Benefit Expectations and Continued Usage of Location-Based Applications for Location Intelligence

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Location-based applications (LBA) are widely used for different purposes ranging from navigation to dating or gaming. Most LBAs ask users to provide access to location data. By disclosing location, users get customized services and businesses can enhance their services with location intelligence methods. This research builds a continuance usage and location disclosure model from the expectation-confirmation perspective. The effect of benefit expectations on usefulness and satisfaction is hypothesized. In addition, the positive effect of usefulness on satisfaction and continuance intention is postulated. After collecting survey data from main LBA users, the results of the analysis support the proposed model.

Keywords: location-based apps, Location disclosure, location intelligence, mobile apps

INTRODUCTION

The increasing usage of mobile applications is coupled with the continuous stream of locational information with the movement of smartphones. Overall, mobile app usage is still on the rise and forecasts project 300 billion downloads and almost one trillion US dollars in revenues by 2023, with the most popular apps being utilities, social networking, tools, communication, travel, and local (Statista, 2019). Unsurprisingly, rapid growth of this significant area is beset by unresolved concerns, such as problematic mobile app continuance and disclosure issues experienced by the growing diversity of smartphone users. This research focuses on these important areas because success of many businesses is dependent on the availability of location information generated constantly by users.

Locational information has become integral to smartphone mobile apps, which have provided numerous valuable tools and services by accessing user information. Location-based services have become an accepted and indispensable feature of mobile communication and targeted marketing has significantly benefited from the active users' data (Hu et al., 2019). More than 90% of smartphone owners use location-based smartphone services (eMarketer, 2016). About 74% obtain destination directions based on their current device location. Over 50% download mobile apps of various kinds and 85% of these share their location when they download and use apps (PewResearch, 2014). A lesser 30% of social media users automatically allow mobile apps to display their location when they post (PewResearch, 2014).

Notwithstanding, users have become more cautious about when and what location information they choose to share (Hu et al., 2019). While full functionality of many mobile apps rely on the user disclosing location information, people are usually hesitant to reveal their whereabouts without receiving sufficient value in return (Ataei, Degbelo, & Kray, 2018; Koohikamali, Gerhart, & Mousavizadeh, 2015). Users who are unaware of the benefits and experience a reduction in satisfaction may mistakenly choose to limit their usage of the app. Attempting to control personal privacy, 19% of cellphone users report they have turned off location tracking entirely (Boyles, Smith, & Madden, 2012).

Location-based apps (LBAs) work only when the requisite location information is available (Rajendran, 2017). LBAs provide users with tailored, customized, personalized, and proximity-based functionalities using the physical geographical location of the mobile device (Paek, Ko, & Shin, 2016; Rook, Sabic, & Zanker, 2018). LBAs allow app providers to access to a real-time user's location information throughout the life of the app. Research indicates that one-third of all mobile apps use location information provided by GPS-enabled smartphones, ostensibly to collect data that will help deliver better services (Keith, Babb, Lowry, Furner, & Abdullat, 2013).

Potential advantages of LBAs are immense. Mobile systems that employ LBAs to track location open up abundant benefits for users and businesses (Smith, 2014). Location intelligence, an IS area that uses LBAs, is an emerging trend in business intelligence and data analytics domains (Pick, Turetken, Deokar, & Sarkar, 2017). Location intelligence is the upcoming trend in business intelligence and data analytics domains (Carto, 2018). In addition, LBAs are the next frontier in mobile technology because being able to track users' location opens up endless benefits for users and businesses (Smith, 2014). According to a recent survey, 54% of business managers believe their business collect location data using mobile devices or apps (Carto, 2018). Among challenges many organizations face, gathering real-time location data and ensuring the data quality are the two most important areas (Carto, 2018).

LBAs that exhibit different features can shape varied user perceptions of app usefulness. For example, navigation apps essentially become useless to provide location-based services if the user location information is inaccessible. Conversely, social networking apps can still be useful without accessing the user location. Other effects are less well known, which leads to our LBA research problem. Prior research has focused on privacy concerns of mobile app usage (Chen, 2013; Koohikamali et al., 2015), but accorded scant attention to analyzing user benefit expectations of LBAs, especially with respect to perceptions of app usefulness and user satisfaction. Recently, researchers have recognized the importance of location information as a separate area of inquiry, known as location intelligence and analytics (Pick et al., 2017). The absence of scholarly attention to continued usage LBAs leads us to call for more attention to this area (Tsai, Kelley, Cranor, & Sadeh, 2010).

