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Determinants of behavioral intention to use the Personalized Location-based Mobile Tourism Application: An empirical study by integrating TAM with ISSM

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Abstract

With the advent of the two-day weekend and improvements in the public transit system, people have begun to focus on leisure activities. When the YouBike public bicycle system was installed in the city of Taichung, Taiwan, it created a convenient transportation system network that was set up perfectly for a tremendous impact on the local tourism industry. This has happened in parallel with the development and proliferation of smartphones and wireless networks. The functions of mobile applications ("apps") have become more powerful over time, allowing people to access travel information and share their experiences almost instantaneously. Since a smartphone's positioning system can be used to provide more personalized information and services, the development trend is heading toward location-based services (LBSs) that can bring the app's functionality closer to the needs of the user.

This study develops a personalized location-based mobile tourism application (PLMTA) for travel planning. The PLMTA combines hybrid filtering technology with the ant colony optimization (ACO) algorithm to make more efficient customized tourism recommendations. It allows users to more effectively search through travel information and arrange their trip. This study also integrates the technology acceptance model (TAM) and the information system success model (ISSM) to present a research model that explores users' intention to use the PLMTA. The questionnaire survey method is used to collect our data, and the hypotheses are tested via structural equation modeling (SEM). The results show that information quality, perceived ease of use, and perceived usefulness significantly affect the intention to use PLMTA, while information quality and perceived convenience are found to have an influence on perceived usefulness. Information quality, system quality, and perceived convenience are found to significantly affect perceived ease of use, which consequently affects the intention to use the system.

Keywords: Location-based Services, Ant Colony Optimization, Technology Acceptance Model**,** Information System Success Model

1. Introduction

According to a survey by eMarketer (2014), the number of smartphone users reached 17.5 billion, globally, in 2014, having just passed 10 billion mark in 2012 [1]. In addition, the smartphone penetration rate is expected to be close to 50% in 2017 [1]. The booming development of smartphones and the increasing sophistication of positioning systems and navigation functions have spurred the constant development of new mobile apps. The smartphone's powerful functionalities can be combined with location-based services (LBSs) which use the mobile phone's positioning function to capture the user's location in order to provide personalized services suitable to that location for greater convenience. The combinations of these smart technology applications and location-based services can be quite diverse. For example, retailers use indoor navigation technology to provide location-based services, using mobile "push" notifications to deliver ads, thus providing appropriate, personalized marketing based on the consumer's location to enhance the quality of the customer experience. This kind of technology is set to become an important development trend in the future (Market Intelligence & Consulting Institute, 2015). Combining LBS and mobile phone apps has already become a global trend, providing convenient geographic information and information that relates directly to the user's specific location. Examples include store promotions, exhibition activity information, coupons and mobile education. As location-based services have matured, Click-and-Mortar has become both a possibility and a reality (TELDAP e-Newsletter, 2010).

In response to advances in information technology, new information systems are constantly being developed, and an increasing number of apps has accompanied the flourishing of smartphones and network services. The tourism recommender system is one such app. From the original, web-based-only system interface to mobile apps, users now have a variety of flexible options. The rapid development of science and technology has allowed tourism recommender systems to increase their functionality with new artificial intelligence technology such as multi-agent technology, optimization algorithms, cluster analysis, and so on. Recommender systems have become more complete and accurate, with interface designs that are more user-friendly [2].

While many applications combine LBS with mobile apps, the most common type combines the phone's positioning system with a web-based electronic map (e.g., Google Map, Yahoo Local, UrMap). Such applications provide an interface that uses e-maps and geological information system functions to offer users personalized information and services. Combining web-based electronic maps with location-based services allows for recommendations that are more accurate and better aligned with users' current needs. More relevant functions such as route planning, time estimation, and online coupons also become available. The map interface also allows users to be apprised of the distance between points at a glance, giving them more relevant geographical information.

As environmental awareness has increased, global warming and energy shortages have become increasingly apparent. To improve air quality and noise issues, many countries have begun to actively promote green vehicles. The bicycle sharing system is one such method [3]. The Taipei City Government worked in cooperation with Taiwanese bicycle company Giant to promote the YouBike public bicycle sharing system in Taipei, Taiwan. YouBike uses advanced radio frequency identification (RFID) technology, for increased user convenience. Chung (2010) found that the level of satisfaction users feel regarding YouBike's overall service is good, but attention must be paid to factors such as user perceived quality (both system and service quality) and corporate image (brand awareness) in order to build customer loyalty, which enhances users' willingness to continue to use the YouBike system [4]. In view of YouBike's success in Taipei, the city government of Taichung, in central Taiwan, began building a public bicycle sharing system called "iBike" in 2014. The government hopes to construct a comprehensive and convenient public transportation system network for short distance transport, improving its citizens' quality of life and promoting tourism.

