB3	The location based services send location sensitive discount tickets from local stores in the visited city	3.367	1.382
SEB4	The location based services I currently use saves energy	2.911	1.419

5.2. Analysis of the Measurement Model

This model was constructed with items of a reflective character, since they share concepts and, therefore, are interchangeable to be equivalent manifestations of the same construct ([90]).

First, we measured the individual reliability of the load (λ) of the indicator, and it is usual to establish the minimum level for its acceptance as part of the construct in $\lambda \geq 0.707$ [91].

However, other authors diverge from this rule, considering it to be excessively rigid in the initial stages of scale development and, in general, in poorly studied subjects, accepting in these cases minimum values higher than 0.5 or 0.6 [92]. The commonality of a manifested variable (λ^2) is that part of its variance that is explained by the factor or construct [93]. All values exceeded this minimum load.

To test the consistency of a construct, Cronbach's alpha and its composite reliability (CR) were used. This evaluation measures the consistency of a construct based on its indicators [94], that is, the rigor with which these items are measuring the same latent variable.

Cronbach's alpha determines a consistency index for each construct and presents values between 0 and 1. The lower limit for acceptance of the reliability of the construct is usually set between 0.6 and 0.7 [95]. The highest validity will be in values close to 1. All variables were in those values of minimum validity (see Table 5).

Table 5. Cronbach Alpha, Composite Reliability and AVE.

Variable	Cronbach Alpha	AVE	Composite Reliability
Attitude (A)	0.79	0.62	0.86
Behavioral Intention to use (BIU)	0.87	0.88	0.94
Perceived ease of use (PEOU)	0.76	0.68	0.86
Perceived usefulness (PU)	0.76	0.58	0.85
Privacy (P)	0.80	0.90	0.80
Social and environmental benefits (SEB)	0.70	0.80	0.70

AVE (Average Variance Extracted) is defined as the average extracted variance, and reports how much variance a construct of its indicators achieves relative to the amount of variance due to the measurement error [96]. The recommendation of these authors is that AVE is ≥0.50, which we can interpret as that more than 50% of the variance of the construct is due to its indicators.

Discriminate validity marks the extent to which a construct is different from others. A high value would indicate weak correlations between constructs. Two types of analysis are used for this test. On the one hand, cross loads, i.e., no indicator shares more load with another that is not the construct itself. On the other hand, as can be seen in Table 6, it has been verified that the square root of the Average Variance Extracted (AVE) is greater than the relation between the construct and the rest of the constructs of the model [96].

A construct should share more variance with its measurements or indicators than with other constructs in a given model [97]. To verify this, we must see if the square root of the AVE is greater than the correlation between the construct and the rest of constructs of the model. In our case, this condition is true for all latent variables (see Table 6). Therefore, we can affirm that the constructs share more variance with their indicators than with other constructs of the investigated model [97] and discriminate validity is confirmed based on this first analysis.

Table 6. Discriminate Validity.

	(A)	(BIU)	(PEOU)	(PU)	(P)	(SEB)
Attitude (A)	0.79					
Behavioral Intention to use (BIU)	0.63	0.94				
Perceived ease of use (PEOU)	0.61	0.54	0.82			
Perceived usefulness (PU)	0.76	0.64	0.61	0.76		
Privacy (P)	0.63	0.61	0.57	0.84	0.91	
Social and environmental benefits (SEB)	0.54	0.51	0.55	0.68	0.58	0.71

5.3. Analysis of the Structural Model

Standardized path coefficients (β) provide the extent to which predictor variables contribute to the explained variance of internal variables. The variance explained in an endogenous construct by another latent variable can be measured from the absolute value of the multiplication of the path coefficient with the correlation coefficient of the two variables [98].

The analysis of these coefficients and their statistical significance will allow us to compare the proposed research hypotheses. Several authors, such as [92], consider that a value of β is considered acceptable if it is ≥0.2, although it is desirable that it be >0.3.

In any case, the calculation of the path coefficients must be accompanied by some measure that reports its statistical significance and, ultimately, the quality of the adjustment made. The quality of fit has been measured with the t-statistic resulting from applying the bootstrap resampling test to 500 subsamples. The Student's t-distribution of a queue has been used, given that the model has specified the direction of relations.