The extracted value from data available to businesses could be maximized if the location data strategies and location intelligence can inform actionable decisions (Forbes, 2018). According to the result of a survey of 200 executives, 54% believe that location is collected through mobile apps in their organization (Carto, 2018). If users discontinue disclosing their location through mobile apps or do not use the LBAs, the success of location intelligence would be impossible. Surprisingly, little prior research has considered the significant benefits associated with mobile location disclosure (Sadeh et al., 2009). Accordingly, the purpose of this research is to fill the perceived continuance usage and location disclosure research gaps that exist in mobile app research, specifically from the expectation-confirmation theory (ECT) perspective (Bhattacherjee, 2001; Thong, Hong, & Tam, 2006). The aforementioned research gaps lead us to pose following research questions: (1) From the ECT perspective, how is continuance usage of LBA affected by usefulness, satisfaction, and benefit expectations? (2) For LBAs, how are user continuance usage and disclosure related? To answer the proposed research questions, the current study views perception of expected benefits and usefulness through the lens of expectation-confirmation theory (Bhattacherjee, 2001).

Our study is different from the limited body of research in two ways. First, recent innovations in internet-of-things, smart devices, and mobile apps, demonstrated the importance of location information for many users and businesses as many applications have become dependent on location information shared by users. Second, our research focuses on the specific type of applications that are using location to be more functional compared to other research investigating the location-based services on mobile devices. Thus, the main objective of this research is twofold: (1) to propose an expanded continuance usage intention of LBAs; and (2) to empirically test the proposed research model using the survey data collected from LBA. The proposed LBA model is tested with the survey data. Finally, the practical and theoretical impacts of this research are discussed.

LITERATURE REVIEW

Location-based Applications and Location Intelligence

Few users demonstrate concern over just how thoroughly smartphones mirror their lives, appreciating instead the many capabilities and conveniences they offer beyond basic phone conversation (Böhmer, Hecht, Schöning, Krüger, & Bauer, 2011). Still, due to the rapid development of smartphones, asking the consumer to fully understand the implications of proliferating smartphone features is a tall order. In less than a decade, mobile phones have evolved from communication-only devices to sophisticated multi-tasking tools that contain numerous mobile apps, so that they have been characterized as the Swiss army knife of technology (Satyanarayanan, 2005). Mobile apps are software applications designed specifically for smartphones, tablets, and other mobile devices (Statista, 2015). Location-based applications (LBAs) allow app providers to access to a real-time user's location information throughout the life of the app.

Location intelligence as an emerging subfield of data science spectrum and refers to the wide range of spatial analysis techniques to understand hidden patterns of spatially-based phenomenon, events, decisions, and behaviors. Location intelligence ultimate goal is to turn location data into desired business outcomes (Carto, 2018). Most of data in the world has a spatial dimension that proves the importance of having access to user's locational data. Mobile devices, due to the ubiquitous nature of them can create stream of users' whereabouts. To achieve the goal of location analytics or effective location intelligence, having access to users' location is crucial.

Perceived Benefit Expectations

Perceived benefit is a two-dimensional construct known as value dimensions (Overby & Lee, 2006). Utilitarian dimension refers to the functional and practical benefits and hedonic dimension reelects the aesthetic and enjoyment benefits (Chitturi, Raghunathan, & Mahajan, 2008). Perceived usefulness is used to measure utilitarian benefit and perceived enjoyment is used to capture the hedonic benefit (Sun, Fang, Lim, & Chen, 2010).

The direct and indirect advantages of adopting an IS comprise the two main types of perceived benefits (Lee, 2009). For example, online mobile banking accords users a wider selection of financial benefits over physical banking, as well as information transparency (Lee, 2009). With risks, come potential benefits—otherwise a rational user would not take risks. Both have been shown to precede attitudes about privacy sharing (Kim, Ferrin, & Rao, 2009; Peter & Tarpey, 1975). Sharing information about visited locations can positively impact society. If information about inferior locations is shared, all society will benefit from the experiences of a few users.

The perceived benefit is the reward that expected by the user (Chen & Dubinsky, 2003). Similar to this idea, research indicates that background context and perceived value will impact disclosure behavior (Tow, Dell, & Venable, 2010). Mobile app users decide to take risks in exchange for potential benefits of LBAs (Aloudat & Michael, 2011). Xu et al. (Xu, Teo, Tan, & Agarwal, 2009) found that general benefits positively influence intention to disclose location. LBAs provide benefits to users alongside the cost of imposing several risks to their privacy (Poikela, Wechsung, & Möller, 2015; Xu et al., 2009). During the continuing usage, users' behavior is re-formed due to actual experiences (Koohikamali, French, & Kim, 2019). Consequently, in the context of LBAs, continued usage behavior is closely related with satisfaction of the app.

LBAs Continued Use

LBAs can collect and disclose user location information, either intentionally or unintentionally disclosed by users (Tessem & Nyre, 2013). Intentional disclosure can occur when users check in to location-based apps (e.g., on the Foursquare app) or when they grant permission to navigation apps to calculate a destination route by using their current location (e.g. on the Google Maps app). Unintentional disclosure can occur when users are unaware that a mobile app is collecting their location information (e.g., installing an app without realizing it collects location information). Chia et al. (2012) study show access permission decisions made by careful users are usually based on simple signals such as app ratings, popularity, and number of downloads.