Tourism recommender systems rarely use the mode of transportation as the main consideration for system design. However, traffic problems are a major problem for foreign tourists. Personalized recommendations are for individual users, providing one-on-one recommendation results [5, 6]. Many studies indicate that tourism recommender systems that offer personalized services are more likely to attract user interest and can more effectively assist users to plan their trips, thereby enhancing user satisfaction [7, 8, 9, 10]. Therefore, this study designs a personalized location-based mobile tourism application (PLMTA). This PLMTA uses hybrid filtering technology to gather tourism information more efficiently. The system also adopts an ant colony optimization (ACO) algorithm to customize tourism recommendations with location-relevant featured transportation to make trip planning easier. Thus, this study designs a set of tour planning functions based on the iBike system in metropolitan Taichung. In addition to tourism recommendation functions, the app participates in the promotion and development of Taichung's iBike system. It includes iBike stations and neighboring attractions as tour planning options, helping tourists to plan their Taichung trip more flexibly and conveniently. Lastly, this study integrates the technology acceptance model (TAM) and the information system success model (ISSM) to construct a research model to investigate users' intention to use the PLMTA. The study aims to understand how to design and develop a mobile tourism application as a personalized recommender system that is attractive to users and can improve daily life through "smart living."

2. Literature Review

2.1. Recommender Systems and Related Technologies

A recommender system is defined as one that provides "personal data or preferences as input data, after system processing and cross-check, to provide recommendation results to the appropriate recipients" [6]. Algorithm improvements and breakthroughs allow recommender systems to target specific groups. There are two main technical applications in a recommender system: content filtering (CB) and collaborative filtering (CF). Since these two technologies have different issues, their applications are limited. Over the years, numerous attempts have been made to overcome these limitations, and many different recommender system technologies have been developed. The four introduced below are the most common [11, 12].

(1) Content Filtering (CB)

Content filtering, analyzes user preferences, past selection history records, and information regarding chosen products in order to recommend products that are similar to customers' preferences. In the initial stage, a questionnaire is used to gather the preferences of new users. Cross-referencing and filtering produce a list of similar products to be recommended. Recommendation results based on content filtering are generally better than those based on collaborative filtering. However, the recommendation results tend to be too similar, offering users only a limited selection. Moreover, it is impossible to recommend products to brand new users or to those who rarely fill out questionnaires.

(2) Collaborative Filtering (CF)

Collaborative filtering involves collecting the preferences of groups of users who have similar interests or the same experience. This kind of filtering can be further divided into two types: user-based and item-based. User-based collaborative filtering analyzes all users' demand and preference for commodities, and conducts a similarity cross-reference to find other users whose preferences are similar to those of the current user as the basis for a recommendation. On the other hand, Sarwar et al. (1999) concluded that, in order to attract user attention, an item must be similar to those that have high ratings [13]. Therefore, item-based collaborative filtering is based on the calculated similarities between items instead of the calculated similarities between users. The problem with collaborative filtering, however, is that new products are ignored by the filter because they have no usage records. Therefore, it is not appropriate to use the collaborative filtering recommendation method for new products.

(3) Hybrid Filtering

Since content filtering and collaborative filtering recommendations have distinctly different limitations, many recommender systems overcome these by using a hybrid method which combines the two. There are three common hybrid approaches: one is to execute content filtering and collaborative filtering separately, and then combine the prediction results; another is to integrate some features of content filtering into the collaborative filtering; and the last is to integrate some features of collaborative filtering into the content filtering.

(4) Demographic Filtering (DF)

Demographic filtering employs the user's personal attributes (e.g., gender, occupation, age) to find other users with similar attributes. This kind of filtering classifies users with similar features into groups and tracks the preferences and behavior of other users in the same category.

The range of recommender system applications has become quite extensive. As the popularity of smartphones has risen, mobile app recommender systems that use positioning services have become a major trend. Based on the geographical location acquired from the smartphone's positioning system, the filters find more appropriate results which are then recommended to users. When the recommended results and services align with users' expectations, users are more satisfied with the app. Recommender apps commonly feature neighboring restaurants, gas stations, parking lots, and public transportation, all of which are highly relevant to people's daily lives. As information technology continues to evolve, recommender systems can be applied to more fields and other aspects of daily living. When combined with the real-time and ubiquity of mobile apps, recommender systems can increase convenience and improve people's quality of life.

Since each filtering approach produces different results, recommender system that adopt only one filtering technology are more limited in their ability to match the usage context and fulfill users' requirements. Therefore, this study adopts hybrid filtering as the main filtering approach in the PLMTA.

2.2. Tourism Recommender Systems

In response to the rapid evolution of smartphones and mobile networks, users are no longer constrained by time and space. A tour recommender system works in combination with the smartphone's positioning system to collect tour information that more closely meets the user's needs, providing a higher quality LBS. It is more flexible to use and the operation is more immediate, so overall efficiency is enhanced. Borras et al. (2014) organized and analyzed tourism recommender systems from 2008 to 2013 and found that, in comparison to collaborative and demographic filtering, content filtering technology was adopted by more tourism recommender systems [2]. Tourism recommender systems that use only a single filtering technology are now in the minority. Hybrid filtering that combines two or more technologies is now used by 53% of such systems, resolving a diverse set of problems.

Borras et al. (2014) also pointed out that tourism recommender system functions can be generally divided into four categories: recommended tour destinations and packages, recommended attractions and ratings, trip planning, and social networking [2]. The main function of most tourism recommender systems is to recommend and rate attractions. Fewer systems have trip planning as their main function. Some recommender systems work in combination with the information sharing functions of social networks. Few tourism recommender systems provide complete tour destination information and tour packages as their main function.