From this, the following values are used as references for statistical significance: $t = 1.64791345$ for 95% confidence, $t = 2.333843952$ for 99% and $t = 3.106644601$ for 99.9%. The values reached in this test, together with the standard regression coefficients, have been collected in Table 7 and allow us to analyze the hypotheses of the proposed structural model.

When analyzing the predictive power of the model in terms of the variance explained, [92] considers that values for R^2 of 0.67, 0.33 and 0.19 can be considered as, respectively, strong, moderate and weak. [98], meanwhile, indicate that when the R^2 values are less than 0.1, the hypothesized relationships have a very low predictive level, although they may be statistically significant. The results obtained indicate that the model explains 45.9% (see Figure 2) of the total variance, since that is the R^2 value obtained by the Behavioral Intention to Use dependent construct. Perceived Usefulness explains 76.8%, Attitude 61.1% and Perceived Ease to Use 39.4%. The predictive power of internal variables is moderate, although Attitude is moderately strong [92]. The R^2 values of all endogenous variables far exceed the minimum threshold of 0.1, confirming the predictive value of the model [98].

Table 7. Path coefficients and statistical significance.

	Hypothesis	β (Coef Path)	Statistic *T*	Result
1	Attitude (A) → Behavioral Intention to use (BIU)	0.325	3.078	Supported **
2	Perceived usefulness (PU) → Attitude (A)	0.225	2.900	Supported **
3	Perceived ease of use (PEOU) → Perceived usefulness (PU)	0.122	2.563	Supported **
4	Perceived ease of use (PEOU) → Attitude (A)	0.623	9.608	Supported ***
5	Perceived usefulness (PU) → Behavioral Intention to use (BIU)	0.399	3.776	Supported ***
6	Privacy (P) → Perceived usefulness (PU)	0.376	5.085	Supported ***
7	Privacy (P) → Perceived ease of use (PEOU)	0.617	11.604	Supported ***
8	Social and environmental benefits (SEB) → Perceived ease of use (PEOU)	0.329	4.700	Supported ***
9	Social and environmental benefits (SEB) → Perceived usefulness (PU)	0.254	4.767	Supported ***

Notes: For $n = 500$ subsamples, based on distribution t (499) of Student in single queue: * $p < 0.05$ ($t(0.05;499) = 1.64791345$); ** $p < 0.01$ ($t(0.01;499) = 2.333843952$); *** $p < 0.001$ ($t(0.001;499) = 3.106644601$).

The structural analysis yields significant data that we have analyzed with the β of each construct. Thus, Perceived Ease to Use with regard to Attitude yields the highest results (β = 0.62; $t = 9.608$), with H4 being fulfilled.

Perceived Usefulness, measured in terms of Perceived Ease to Use, does not reach the minimum of 0.2, however, in terms of significance, it reaches 99% (β = 0.12; $t = 2.563$), with H3 being fulfilled and yielding the lowest value.

Other hypotheses with the same degree of significance (99%) are H1, where Attitude (A) has positively influenced Behavioral Intention to use (BIU), and H2, where Perceived Usefulness (PU) has been shown to have a positive influence on Attitude (A) (β = 0.225, $t = 2.900$). The remaining hypotheses have been shown to be true with a degree of significance of 99.9%. H5 was demonstrated, and Perceived Usefulness (PU) determines Behavioral Intention to Use (BIU) (β = 0.399; $t = 3.776$).

Finally, the variables external to the TAM model are confirmed. H6 Privacy positively influences Perceived usefulness (β = 0.37, t = 5.085) and H7 is supported, since Prevalence positively influences Perceived Ease to Use (β = 0.61; t = 11.604). Regarding the construct Social and environmental benefits (SEB) is confirmed, equally H_8 influences Perceived Ease of Use (β = 0.32; t = 4.700) with 99.9% significance. H9 Social and Environmental Benefits (SEB) also determine Perceived Usefulness (β = 0.25; t = 4.767).