In the many previous Information Systems (IS) studies, user satisfaction is the important gauge to the IS continuance behavior (Bhattacherjee, 2001; DeLone & McLean, 2013). Previous studies discuss user satisfaction has a strong effect on IS usage behavior and positive perceived net benefits reinforce subsequent usage of an IS (DeLone & McLean, 2013). A user's satisfaction is the feeling about the prior IS usages (Bhattacherjee, 2001). A post-acceptance model of IS continuance built on the expectation confirmation theory (ECT) suggests satisfaction and usefulness are positively related with the IS continuance intention (Bhattacherjee, 2001).

THEORETICAL BACKGROUND

Expectation Confirmation Theory

The concept of cognitive dissonance has been applied to different theories in different contexts. Cognitive dissonance refers to the situation in which an individual perceive consistency among different things. The Cognitive Dissonance Theory (CDT) susgeests that in these situations the individual try tio minimize the existing inconsistency (Festinger, 1962). One of the theories which is built up based on CDT is expectation confirmation theory (ECT) (Lin, Wu, & Tsai, 2005). Expectation confirmation model is one of the theories that applied in several IS research (Bhattacherjee, 2001; Lin et al., 2005; Thong et al., 2006) to explain how users' satisfaction influences on their intention to use of information systems.

ECT applied in different contexts to study variety of dependent variables such as users' reaction to services, employee's new software acceptance, and users' technology acceptance (Brown, Venkatesh, & Goyal, 2014). This theory was developed by Oliver (1980) and applied by Bhattacherjee (Bhattacherjee, 2001) in the electronic commerce context. Although this theory has been applied in different contexts, core concepts in every research in this domain are expectation and disconfirmation (Oliver, 1980). Oliver (1980) argues that consumers' purchase decision creates a reference for consumers' comparative judgement. If a product outperforms than expected there is a positive disconfirmation and if the product performs poorer than expected, there is a negative disconfirmation. Positive disconfirmation increase consumers' satisfaction and their intention to purchase a product. Goal attainment theory developed by King (1992) postulates that individuals' level of satisfaction is determined based on their initial goals and the extent to which the goals are attained (Festinger, 1962). In other words, this theory suggests that the level of satisfaction from performing a behavior is the result of cost-benefit calculus. The original theory argues that individuals set several goals for most of their activities. Their level of satisfaction is determined by the extent to which the goals are attained.

Bhattacherjee (Bhattacherjee, 2001) applied ECT and Technology Acceptance Model (TAM) to explain IS use continuance intention. Bhattacherjee (Bhattacherjee, 2001) suggests that IS use continuance decision is similar to the consumers' repurchase decision in different ways. First, both decisions are followed by an initial experience with the system/product, second, this initial experience/use affects the decision, and third, may reverse the initial decision to use/buy a product. Acquiring the initial experience often has monetary or/and non- monetary costs for IS users. As it was discussed earlier the two major parts of ECT are expectation and confirmation. To be able to understand Bhattacherjee's post acceptance model of IS continuance, it is necessary to understand IS users' expectation in the IS research. Based upon TAM, perceived usefulness is an antecedent of users intention to continue to use IS (Davis, 1989; Karahanna, Straub, & Chervany, 1999). perceived usefulness was used as a measure of user expectation (Bhattacherjee, 2001). Therefore, Bhattacherjee argues that expectation of IS users in the post acceptance stage is not different from their perceived usefulness of the IS that they use. Internet users' level of satisfaction positively influences their intention to use of location services. Bhattacherjee (Bhattacherjee, 2001) argued that consumers' post-purchase behavior (repurchase intention) is the result of consumers' satisfaction. Due to the quick turn around on usage behavior in the context of mobile apps and specifically LBAs, this study applies the Bhattacherjee's post acceptance model of IS continuance which was driven from ECT and TAM.

Hypotheses Development

Using IS has some monetary and/or non-monetary cost for the users. Therefore, users expect to perceive some benefits from using the IS (Bhattacherjee, 2001). This is true in any context. For example in the context of organization, employees need to sacrifice time and the organization needs to spend money on acquiring an IS and training employees to use it. In the context of online shopping, online customers need to spend time on the internet, pay for utilities, and etc. to be able to shop online. All these users expect some benefits from using these systems. According to Xu et al. (Xu et al., 2009) LBS users perceive three different benefits from disclosing their information. These three types of benefits are personalization, positioning, and timeliness. Personalization refers to the value that LBA users perceive from experiencing the personalized functions on LBA. Positioning and timeliness refer to the value that LBA user perceive from having access to information and services in the right time and at the right place (Xu et al., 2009). Users benefit expectation refers to their anticipated gained through using an information system (Lee, 2010; Tam, Santos, & Oliveira, 2018). When users expect more benefits from using LBAs, they are more likely to perceive the LBA useful. The reason is that they perceive benefits from using the system which fulfills the cost of using LBA. If the users expect no benefit from using the LBA then the LBA only cost them. Therefore, they are not going to perceive it helpful. Hence we propose:

H1: *LBA Users' benefit expectation positively influences their perceived usefulness of LBA.*

According to ECT, users' satisfaction is influenced by two factors: their expectation and the extent to which their expectation would be confirmed after usage (Bhattacherjee, 2001; Brown et al., 2014; Oliver, 1980). A LBA user who expect to get more benefit from using the LBA are more likely to be satisfied after using LBA. The reason is that their initial expectation was set based on the rational decision of choosing a specific LBA among the others. According to Bhattacherjee (Bhattacherjee, 2001), these rational users will not continue to use a system that cost them and does not have benefit for them. Thus, user' benefit expectation is associated with the satisfaction of LBA users. Those users whose expectation confirmed perceive LBA more useful.