Batet et al. (2012) proposed the Turist@ system based on multi-agent technology to give personalized tour attraction recommendations more effectively [14]. Yang and Hwang (2013) proposed the ITravel recommender system in a mobile peer-to-peer environment [15], allowing users to discuss the reviews of attractions via peer-to-peer communication. The map interface lists the user's nearby friends so that the user can ask their opinions regarding trip plans and adjustments. Zhou et al. (2014) developed the SoLoMo system using the k-nearest neighbors algorithm to consider both geographical distance and social distance as the basis for its recommendations [16]. Chiang and Huang (2015) designed an algorithm that takes time, user preferences and other factors into consideration to recommend the most appropriate itinerary [17]. He et al. (2016) developed the

SocoTraveler model to leverage the individual travel history and social influence of co-travelers to analyze personal interests and then provide potential recommendations for users [18]. Cenamor et al. (2017) proposed the PlanTour system to provide personalized tourist plans by collecting human-generated information from travel social network sites in the “minube” travel app [19].

2.3. Location-Based Services

Location-based services provide the most appropriate services and information that can be offered at the users’ current location after confirming the user’s geographical position via the combined functionality of a mobile device, mobile network, and the global positioning system [20]. The Open Geospatial Consortium (2005) decreed that servicing mobile network users by combining wireless network service with geographical information shall be referred to as “location-based service” [21]. As the penetration rate of smartphones is high and with the rapid changes in mobile networks, new mobile apps are being developed constantly and continuously. Using geographic location information, LBS mobile apps provide more satisfying personalized services.

Statistics gathered by market research website eMarketer (2014) indicate that approximately 60% of mobile phone users use an LBS mobile app at least once a month, and this usage trend has increased year after year [1]. LBS applications are becoming increasingly diverse, often used in searches for nearby shops and restaurants. Samsioe & Samsioe (2002) pointed out that applying LBS to e-commerce provides users with the best service quality by offering specific services based on the geographical location obtained by the positioning system of the mobile device [22]. Location-based services are also widely used in mobile commerce, in which the most appropriate services and advertisements are pushed to potential consumers according to their needs and current location [23]. Thus, the major trend is to combine LBS and electronic maps to allow the user to have a clear concept of travel time and distance. Applying this concept to a tourism recommender system can facilitate the collection of tour information and tour planning.

Yang and Wang (2009) integrated GPS and web2.0 to create a set of mobile location-based information recommender systems to provide personalized recommendations [24]. Their system used the dynamic 3D text cloud to make data collection more efficient and provide users with dynamic recommendations based on synergy-added information. Yu et al. (2009) built an intelligent mashup recommender system based on the concept of ontology [25]. Once users revealed their tourism needs and preferences, the system took demand conditions and past experience into consideration to recommend appropriate tourism information. Husain and Dih (2012) adopted the TF-IDF (Term Frequency-Inverse Document Frequency) algorithm to filter the content and build a personalized location-based tourism recommender system [26]. Gavalas et al. (2014) adopted the systematic approach to review the state-of-the-art in recommender systems, especially for the classification of mobile tourism applications. They determined that a massive amount of information can be gathered from LBSs, web technologies and social networking to provide highly accurate and effective tourism recommendations [27].

2.4. Ant Colony Optimization (ACO)

The ant algorithm was first proposed by Dorigo in 1996, originally intended to solve the problems of traveling salespeople [28]. To enhance the efficiency of the algorithm and to maximize its ability to solve more complicated optimization problems with more clusters or with incomplete information, Dorigo & Gambardella improved the ant algorithm in 1997 and proposed the concept of ant colony optimization (ACO) [29]. ACO is a probabilistic technique for finding the optimal path. The idea is to simulate the way ants search for food in natural life. When ants leave the colony to search for food, their paths initially wander randomly along average lines. Ants deposit pheromones along the path trail. Since it takes more time for ants to travel down longer paths and back again, those pheromones have more time to evaporate. Over time, the pheromones on longer paths evaporate, and fewer ants will follow the trail. The next time the ants choose paths, they will choose the shorter paths which have a higher pheromone density. Since pheromone density is the basis for identifying the shorter paths, the combined result of all shorter paths chosen will reveal the shortest path.

Ant colony optimization is a probabilistic optimizing method. When artificial ants optimize a path, they will consider the transition probability for the selection of next node. The main considerations are pheromone density and length of line segments. The formula for transition probability is shown as Eq. (1):

$$P_{ij}^{s}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\propto} \times [\eta_{ij}]^{\beta}}{\sum_{u \in J_s(t)} [\tau_{iu}(t)]^{\propto} \times [\eta_{iu}]^{\beta}} , & if \quad j \in J_s\,(i) \\ 0 , & others \end{cases} \tag{1}$$

Here, $\tau_{ij}(t)$ refers to the pheromone density of the line segment $(i,\ j)$ at time t. $J_s\,(i)$ refers to the set of neighboring nodes that ant s has not yet visited at node i. η_{ij} refers to the expected value, usually a reciprocal of the length of line segment $(i,\ j)$. $\propto$ and β refer to the parameters determining the relative importance between pheromone and distance; usually the value of β is greater.

