Balancing User Privacy Concerns in the Adoption of Location-Based Services: An Empirical Analysis across Pull-Based and Push-Based Applications

Heng Xu
College of Information Sciences and Technology
Pennsylvania State University
hxu@ist.psu.edu

Sumeet Gupta
Shri Shankaracharya College of Engineering and Technology, India
sumeetguptadr@gmail.com

Pan Shi
College of Information Sciences and Technology
Pennsylvania State University
pzs125@ist.psu.edu

ABSTRACT

Location-Based Services (LBS) bring unprecedented mobility and personalization value to nomadic individuals and hence carry great commercial potential. However, the commercial potential of LBS is obscured by the user's concerns for privacy whereby the LBS provider can misuse the confidential personal information of users and in extreme circumstances place an individual in danger or seriously jeopardize his or her social life or finances. Therefore, we study the adoption of LBS through a privacy calculus lens. Privacy calculus argues that individuals, when requested to provide personal information to corporations, perform a cost-benefit analysis to assess the outcomes they would face in return for the information, and respond accordingly. We study both pull-based and push-based LBS to have a comprehensive view of LBS adoption. The results of the study reveal that individual's privacy concerns influence their intention to adopt directly in case of push-based LBS and indirectly in case of pull-based services. The implications for theory and practice are discussed.

Categories and Subject Descriptors
J.4 [Social and Behavioral Sciences]: Psychology; K.4.4 [Electronic Commerce]: Security; H.1.2 [User/Machine Systems]: Human factors.

General Terms
Management, Security, Human Factors.

Keywords
Location-Based Services (LBS), Location Commerce (L-Commerce), Privacy Calculus, Technology Adoption

1. INTRODUCTION

Location-Based Services (LBS) use positioning technologies to provide individual users with reachability and accessibility that would otherwise not be available in the conventional commercial realm. In the literature, LBS are defined as network-based services that integrate a derived estimate of a mobile device's location or position with other information so as to provide added value to the user [25, 41]. These services include emergency and safety-related services, location-sensitive billing, entertainment, navigation, asset tracking, directory and city guides, traffic updates, and location-based advertising [4, 25]. Among various LBS applications, those commercial location-sensitive services that utilize geographical positioning information to provide value-added services are generally marketed under the term 'Location-Commerce' or 'L-Commerce' [20]. The importance of LBS has increased more today than anytime earlier because they bring unprecedented mobility and personalization value to mobile user.

The growth trajectory of LBS is striking. According to a recent report from Allied Business Intelligence Inc., LBS revenues are expected to reach an annual global total of $13.3 billion by 2013, up from an estimated $515 million during 2007 [1]. Acknowledging the market potential, some operators, such as KDDI and NTT DoCoMo in Japan and E-Plus in Germany, have made LBS a core part of their strategy and are focusing on deploying accurate location technology and services as a differentiation mechanism. Unsurprisingly, the commercial potential and rapid growth of L-Commerce have been accompanied by concerns regarding the collection and dissemination of individual information by service providers and merchants. These concerns pertain to the confidentiality of accumulated individual data [58] and the potential risks that individuals experience over the possible breach of confidentiality [5]. In extreme circumstances, improper handling of location information can place an individual in danger or seriously jeopardize her social life or finances. The convenience of LBS notwithstanding, individuals worry about such privacy intrusions – the Big Brother imagery [43] looms in the popular press where LBS is discussed [36]. To the degree that privacy concerns represent a major inhibiting factor in individuals' adoption of L-Commerce [11], it is important to respond to the call of "No L-Commerce without L-Privacy" [26] by addressing the role of privacy in the adoption of L-Commerce.

The notion that there may be both positive and negative consequences accruing from LBS usage is implicit in the idea of 'privacy calculus' [13] in the information privacy literature. The concept of privacy calculus argues that individuals, when requested to provide personal information to corporations, would perform a cost-benefit analysis to assess the outcomes they would face in return for the information, and respond accordingly [13, 14]. This proposition of privacy calculus provides impetus for us to develop and test a research model with contrary factors capturing elements of privacy calculus. Relatively, the model developed here attempts to understand the delicate balance between individual privacy concerns and instrumental values that influence behavioral intentions to adopt LBS. In addition, acknowledging that LBS in different forms yield distinct benefits and privacy costs for individuals [26, 58], we test our model using two types of LBS. Particularly, we study pull-based LBS, in which individuals request information and services based on their locations, and push-based LBS, in which location-sensitive content is automatically sent to individuals based on tracking their locations.