According to Tam et al. (Tam et al., 2018), the confirmation of users' expectation influence perceived usefulness and consequently their satisfaction. Perceived usefulness and ease of use are constructs that were used by Davis (Davis, 1989) and many other researchers In IS as beliefs that influence IS post acceptance behaviors (Bhattacherjee, 2001). One of the major concequenses of post acceptance behavior is users'satisfaction. Therefore, we expect that LBA users who perceive the LBA as a useful application be more satisfied than those who do not have such perception. This leads to the following hypothesis:

H2: *LBA Users' benefit expectation positively influences their satisfaction.*

H3: *LBA Users' perceived usefulness influences their satisfaction.*

The level of satisfaction of LBA users positively affect their intention to use of LBA. According to Bhattacherjee (Bhattacherjee, 2001) satisfied users are more likely to continue their behavior. Therefore, LBA users who are satisfied by attaining their goals are more intended to use LBA in the future compare to dissatisfied users. People have different goals or "expectations" at the beginning (Oliver, 1980). The extent to which these goals will be satisfied by the LBA services affect their intention to continue to use LBA. More satisfied users who achieved more of their goals than the others are more likely to use LBA in the future.

In addition to the satisfaction perceived usefulness is also associated with LBA user's intention to continue to use. The reason is that when an information system is useful, users get monetary and/or non-monetary benefits from using it (Bhattacherjee, 2001). Therefore, they are motivated to use it again to get more benefits. In fact, LBA users perceive several benefits from using these services. These benefits increase their satisfaction from LBA. One possible explanation for the positive effect of perceived benefits on satisfaction is that benefits of using LBA help users to achieve their goals and according to goal attainment theory (King, 1992) individuals will be more satisfied whenever they achieve their goals. Therefore, this study hypothesizes that:

H4: *LBA users' satisfaction positively influences their intention to continue to use LBA.*

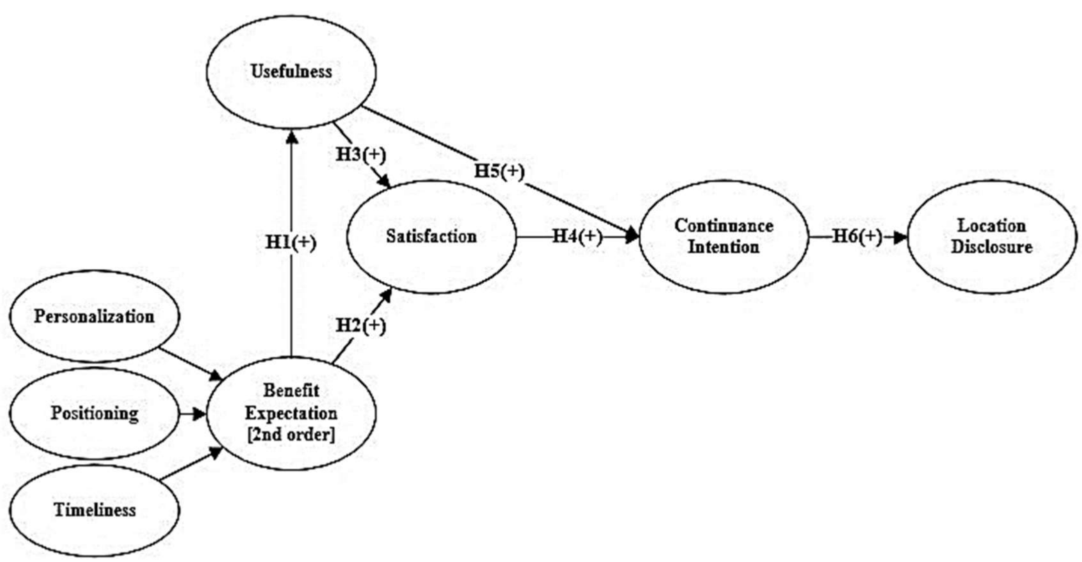
H5: *LBA Users' perceived usefulness positively influences their intention to continue to use LBA.*

Theory of reasoned action suggests that individuals who are intended to perform a behavior are more likely to perform that behavior (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). LBA users who are intended to continue to use LBA are more likely to share their location on LBA. One possible reason for is that they are satisfied with LBA and they want to benefit from using the LBA. To get benefit from an application whose core value creation process is based on users' location, location disclosure is inevitable. As a result, we suggest the following hypotheses:

H6: *LBA Users' intention to continue to use LBA positively influences their location disclosure on LBA.*

Based on the foregoing theories we developed the following research model (Figure 1) to study the antecedents of intention to continue to use LBAs.