Pheromone evaporation refers to the phenomenon in which pheromones deposited on the ground after the ant has chosen its path dissipate over time. In an ant algorithm, pheromone evaporation in the natural world is emulated to avoid the unlimited accumulation of pheromones on a certain path, which can result in artificial ants constantly exploring other poor solutions.

Therefore, after an artificial ant selects all nodes, a solution is constructed and the pheromone density on the paths must be updated. After all artificial ants complete a journey, an "overall updating method" is executed to set the pheromone density. This pheromone updating is conducted according to path performance. The formula is shown as Eq. (2):

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{S=1\sim n} \Delta\tau_{ij}{}^{s} \tag{2}$$

Here, $\tau_{ij}(t)$ refers to the pheromone density from node i to node j at time t. ρ refers to the pheromone evaporation coefficient ($0 < \rho < 1$). $\Delta\tau_{ij}{}^{s}$ is the remaining pheromone density of ant s on line segment (i, j). The calculation is shown as Eq. (3):

$$\Delta\tau_{ij}{}^{s} = \begin{cases} \frac{Q}{L_s} \\ 0 \end{cases} \tag{3}$$

Q is the pheromone density each ant can secrete. L_s is the solution obtained by the sth ant. Each time a pheromone update is done, an iteration is deemed complete. When the optimal solution generated no longer changes or a certain number of iterations is reached, the ant colony optimization is complete.

Ant colony optimization has been widely used to solve various engineering optimization problems, and some studies have applied it to tourism. Claes and Holvoet (2011) used ant colony optimization to solve schedule planning issues and construct a transportation system [30]. ACO can predict the best path and transit time to estimate costs in terms of time and money. Ant colony optimization has been shown to outperform the traditional static routing algorithm. Claes and Holvoet (2012) improved the ant colony optimization by adding pheromone updating to transportation routes for more accurate route planning and prediction, resulting in more intelligent traffic systems [31]. Although many algorithms can solve the shortest path problem, after evaluating the options in regards to efficiency and accuracy, the majority of studies have adopted ant colony optimization [32, 33]. Using this algorithm for tour planning helps users conveniently and effectively find the best path.

3. System Design and Performance Evaluation

3.1. System Platform and Architecture

The personalized location-based mobile tourism application (PLMTA) developed in this study is based on the LBS concept. The user's geographical location is fed to the system via the smartphone's positioning function. After the system applies filtering and matching, the resulting data is written to the database and appropriate information is then presented to the user. This study adopted Notepad as the development platform, JavaScript as the main system programming language, and HTML5 and CSS as the screen layout tools,. Phone Gap was used to present the system in app format. This study also adopted Google Spreadsheet as the cloud database for the system using the Google Maps API.

Using Google Spreadsheet provides the system with such cloud computing advantages as cost-effectiveness, server cooperation, on-demand provisioning, and geographic diversity. It is also allows us to build a more dynamic and cost-effective information management infrastructure [34]. The PLMTA database is divided into two parts: one is to collect information on attractions and iBike stations in the

Taichung area, including attraction (or station) profiles, location coordinates, pictures, related videos and audios, or introductory information. The other is to record users' personal attraction preferences and the list of attractions selected as the reference for future attraction filtering and recommendations.

3.2. System Execution Screen

The system is mainly divided into four parts: attraction and iBike station information, theme travel, tour planning, and information on neighboring stores. The functions are described as follows.

(1) Attraction and iBike Station Information

"Attraction Information" is designed to collect information regarding attractions in the Taichung area and provide various kinds of travel information. The execution screen is shown in Figs. 1-3. Taichung area attractions and iBike stations and their related information are collected and organized to assist users to obtain travel information more conveniently. This function is divided into three modes: list of attractions, list of stations, and map mode. In addition to pictures and text descriptions, the attraction information includes recommendation information regarding neighboring attractions, and links to blogs or video and audio files.

Figure 1. List of Attractions

Figure 2. List of Stations

Figure 3. Map Mode

(2) Theme Travel

"Theme Travel" is designed to provide several travel themes based Taichung's famous attractions and unique features. The system can recommend differently themed, pre-planned tours, and users can pick from a variety of interesting itineraries.

(3) Tour Planning

"Tour Planning" is designed to help users effectively plan their own itinerary. Tour planning can be divided into three parts: user reference and information inquiry, attraction filtering and recommendation result, and route planning. First a questionnaire survey is conducted to gather the user's attraction preferences, as shown in Fig. 4. If the user has used the system before, it will automatically obtain previously-noted preferences. After the user's attraction preferences are confirmed, preliminary filtering is done based on attraction, as shown in Fig. 5.

To ensure that user preferences do not overly restrict the recommendation results, the system will also recommend different attractions chosen by user groups with similar preferences. After the recommended attraction list is provided and the user has selected the attractions to be visited, route planning is accomplished via the ant colony optimization (ACO) algorithm, as shown in Fig. 6. Finally, the system generates a recommended itinerary and displays it to the user. The electronic map interface using the Google Maps API gives users a clear view of travel time and distance. It also lists nearby iBike stations and other related information for user reference, as shown in Fig. 7.