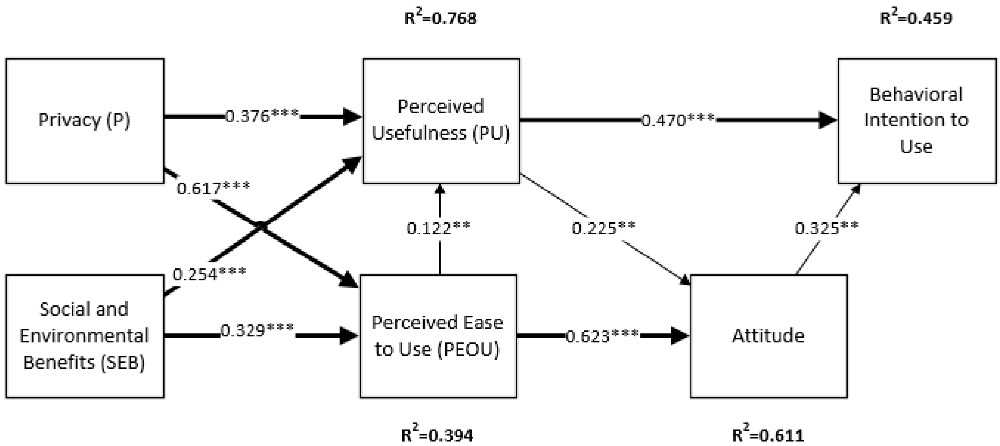

Figure 2. Results of structural equation modeling. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

6. Discussion

The findings achieved in this research are related to the objectives of the study. This study aimed to investigate the technological acceptance of LBS by including a variable focused on social and environmental benefits in the tourism context, obtaining relevant information from a sample of tourists. The results of this study indicated that tourists visiting a Spanish city, such as Seville, are willing to accept these services within a particular adoption model, in our case the TAM model with two external variables: Privacy and Social and Environmental Benefits. This conclusion is reached after the analysis of the results, the contrast of the hypotheses, which were supported, and the predictive capacity obtained in the coefficient of determination (R^2), which overcame the minimal threshold of 0.1 for all the internal variables, which confirms the predictive ability of the model [98].

The TAM adoption model has been used with all its original variables. Two external variables have been added to these, which are Privacy and, Social and Environmental Benefits. The obtained result affirms that all the hypotheses have been supported in our investigation. Therefore, in the first place it can be concluded that the TAM model is fully applicable to LBS technology in the field of Tourism. This is corroborated by the percentage of variance explained by the main dependent variable: Behavioral Intention of use, which reaches R^2 = 45.9, reflects a moderate predictive power of the main internal variable. Attitude has moderately strong predictive power [92]. We must emphasize the predictive power of the Perceived Usefulness construct (R^2 = 76.8).

The social and environmental benefits of LBS in the tourism sector influence user behavior and contribute to sustainable development. The different items in this variable had similar behaviors. Thus, the results show that the sample values "The location based services I currently use support tourism activities and cultural events", so the ease in finding these activities or the facility to acquire tickets has been well recognized. However, "The location based services I currently use saves energy" behaves very differently, since most respondents hold a position close to the "Neither agree nor disagree" response. Thus, it is not claimed that LBS contributes to saving fuel in vehicles and transport thanks to geolocation.

On the other hand the claims: "The location based services send personal advertisements that help to respect the environment" and "The location based services send location sensitive discount tickets from local stores in the visited city" seem not to reach consensus with the respondents, since the average reached is close to the "Neither agree nor disagree" response. Therefore, it seems that the sending of personal announcements by LBS, which help to respect the environment, the location of recycling points, the delivery of garbage, particularly vulnerable areas or the protection of endangered species, seem to be aspects to which the respondents give importance together, since the means of the scales reach values close to the response "Neither agree nor disagree". Likewise occurs with the sensitivity to the market and local stores, where similar values are obtained. The sample does not reach a consensus towards agreement or disagreement; that is, it does not seem that LBS helping with the sending of geolocalized discount tickets could help to understand that LBS brings a social benefit. All this leads us to think that tourists do not yet have a sufficient level of knowledge about the possibilities of this technology and that the applications that will favor the sustainable development of cities for tourist interest are not yet numerous enough, and above all, well known.