FIGURE 1
PROPOSED LBA CONTINUANCE MODEL



METHODOLOGY

Study Design and Procedure

To explain the antecedents of LBA usage behavior, this research develops a research model based on goal attainment theory integrated with expectation-confirmation theory. To collect the data used for testing the proposed model, a survey method is used. The measures of this research were all identified and adopted in the related literature, to achieve strong content validity (Lynn, 1986). Construct measurement items are developed on 7-point Likert scale ranging from strongly disagree to strongly agree. Personalization, positioning, and timeliness dimensions of perceived benefit were adopted from (Xu et al., 2009). Measurement items of intention to continue to use LBAs were adopted from (Bhattacherjee, 2001). The items and their sources are listed in Appendix A.

Survey Administration

Online survey questionnaires were distributed to students enrolled in a large university in the US. Students are typical users of LBAs thus are excellent subjects to location disclosure behavior. The collected sample dataset contained 350 samples, however there were several incomplete and missing response that were removed. In addition, we removed responses that are filled in less than 8 minutes as the average time needed to sufficiently read and answer the questionnaire. The final dataset contains total of 319 respondents. Table 1 lists demographic information of respondents. Respondents were asked to identify the main reasons to use LBAs. The main motives indicated by respondents to use LBAs are shown in Table 2.

TABLE 1
DEMOGRAPHIC INFORMATION

Gender	
Male (53%), Female (46%), Other (1%)	
Age	
Mean (22), Min (18), Max (49)	
Academic standing	
Freshman (1%), Sophomore (24%), Junior (52%) Senior (21%), Graduate (3%)	
Dispensable income per year	
Below $5,000	57%
$5,000 - $9,999	22%
$10,000 - $14,999	10%
$15,000 - $19,999	3%
Over $20,000	8%

TABLE 2
MAIN MOTIVATIONS TO USE LBAS

Why do you use LBAs?	Total Count (%)
Navigation	180 (56%)
Find nearby places	149 (46%)
Monitor traffic	110 (34%)
Monitor weather	106 (33%)
Connect to people around me	96 (30%)
Find nearby events	68 (21%)
Get news around me	49 (15%)
View people's activities around me	47 (15%)

Geo-tag on social networks	47 (15%)
Track my fitness activity	28 (9%)
Find nearby parking	28 (9%)
Find a ride	20 (6%)
Find nearby sights	12 (4%)
Play location-based games	7 (2%)

TABLE 3
USAGE FREQUENCY

LBAs use frequency (per day in the last month)	
None	16 (5%)
1-3	144 (45%)
4-6	64 (20%)
7-9	22 (7%)
More than 10	73 (23%)

DATA ANALYSIS

The authors test the posited model with partial least squares (PLS) analysis, because PLS employs a component-based approach for estimation that minimizes residual distributions (Chin, 1998), and is best suited for testing complex relationships by avoiding inadmissible solutions and factor indeterminacy (Chen, Wang, Herath, & Rao, 2011). Furthermore, PLS is appropriate for modeling second-order constructs (Turel, Serenko, & Bontis, 2010). Smart PLS 3 is the software used to test the measurement model because it allows to model latent constructs as formative/reflective (Ringle, Wende, & Will, 2005). To establish the reliability and validity of measures before analyzing the structural model, a two-step approach recommended by (Anderson Gerbing, David W., 1988) is employed for data analysis. First, the analysis of the measurement is conducted to assess internal consistency, measurement reliability, convergent validity, and discriminant validity. Second, the structural relationship of latent constructs is analyzed. Perceived benefit construct is operationalized as second-order formative because dimensions form the latent variable and underlying dimensions are not highly correlated and are not interchangeable (Petter, Straub, & Rai, 2007).

Measurement Model

Two different approaches were used to assess measurement models of first-order reflective and second-order formative construct. To evaluate measurement model reliability and validity of first-order constructs in PLS, item reliability, convergent validity and discriminant validity are presented. Appendix B represent descriptive statistics and correlation coefficients of research construct. To assess individual item reliability, inter-item loadings are examined. Factor loading above 0.7 represent sufficient reliability of items (Hulland, 1999). Results show, all inter-item loadings are higher than 0.7 and show adequate item reliability.

To evaluate convergent validity, the reliability of reflective first-order constructs, composite reliability, and average variance extracted (AVE) are assessed (Fornell & Larcker, 1981). Cronbach's alpha and item loadings greater are used to assess construct reliability and composite reliability, correspondingly. Both measures are acceptable for values greater than 0.7 (Nunnally, 1967; Werts, Linn, & Jöreskog, 1974). AVE scores of 0.5 and more are desirable. Convergent validity is established by examining Cronbach's alpha values and AVEs in Appendix B.