Figure 4. Tour Planning with user preferences

Figure 5. Tour Planning with attraction filtering

Figure 6. Recommendation Results

Figure 7. Detail Information for route planning

(4) Information about Neighboring Stores

"Neighboring Stores" is designed to provide other related information such as nearby restaurants and hotels. This uses the Googles Places extension function of the Google Maps API to provide information about neighboring stores so that users can more conveniently obtain information regarding food, clothing, housing and transportation in the local area.

3.3. System Performance Evaluation

Authoritative U.S. survey agency J.D. Power (2013) found that phone performance is the key factor that consumers value the most in regards to smartphones [35]. Mobile app developers always take performance into consideration. Apps that close unexpectedly or crash the phone lower users' evaluations of and satisfaction with mobile apps. This research chose one optimizing algorithm for tour planning. Based on the results of various algorithms evaluated in the previous section, ant colony optimization was found to be remarkably efficient at solving traveling salesperson problems; thus this research adopted ant colony optimization as the basis of the tour planning system. This algorithm allows the overall operation of the mobile app to be more efficient while maintaining the smoothness of the smartphone application.

Based on the literature and our own testing, we configured our system with the most appropriate parameter settings as follows. The pheromone factor ($\propto$) was set to 1, the visibility factor (β) was set to 2, and the pheromone evaporation rate (ρ) was set to 0.1 [29, 36, 37]. This research assessed the efficiency of ant colony optimization for route planning. Five, seven and ten attractions were randomly chosen for solving the TSP (traveling salesperson problem) 50 times, respectively.

The results are shown in Table 1.

Table 1. System Effectiveness Evaluation

Unit: millisecond (ms)

	5 Attractions	7 Attractions	10 Attractions
Average Value	319.48	321.56	327.96

As shown in Table 1, the differences in solving efficiency for 5 attractions, 7 attractions, and 10 attractions are not significant. Continuing advances in hardware and network equipment have increased people's speed requirements for network services or apps. Waiting times within 0.1 seconds give users the sense that the app completes tasks instantaneously, providing the perfect operation speed experience. When waiting times rise to around one second, users begin to feel like they are waiting, but they usually are willing to do so since the wait time is within the acceptable range. Therefore, most systems or apps set their optimization goal to 1.0 seconds. Once the wait time exceeds 5 seconds, users are no longer satisfied and their intention to use the system again is dramatically reduced. The processing time of the route planning function in this study, under all three scenarios, is less than one second, which is acceptable to users.

4. Assessment of Intention to Use

This study explores users' intention to use the PLMTA and establishes a research model and hypotheses. Data collection for analysis is conducted via a questionnaire. This research conducts confirmatory factor analysis (CFA) and structural equation modeling (SEM).

4.1. Research Model

Many studies have explored users' willingness to accept technology based on technology acceptance models. Some studies have incorporated other factors as external variables in order to increase the explanatory power of the model and take more potential factors into account. To design a research model to explore user's intention to use PLMTA, this study adopts the technology acceptance model (TAM) as the theoretical basis and combines it with the information system success model (ISSM). Information quality, system quality and perceived convenience are considered as external variables.

(1) Information system success model

The information system success model was proposed by DeLone & McLean in 1992 [38]. Six factors are involved in evaluating the success of an information system: system quality, information quality, system use, user satisfaction, the effect on the individual user, and the effect on the organization.

Information quality refers to the accuracy, reliability, completeness, timeliness, and correlation of the data produced by the information system [38]. According to Seddon & Kiew (2007), information quality affects perceived usefulness, thereby affecting users' satisfaction with the information system [39]. Montazemi & Qahri-Saremi (2015) found that information quality has a strong influence on perceived usefulness, thereby increasing the intention of users to continue to adopt online banking service [40]. When information quality is better, users find the output information to be more helpful and are thus willing to use the information system more frequently [41, 42].

System quality refers to the essential features of the system that produce information. Chen & Hsiao (2012) explored user adoption of medical systems and found that system quality has a strong influence on perceived ease of use, thereby having a strong influence on user adoption intention [43]. Some studies have found that system quality has a positive effect on perceived ease of use, thereby affecting users' willingness to shop online [44, 45].

(2) Perceived Convenience

Many scholars have proposed different perspectives regarding convenience. From a marketing perspective, Brown (1989) stated that "convenience" can be seen as a type of marketing strategy applied to consumer products [46]. Providing consumers with products or services that give them a sense of "convenience" will increase their intention to purchase.

Perceived convenience refers to the degree to which users feel the products or services are easily found and used. Since this sense of convenience felt by users is not constrained to time, convenient operation of the product or service should also be considered. Hsu & Chang (2013) explored users' acceptance of the Moodle teaching platform and found that perceived convenience has a strong influence on perceived usefulness, thereby affecting the intention to continue to use the system [47]. Yoon & Kim (2007) evaluated users' intention to accept a wireless LAN and found that perceived convenience has a positive effect on perceived usefulness, thereby affecting behavioral intention [48]. Tang & Chiang (2009) explored factors affecting behavioral intention regarding mobile environment knowledge management and found that perceived convenience is a major factor that positively affects perceived ease of use, thereby affecting usage attitudes and behavioral intention [49].