LBS is a solution that makes the deployment of tourism activities easier, more useful and improves attitudes towards it. It is really striking to discover that, in the technological context of LBS, the two causal relationships of the original TAM model, which act most significantly (99.9%) are Perceived Usefulness with Behavioral Intention of Use and Perception Ease of Use with Attitude. Both relations obtain high path coefficients (β), which lead us to conclude that, in the LBS context in tourism, there are two special circumstances. On the one hand, it seems crucial that there is a perception of clear and strong usefulness, since it is the variable that most influences the Behavioral Intention of Use, which could indicate that the localization service providers should pay special attention to assuring that users perceive the true value of the service they provide. On the other hand, Attitude is totally conditioned by the Perceived Ease of Use, to a greater extent than Perceived Usefulness, which leads us to conclude that the developers of these technologies should implement them emphasizing the usability and accessibility to improve the attitude of the users. This improvement is confirmed by the fact that Attitude directly conditions Behavioral Intention of Use.

The Perceived Usefulness construct has its variance explained based on Privacy, Social and Environmental Benefits and Perceived Ease of Use. Its high predictive capacity stands out and allows us to conclude that confidence in Privacy and Social and Environmental Benefits are perceived as very useful by users. It does not appear to be in influencers of perceived ease of use, since $R^2 = 0.394$ and therefore its productive capacity is moderate to low. In conclusion, although there may be additional factors, it can be stated that the model has a high predictive level and a substantial part of the variance of the variables is explained by this.

7. Conclusions

The study examines the behavior of users who take part in tourist activities, who use LBS applications and their results have significant implications, different to previous studies that used TAM, given the very specific context in which they have been done and, above all, the use of a variable never used in any previous study: social and economic benefits. As a conclusion, in the tourism context, the adoption of LBS depends on the benefits obtained, from the social and environmental point of view.

The next conclusion we reach is the demonstration that the TAM adoption model with all its original variables is fully valid and applicable to LBS. To these original variables were added two external variables: Privacy and Social and environmental benefits. It can be concluded that the TAM model is fully applicable to LBS technology in the field of Tourism with these two variables as independent.

In particular, the present study makes a valuable theoretical contribution to the field of information privacy through the measurement of confidence in the privacy measures adopted by the LBS provider, but especially contributes to reflect the importance of social and environmental benefits in the behavior of use, to develop sustainable tourism. This statement is based, fundamentally, on the variables used have not previously been used in TAM, and models in which it is reflected in a set of very novel items. Likewise, their degree of direct influence on the perception of usability and the perception of utility, and indirectly on the final dependent variable of the model: behavioral intention to use LBS has not been studied.

Our results also indicate that these two variables mentioned above influence behavioral intention in terms of Perceived Ease of Use and Perceived Utility, but above all latter. The perceived ease of use, in our results, does not have the same influence on the attitude as Perceived Usefulness. In addition, the results confirmed that perceived utility is a strong direct predictor of Attitude and Behavioral Intention to Use.

Interestingly, the role of trust in privacy was found to be important in the individual perception of the usefulness of LBS services since the existence of the influence of Privacy in Perceived Usefulness was significantly contrasted, finding that this hypothesis was supported. However, from the perspective of privacy concerns, the results indicated that tourists generally feel secure in providing information about their location and are not overly concerned about LBS for tourism not being able to take action to prevent unauthorized access to their location data.

The negative influence that is directly or indirectly exerted by Privacy on Behavioral Intention of Use has been confirmed empirically in numerous studies on LBS adoption [75,99] and others have interpreted it as Privacy having a moderating effect on all other relationships [64]. Our study shows, in a positive sense, that Privacy Confidence increases Perceived Usefulness and Perceived Ease of Use. Especially, Perceived Usefulness is influenced by Privacy Trust, which indirectly influences Behavioral Intention of Use. Which leads us to believe that confidence in Privacy is a stimulant to improve the usefulness and as a consequence, Behavioral Intention to Use in the TAM model. This conclusion is reached in the context of tourism, where risk aversion could be minimized because it develops in a pleasant environment and during vacation periods. That is, this would indicate that in a non-labor environment, there is also a certain aversion to risk that can lead to loss of privacy and therefore the user doubts whether or not to use LBS in certain circumstances. Therefore, it is confirmed that risk aversion continues to exist, even in groups that operate in more relaxed environments, such as the use of LBS for the enjoyment of tourist activities.