To establish discriminant validity, inter-item correlations should be greater than outer loadings of constructs, square root of AVEs should be greater than its construct correlation, and correlation between constructs should be less than 0.85 threshold (Chin, 1998; Kline, 2015). Factor loadings and Appendix B demonstrate both conditions for discriminant validity present, establishes discriminant validity of the measurement model. For second-order formative constructs, weights, variance inflation factors (VIFs), and the loadings were assessed and Warp PLS 5.0 is used to calculate corresponding values. All weights are significant and VIFs were less than 5, confirming the use of the second-order formative construct.

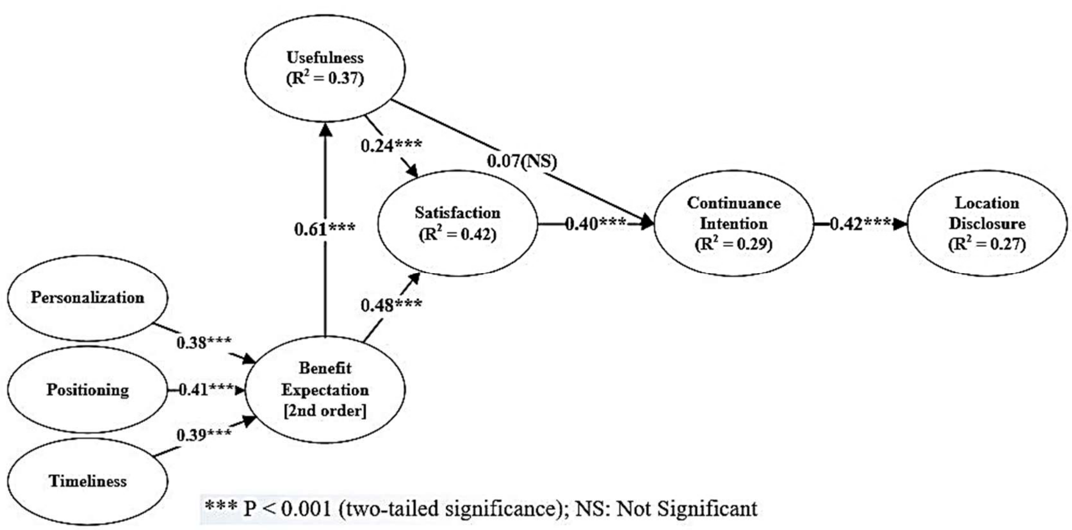
In a study with a survey questionnaire for data collection, researchers should check for the presence of common method bias to avoid erroneous conclusions (Campbell & Fiske, 1959). In this research, common method bias is evaluated using Harman's single factor test and the method suggested by Liang et al. (2007) method. Harman's single factor test indicate common method bias may exist under two conditions. First, a single factor emerges from the un-rotated factor solution. Second, a single factor accounts for the majority of the variance within variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). First, all the 26 items entered the explanatory factor analysis (EFA) and the un-rotated solution results in seven total factors, which equals the number of latent variables in the posited model. Second, the un-rotated single factors from the explanatory factor analysis accounts for 37.7% of the variance in the data which is less the 50% bound. Furthermore, threat of common method bias is examined following the procedure suggested by Liang et al. (2007). According to the results, all the method factor loadings, except one are insignificant. Hence, neither of two indicators for common method bias occurred in this study.

Structural Model

The structural model was estimated with Smart PLS 3. The explanatory power of the structural model is assessed through path coefficients and R-square scores of endogenous variables. The obtained path coefficients and their corresponding significance level is shown in Figure 2. PLS does not directly support second-order factors. Hence, second-order constructs were operationalized using the repeated-indicators approach (Lohmöller, 2013).

The PLS results indicate, all hypothesized paths were significant, expect the relationship between usefulness and continued intention to use. The results demonstrate the positive relationship between benefit expectations and usefulness ($\beta=0.61$, $p<0.001$, H1) and between usefulness and satisfaction ($\beta=0.24$, $p<0.001$, H2). Also, the results showed, benefit expectations positively relate with satisfaction ($\beta=0.48$, $p<0.001$, H3). In addition, the relationship between satisfaction and continued intention to use was significant ($\beta=0.40$, $p<0.001$, H4). Finally, the results indicate a significant relationship between continued intention to use and location disclosure ($\beta=0.42$, $p<0.001$, H6). The only relationship that was not significant was the relationship between usefulness and continued intention to use, rejecting the H5.

FIGURE 2
STRUCTURAL ANALYSIS OF THE MODEL



DISCUSSION

This research investigated the continued intention to use LBAs and location disclosure from the expectation-confirmation theory (ECT) perspective. ECT is an appropriate grounding theory because it can explain why users quickly abandon or uninstall mobile apps specially LBAs. We explored the effect of benefit expectations (timeliness, personalization, and positioning) on the usefulness of LBAs. Further, we investigated the effect of usefulness on satisfaction and continued intention to use. The focus of research proposed that benefit expectations positively influence usefulness. It also proposed that usefulness influences both satisfaction and continued intention to use LBAs. From the ECT perspective, the level of satisfaction and usefulness of using LBA is results from the confirmation of benefit expectations calculus.