(3) Technology Acceptance Model

Evolving from the Theory of Reasoned Action (TRA), the TAM was proposed by Davis in 1989, [50]. The TAM has been used to interpret users' acceptance of information technology. It comprises three dimensions: perceived ease of use, perceived usefulness, and usage behavioral intention. First, the perceived usefulness represents the degree of users believe the technology usage will enhance their job performance. When perceived usefulness is high, users believe that the information technology will help them perform their jobs better, thus increasing their intention to use the information technology. Second, the perceived ease of use represents the degree of complexity of the information technology. When the complexity of the information technology is lower, the system is easier to operate, increasing users' intention to use the information technology.

Many studies have shown that perceived ease of use and perceived usefulness have a strong influence on the intention to adopt the novel technology, and that perceived ease of use has a strong influence on perceived usefulness [51, 52]. Some studies have included external factors along with the TAM for exploration purposes. Egea & Gonzalez (2011) incorporated sense of trust as an external variable in the TAM to explore the intention to use an electronic medical record system [53].

This research explores users' intention to use the proposed PLMTA system, combining the TAM and the ISSM, and incorporating information quality, system quality, and perceived convenience as external variables. The research model is shown in Figure 8:

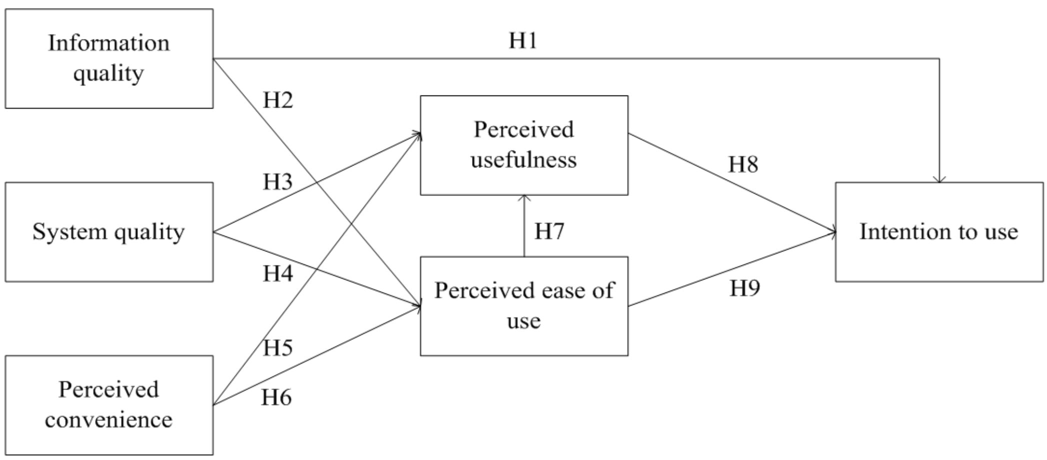

Figure 8. Research Model

4.2. Research Hypotheses

This research uses the TAM as a basis, adding information quality, system quality and perceived convenience as external variables. The following hypotheses are proposed.

H1: The information quality of the PLMTA will positively influence on users' intention to use the system.

H2: The information quality of the PLMTA will positively influence on users' perceived ease of use.

H3: The system quality of the PLMTA will positively influence on users' perceived usefulness.

H4: The system quality of the PLMTA will positively influence on users' perceived ease of use.

H5: Users' perceived convenience regarding the PLMTA will positively influence on perceived usefulness.

H6: User's perceived convenience regarding the PLMTA will positively influence on perceived ease of use.

H7: Users' perceived ease of use regarding the PLMTA will positively influence on perceived usefulness.

H8: User's perceived usefulness regarding the PLMTA will positively influence on their intention to use the system.

H9: User's perceived ease of use regarding the PLMTA will positively influence on their intention to use the system.

4.3. Questionnaire Design and Descriptive Statistic

This study explores users' intention to use the PLMTA and uses a questionnaire approach for data collection. The questionnaire is divided into 7 dimensions and has a total of 25 questions. All items are measured using a 5-point Likert-type scale (1 = strongly disagree, and 5 = strongly agree). This study used the "mysurvey" platform to create the questionnaire online and released it in popular forums. The total number of questionnaires collected was 213. After eliminating invalid samples, 176 valid samples remained. Males accounted for approximately 62% of the respondents, while females accounted for 38%. The majority of the respondents were 21-30 years old (approximately 66%). The majority of the respondents had a college degree (70%). Students accounted for 73% of the sample.

Gorsuch (1983) suggested that the sample size should be larger than 5 times the number of questions, and greater than 100 [54]. This research meets the criteria. The survey questions and their average value are shown in Table 2. The average value of each question is greater than 3.5, indicating that users have good feedback on each factor of the system.