Social and Environmental Benefits is the other variable external to the original TAM model. Similar to Privacy, its direct influence on Perceived Usefulness and Perceived Ease of Use has been studied, as has its indirect influence on Attitude and especially on Behavioral Intention to Use.

The results obtained show that it positively influences Perceived Usefulness and Perceived Ease of Use. This direct influence on these variables indirectly influences Behavior Intention to Use LBS, which indicates that social and environmental benefits influence the final behavior of users and in a positive way. This discovery is a unique achievement of this research that can demonstrate that the LBS are affected by their capacities to benefit the society with respect to the environment, culture or the sustainable development of these.

This study has several limitations, which can be addressed in future research. Although the survey response rate for this study turned out to be statistically adequate, a desirable goal was to obtain a higher response rate as well as to be able to compare with LBS user groups, such as city residents. Another limitation was the inclusion of the influence of social networks on the model, which may constitute an extension of this research.

Finally, the results of this research will be of great use to the scientific community investigating the adoption of technologies, but also to tourism companies, technology experts, marketing managers and developers of mobile applications based on LBS. These may take decisions based on lower risks, if they know the main factors of influence and consider them in their professional activities.

Acknowledgments: This research work was assisted by the Consorcio de Turismo de Sevilla, which allowed the data collection in the Tourist Offices of Seville City. The dissemination of this research has the support of the European Regional Development Fund and the European Social Fund of the European Union, conceded within the framework of the Programme Support for the Implementation of Research Activities and Technological Development, Dissemination and Transfer of Knowledge by Extremadura Research Groups, which is managed by the Council of Economy and Infrastructure of the Regional Government of Extremadura, Spain (Reference No. GR15170).

Author Contributions: The outline of the study was led by Pedro R. Palos Sanchez. Subsequently, it implemented the questionnaire that served as the basis of the survey. José M. Hernandez-Mogollon and Ana M. Campon-Cerro analyzed the data and interpreted them. The authors wrote the manuscript and incorporated improvements to the final version. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Survey questions.

Construct Name	Item Code	Variable/Dimension and Survey Questions	Average ($\bar{x}$)	Standard Deviation (σ)
Attitude [56,100–102]	A1	I like the idea of using location-based services tourism	4.059	1.091
	A2	I would consider using location-based services for tourism good idea	4.428	1.194
	A3	I think location-based services for tourism make my holidays more convenient	4.289	1.069
	A4	In general, the idea of using location-based services for tourism might be beneficial to my family and me	4.428	1.017
Behavioral intention to use [56,58,101]	BIU1	I expect to use location-based services for tourism	4.256	1.182
	BIU2	I expect the information from the location-based services for tourism to be useful	4.223	1.116
Perceived ease of use [56,58,101]	PEOU1	My interaction with the location-based services for tourism is clear and understandable	4.278	1.178
	PEOU2	Interacting with the location-based services for tourism does not require a lot of mental effort	4.884	0.917
	PEOU3	I find the location-based services for tourism to be easy to use	4.184	1.179
Perceived usefulness [56,58,101]	PU1	Using the location-based services, I receive an alert notification from an online travel company	3.428	1.017
	PU2	Using the location-based services for tourism, I find monuments and places of interest more quickly	3.926	1.135
	PU3	Using the location-based services for tourism, I receive personalized offers	3.091	1.213
	PU4	Using the location-based services for tourism, I travel faster	3.099	1.419
Privacy [64,68,69,71,75]	P1	Overall, I feel safe when providing location information to the company because LBS, collects too much location information about me	3.607	1.205
	P2	I am not concerned that the LBS for tourism may not take measures to prevent unauthorized access to my location information	3.557	1.234
Social and environmental benefits [35,83–85]	SEB1	The location based services I currently use Support tourism activities and cultural events	4.217	0.884
	SEB2	The location based services send personal advertisements that help to respect the environment.	3.033	1.370
	SEB3	The location based services send location sensitive discount tickets from local stores in the visited city	3.367	1.382
	SEB4	The location based services I currently use saves energy	2.911	1.419

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