Results of the analysis indicated support for five of six hypotheses, excepting only the relationship between usefulness and intention to continue to use. We found that benefit expectations including timeliness, personalization, and positioning positively influence usefulness and satisfaction. We also found that usefulness of LBAs positively influence the satisfaction. One possible explanation for the insignificant relationship between usefulness and continuance intention of LBAs is that human tendencies to continue using LBAs is defined only by satisfaction, instead of perceptions of usefulness. For example, if a navigation app that is definitely useful for steering to a destination cannot function offline, users would reject it. On the other hand, if the expectations of benefit are reasonably high, users would continue using such LBAs. LBA users may pursue certain benefits based on their a priori benefit expectations. From users' perspectives, there could be misalignment between what is perceived useful compared what is actually useful. The utilitarian usefulness component is not similar to hedonic usefulness component and the latter matters more in making a decision to discontinue using LBAs. The usefulness instrument covers mainly the navigation related usefulness, although users seek for other kinds of useful features that would be main driver of using LBAs.

Another interesting finding is the relationship between usefulness and continued intention to use is fully mediated by the satisfaction level. The context of LBAs is consistent with the extended ECT study, indicating satisfaction and performance expectancy is the most important driver of continued intention to use mobile apps (Tam et al., 2018). Our results indicate that the effect of perceived benefits on satisfaction is very strong; all three benefit expectations dimensions are at the same level of prominence. In addition, results demonstrate the location disclosure behavior is significantly determined by continued usage. This is an interesting finding for many businesses relying on location information disclosed by users. LBAs should always be considerate of what benefit users expect and in return the users keep using them and share their whereabouts.

Implications

This research contributes to theory and practice in the Information Systems (IS) discipline and related fields. On the theoretical side, using the ECT, 1) this research builds on the current gap in the literature about the continued usage of LBAs and location disclosure. This result strengthens current research, which focuses on mobile apps without attention to the type of app, the utility, and the type of information—which we provide. Through the ECT point of view, results indicate the importance of emphasizing on benefit expectations and satisfaction, rather than just risks, in order for the business to be successful in the continuance usage stage.

Theoretically, prior research has paid less accordance with respect to the effect of satisfaction on continued usage of LBAs and location disclosure. The findings of this study reveal, LBA users' decision to determine the weights expected benefits to continue using LBA is gauged through their satisfaction and the perception of usefulness of the app. The proposed research model can be used in other areas of IS research focusing on specific disclosed information to explain initial expectation and how users' choices under complex situations could change. In addition, this study extends the literature on online location disclosure by focusing on the most important benefits of location disclosure that has not been studied before. The major body of the location disclosure focuses on the impact of consumers concerns such as privacy. However, this study emphasizes on the benefits instead of risks of location disclosure.

The new paradigms of data science and business intelligence embrace location intelligence of location information disclosed by users on mobile apps and devices. Location sharing behavior benefits users several ways. There are other types of benefits that may result from using LBAs and many users are initially unaware. Some of the other benefits resulting from users disclosing their locations include locatability, connectedness, and enjoyment (Sun, Wang, & Shen, 2014). For example, users can track family and friends or provide others with directions to specific locations. More importantly, when emergencies necessitate quickly pinpointing places, property, or people, users may experience untold benefits from location services (Tsai et al., 2010).

Practically, findings of our study can be useful in future analytics applications such as in the area of Internet of things (IOT) because location is an inseparable part of all smart devices connected to the internet (Lee & Lee, 2015) of location intelligence. The focus on location information generated using mobile apps could unravel more insights for future of business intelligence and location intelligence areas. In addition, the analytics of location information should apply more complex methods to uncover spatial patterns in location information due to the change of details in location information. While prior research has explored the continued usage of different technologies and mobile apps, there is a missing piece of the puzzle with regard to a type of apps known as LBAs and how disclosure of location information is influenced by users' satisfaction.

Our model of location disclosure and continuance usage is useful for practitioners to understand how to maximize benefits for both users and the businesses as well as to encourage continuous usage of the application. Mobile app users are reluctant to share their location knowing it diminishes their overall experience (eMarketer, 2015). Not all users are comfortable with location sharing, as evidenced by 73% of smartphone and tablet users articulate that location sharing is either a somewhat or very useful task, 63% still are uncomfortable with disclosing their location (SalesForce & cloud, 2014). Recent debacles resulting from location tracking via mobile apps have heightened risks such as privacy, financial, and time. For example, Google was recently sued over tracking users' location even after the location tracking was set off by the mobile users (Binder, 2018). Media sources describe negative consequences of sharing online location such as stalking, mugging, and robbery (Wernke, Skvortsov, Dürr, & Rothermel, 2014). Developers should consider new privacy regulations and making sure users know how to remove their location history and geo-tagged digital footprints on LBAs.