Table 2. Survey Questions and Average Value

Dimension	Survey Questions	Average Value
Information Quality (IQ)	IQ1: I think the information provided by this app is accurate and credible.	3.713
	IQ2: I think the information provided by this app is complete and informative.	3.828
	IQ3: I think this app responds to my inquired information quickly and instantly.	3.655
	IQ4: Overall, I am satisfied with the information quality	3.695

	of this app.	
System Quality (SQ)	SQ1: I think this app really responds to my needs.	3.672
	SQ2: I think this app allows me to operate specific features (such as navigation) conveniently.	3.598
	SQ3: I think the system architecture of this app is logical.	3.684
Perceived Convenience (PC)	PC1: I think this app makes me saving a lot of time in obtaining information.	3.707
	PC2: I think this app makes it more convenient for me to plan itinerary.	3.718
	PC3: I think this app's searching for information according to my current location makes it easier to find information as I expected.	3.736
	PC4: I think this app assists me to plan itinerary more conveniently.	3.701
	PC5: I think this app makes it easier to collect information.	3.770
Perceived Ease of Use (PEOU)	PEOU1: I think I can easily operate this app.	3.851
	PEOU2: I can very quickly learn how to operate this app.	3.891
	PEOU3: I can very quickly operate this app to get information I need.	3.914
	PEOU4: Overall, I think this app is easy to use.	3.891
	PEOU5: I think the operation interface of this app is easy and straightforward.	3.833
Perceived of Usefulness (PU)	PU1: I think using this app can help me obtain information I need.	3.753
	PU2: I think using this app can increase the efficiency of information collection.	3.787
	PU3: I think how app incorporated iBike information helps me in tour planning.	3.747
	PU4: Overall, I think using this app is useful.	3.764
Intention to Use (IU)	IU1: I will give priority to using this app for information collection.	3.466
	IU2: I think using this app for collecting information is the right choice.	3.483
	IU3: I will increase the frequency with which I use this app.	3.431
	IU4: I will continue to use this app in the future.	3.425

5. Result and Analysis

5.1. Reliability and Validity Analysis

For reliability analysis, a Cronbach's Alpha of greater than 0.7 indicates the homogeneity of questions in the same dimension [55]. The reliability analysis of this research is shown in Table 3, and all reliability values are greater than 0.7, showing a high degree of reliability and internal consistency.

This research assessed the convergent validity and discriminant validity of the constructs. Table 3 shows that the factor loading of each dimension is greater than 0.5, thus confirming convergent validity. In this study, although factor loadings for each dimension do not all reach the level of "excellent" (i.e., 0.71), they can be considered "good" (>0.63), as shown in Table 3. Bagozzi & Yi (1988) [56], and Comrey & Lee (1992) [57] all suggested that the average variance extracted (AVE) of potential variables should preferably be greater than 0.50, and component reliability should be greater than 0.7. For discriminant validity to be ensured, the degree of correlation between dimensions must be smaller than that within each dimension. Therefore, a Pearson correlation coefficient matrix is used for validation. In Table 4, the square root of AVE of potential variables is greater than correlation coefficient of other dimensions, ensuring good discriminant validity [58].

Table 3. Reliability and Validity Analysis

Dimensions and Questions		Factor Loading	Component Reliability	AVE Value	Cronbach's Alpha
Information Quality	IQ1	0.814	0.8323	55.47%	0.880
	IQ2	0.708			
	IQ3	0.758			
	IQ4	0.693			
System Quality	SQ1	0.735	0.7959	56.53%	0.812
	SQ2	0.744			
	SQ3	0.776			
Perceived	PC1	0.718	0.8357	50.44%	0.897

Dimensions and Questions		**Factor Loading**	**Component Reliability**	**AVE Value**	**Cronbach's Alpha**
Convenience	PC2	0.720			
	PC3	0.709			
	PC4	0.679			
	PC5	0.724			
Perceived Ease of Use	PEOU1	0.741	0.8498	53.10%	0.907
	PEOU2	0.726			
	PEOU3	0.760			
	PEOU4	0.703			
	PEOU5	0.712			
Perceived Usefulness	PU1	0.851	0.8884	66.57%	0.891
	PU2	0.805			
	PU3	0.780			
	PU4	0.826			
Intention to Use	IU1	0.692	0.8140	52.28%	0.920
	IU2	0.767			
	IU3	0.722			
	IU4	0.709			

Table 4. Discriminant Validity

	Information Quality	System Quality	Perceived Convenience	Perceived Ease of Use	Perceived Usefulness	Intention to Use
Information Quality	**0.745**					
System Quality	0.346	**0.752**				
Perceived Convenience	0.656	0.398	**0.710**			
Perceived Ease of Use	0.655	0.387	0.699	**0.729**		
Perceived Usefulness	0.605	0.366	0.664	0.678	**0.816**	
Intention to Use	0.641	0.448	0.704	0.728	0.75	**0.723**
※ **The diagonal is the square root of AVE within the dimension.**						

5.3. Goodness-of-Fit of Model and Structural Modeling Analysis

Before SEM analysis, the goodness-of-fit of the model must first be evaluated to determine whether the test model and hypotheses are suitable. In this study, χ^2 (176) is 449.964, CMIN/DF is 1.692 and the goodness-of-fit index (GFI) is 0.844. The adjusted goodness-of-fit index (AGFI) is 0.810, and the incremental fit index (IFI) is 0.940. The comparative fit index (CFI) is 0.941 and the root mean square error of approximation (RMSEA) is 0.063. Hair et al. (1988) [58] suggested that GFI should be greater than 0.90 and AGFI should be greater than 0.80. Nevertheless, some studies have pointed out that the fit is acceptable as long as both GFI and AGFI are greater than 0.80. An RMSEA value between 0.05 and 0.08 also indicates an acceptable goodness-of-fit [56, 57, 58]. In this study, each indicator reaches the suggested value; therefore this model is suitable for SEM analysis.