Limitations and Future Research

This study has several limitations. First, the survey data collection method imposes certain limitations on the interpretation of results. Here, survey subjects responded to items based on their perceptions, causing a social desirability bias to the analysis. In addition, app users questioned in the survey recalled their usage experience with LBAs, creating a potential misalignment between survey items and respondent recollection or usage. To remedy this issue, future researchers may wish to collaborate with mobile app developers, collecting actual usage data to increase both the precision and the value of this work.

Second, we selected respondents enrolled in a large public university. As a result, the age group consists mostly of young adults having an average age of 22 years. Although young adults are typical users of LBAs, results would be more generalizable with a more comprehensive sample from diverse age groups. Notwithstanding, students still provide a valid representative sample of general app user population: young adults exhibit higher interest, willingness to explore, and rates of adoption using new mobile apps, while being less hesitant to disclose their location (Burstein, 2017).

CONCLUSION

For location intelligence to be effective, LBA users require detailed location information. Conditioned by positive expectations, mobile app developers and proprietors hope that mobile clients will use their apps extensively and continuously. Nonetheless, many mobile app users delete, uninstall, or stop using apps after just the first interaction. For mobile app purveyors to profit, convincing clients to use their app continuously is crucial. On the other hand, many of today's smartphones are location-enabled by default and allow users to share their whereabouts by default or intentionally.

This research fills the current research gap in the IS literature about the location intelligence and the complex usage of location-based apps. The current study investigated intention to continue using LBAs through the expectation-confirmation theory (ECT) perspective. Results showed while usefulness and satisfaction have direct effect on intention to continue using LBAs, the expectation benefits are indirectly related with intention to continue use. Finally, location disclosure is positively influenced by intention to continue using LBAs, indicating why location intelligence must encourage users to keep using apps so they can create location information.

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APPENDIX A

MEASUREMENT ITEMS

No	Construct	Item	Reference
1	**Intention to continue to use (CUSE)**	I intend to continue using LBAs rather than discontinue its use.	(Bhattacherjee, 2001)
2		My intentions are to continue using LBAs than use traditional ways to locate.	
3		If I could, I would never discontinue my use of LBAs.	
4		I am willing to disclose my location-related information using LBAs in the future.	(Xu et al., 2009)

5	**Location Disclosure (DISC)**	I will probably disclose my location information using LBAs in the near future.	
6		When I use LBAs in the future, I will likely disclose my location.	
7		If there is a chance, I intend to disclose my location when I use LBAs.	
8	**Usefulness (USEF)**	Using LBAs improves my performance in finding places.	(Bharadwaj & Drnevich, 2003)
9		Using LBAs increases my effectiveness in finding locations.	
10		Overall, LBAs are useful in finding locations.	
11		Using LBAs improves my performance in getting directions.	
12		Using LBAs increases my effectiveness in getting directions.	
13		Overall, LBAs are useful in getting directions.	
14	**Personalization benefit (PEBEN)**	The LBAs can provide me with personalized services tailored to my activity context.	(Xu et al., 2009)
15		The LBAs can provide me with more relevant information tailored to my preferences or personal interests.	
16		The LBAs can provide me with the kind of information or service that I might like.	
17	**Positioning benefit (POBEN)**	With the LBAs I am able to get the up-to-date information/services whenever I need to.	(Xu et al., 2009)
18		With the LBAs, I am able to access the relevant information/services at the right place.	
19		With the LBAs, I am able to access the relevant information/services wherever I want to.	
20	**Timeliness benefit (TBEN)**	With LBAs, I can get just-in-time information/services.	(Xu et al., 2009)
21		LBAs provide me an immediate response everywhere I need them.	
22		I get quick access to information/services I need anywhere I go because of LBAs.	
23	**Satisfaction (SAT)**	I am satisfied with the use of LBAs.	(Sun et al., 2010)
24		I am pleased with the use of LBAs.	
25		I am contended with the use of LBAs.	
26		I am delighted with the use of LBAs.	

APPENDIX B
DESCRIPTIVE STATISTICS AND CORRELATION COEFFICIENTS OF RESEARCH CONSTRUCTS

Construct	Mean (SD)	AVE	CR	CA	1	2	3	4	5
BEN	5.25 (1.11)	0.62	0.94	0.92	0.79				
CUSE	4.41 (1.16)	0.76	0.9	0.85	0.40	0.87			
DISC	5.79 (1.01)	0.85	0.96	0.94	0.26	0.42	0.92		
SAT	5.28 (1.11)	0.82	0.95	0.93	0.62	0.44	0.36	0.91	
USEF	5.39 (1.27)	0.88	0.98	0.97	0.61	0.28	0.28	0.53	0.94

Note. Diagonal values are square root of AVEs; CR: Composite reliability; CA: Cronbach's alpha.