The results of path analysis are shown in Figure 9. The explanatory power of perceived usefulness is 50.5%. The explanatory power of perceived ease of use is 54.2%. The explanatory power of intention to use is 60.7%. Both system quality (H3, β=.68, $p<0.001$) and perceived convenience (H5, β=.28, $p<0.01$) have a positively influence on perceived usefulness. However, the hypothesis regarding the effect of perceived ease of use on perceived usefulness is not supported (H7, β=-.08, $p>0.05$). Information quality (H2, β=.42, $p<0.001$), system quality (H4, β=.16, $p<0.05$), and perceived convenience (H6, β=.60, $p<0.001$) all have a positively influence on perceived ease of use. Information quality (H1, β=.23, $p<0.001$), perceived usefulness (H8, β=.18, $p<0.01$), and perceived ease of use (H9, β=.60, $p<0.001$) all have a positively influence on intention usage.

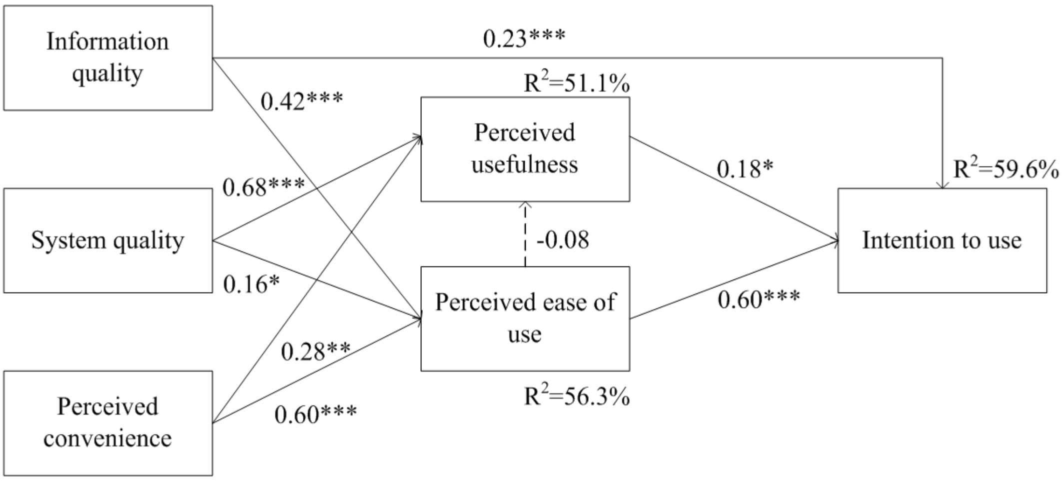

Figure 9. Structural Equation Modeling

6. Conclusion

The personalized location-based mobile tourism application (PLMTA) proposed in this study used ant colony optimization to achieve its tour planning function, allowing the operation of the system to be more effective. The analysis results show that tourism information based on LBS is more convenient to use. Incorporating iBike information as auxiliary data can more effectively help users plan their trips. The explanatory power of each dimension of the research model proposed in this study is higher than 50% (perceived usefulness: 50.5%; perceived ease of use: 54.2%; intention to use: 60.7%). This indicates that the research model is applicable to explore this issue and can be a reference for follow-up studies.

System quality and perceived convenience have a positively influence on perceived usefulness, indicating when users feel that overall operation quality is good and they can conveniently and smoothly operate various functions of the system, they consider the system to be more useful. System quality has the greatest effect on users' perception of system functionality. This implies that a greater focus on system quality is needed for future system development. However, our hypothesis regarding the positive effect of perceived ease of use on perceived usefulness is not supported by the data. This is probably because users believe that the system's ease of use is not relevant to the system's functionality. Information quality, system quality, and perceived convenience all have a positively influence on perceived ease of use. Three factors were found to give users the sense that the system was easy to use, allowing them to operate the system quickly: a) the quality (i.e., accuracy and timeliness) of the information produced by the system, b) the stability and clarity of the system architecture, and c) the users' perception of the convenience brought by the system. Among these, perceived convenience has the greatest effect. When the system design is more detailed, users tend to find the system more convenient, enabling them to operate it more easily. The biggest factor for usage intention to adopt the system is perceived ease of use. Thus, we infer an easy-to-use system design allows users to master the system quickly, greatly increasing their acceptance of the system. Furthermore, information quality and perceived usefulness both own the positively influence on intention to use. This means that the quality of the information and the ability of the system to help users complete their tour planning will positively affect users' willingness to use the system.

The scope of the personalized location-based mobile tourism application (PLMTA) proposed in this study is limited the Taichung area, so the amount of tourism information is also limited. System information will be richer if the scope can be widened to include other areas. Transportation information included in this research is limited to iBike. The operability of the system will be better if more public transportation information is included. In terms of data collection, since it is difficult to control the kinds of subjects sampled via an online questionnaire, the majority of our respondents were young (aged 20-30) and most were students. The prediction results may be more accurate with a more even sample distribution. Since this research proposes only six factors, future studies that incorporate more factors will enhance the explanatory power of our research model.

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ACCEPTED MANUSCRIPT

- it built a Personalized Location-based Mobile Tourism Application (PLMTA)
- it allowed users to effectively search travel information and arrange their trip
- it showed that perceived ease of use significantly affected intention to use PLMTA