The study reported here is novel to the extent that existing empirical research has not examined this complex set of interrelated issues in the LBS context. The synthesis of privacy literature and technology adoption theories may provide a rich understanding of the adoption of technologies that create personal vulnerabilities, and therefore, inform adoption research in the Information Systems (IS) discipline. The findings are also potentially useful to privacy advocates, merchants, and service providers to help shape or justify their decisions concerning L-Commerce. An understanding of individuals' adoption decisions in L-Commerce and their privacy concerns is vital for at least two reasons. First, positioning systems are likely to endure as an important technology because of the significant investments made in their development and associated telecommunication infrastructure [45]. Second, as information technologies increasingly expand the ability for firms to store, process, and exploit personal data, insights obtained from this study are likely to be of value for understanding the adoption of related technologies such as Radio Frequency Identification (RFID) technology.

The rest of this paper proceeds as follows. We first present the theoretical background, describe the conceptual foundations of the proposed model, and develop research hypotheses. This is followed by a discussion of the research method, including scale development and validation, and the experiment. Next, we present results in support of the psychometric properties of the measures and the hypothesis tests. The paper concludes with a discussion of the findings, research limitations, and implications for future research.

2. THEORETICAL BACKGROUND

2.1. Balancing User Privacy Concerns: A Calculus Perspective

Information privacy has been defined as the ability of the individual to control the terms under which personal information is acquired and used [59]. Prior research has repeatedly shown that information privacy continues to be eroded as a result of technology innovations [49]. Not surprisingly then, there is a robust body of research related to privacy concerns that attempts to understand how individuals make decisions regarding the revelation of personal information. In this literature, a key finding is that the concept of privacy is not absolute but, rather, can be interpreted in "economic (cost/benefit) terms" [32]. That is, individuals can be expected to behave as if they are performing a privacy calculus (cost-benefit analysis) in assessing the outcomes they will receive as a result of providing personal information to corporations [28, 40].

A theoretical perspective, consistent with the core idea of privacy calculus that may help predict individuals' propensities to disclose personal information is the rational choice theory [57]. These theories suggest that human action is fundamentally "rational" in character and that individuals will calculate the likely costs and benefits of any action and choose the course of action that maximizes overall rewards. Applying the rational choice perspective to the LBS context, we may interpret the information disclosure in LBS as a non-monetary exchange where consumers disclose their location information in return for value such as locatability and personalization provided by LBS providers. Specifically, consumers behave as if they are performing a risk-benefit analysis (i.e., privacy calculus) in assessing the outcomes they would receive as the result of providing personal information to LBS providers. Our study attempts to develop and test a research model with contrary factors capturing a set of elements in a *calculus* in which users make a delicate balance between privacy concerns, learning costs, and instrumental values that influence behavioral intentions to adopt LBS.

2.2. User Acceptance of Information Technology

Multiple models have been proposed in previous research to explain the adoption and usage of technology by individuals or organizations. Venkatesh et al. [55] proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating elements across eight major user acceptance models (i.e., theory of reasoned action, technology acceptance model, motivational model, theory of planned behavior, a combined theory of planned behavior/technology acceptance model, model of PC utilization, innovation diffusion theory, and social cognitive theory). According to UTAUT, four key constructs determine technology usage intention and behavior: performance expectancy, effort expectancy, social influence and facilitating conditions. Also, individual level factors (e.g., gender, age, experience and voluntariness of use) are posited to moderate the impact of the key constructs on usage intention and behavior. Based on empirical tests, Venkatesh et al. [55] demonstrated that their model accounted for 70% of the variance in usage intention, substantially greater than any of the extant user acceptance models when tested on the same data.

Consistently, our investigation follows the direction of technology acceptance literature by specifying a model that directly capture several constructs of the UTAUT: *behavioral intention* (intention to use LBS), *performance expectancy* (instrumental value of using LBS), *effort expectancy* (learning cost of using LBS), and *individual level factor* (personal innovativeness). Our model also indirectly captures the component of *facilitating conditions*. Venkatesh et al. [55] defined facilitating conditions as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system. This construct captures the aspects of technological and/or organizational environment that is designed to remove barriers to use. In case of LBS, the technology that may facilitate its use is being promoted by many service providers. However, privacy concerns are broadly regarded as the major inhibiting factors in the adoption of LBS [11]. While easing an individual with many location-based services, they also raise issues of privacy particularly of releasing one's personal information to others. Therefore, in this study we use the construct of privacy concerns as a specific aspect of facilitating conditions as proposed in UTAUT. Accordingly, we define *privacy concerns* as the degree to which a user's subjective views of service providers' information practices to prevent misuse of personal information.

Although much theoretical development along the line of UTAUT has occurred in regard to individual behavior with new information technologies, this body of work has paid limited attention to privacy issues. Indeed, a plurality of the theoretical models have chosen to focus on a central belief associated with the use of the target technology from a positive-utility oriented perspective, while paying limited attention to potential negative consequences arising from the adoption and use of new technologies (i.e., the risks that individuals may experience with respect to privacy violations in the L-Commerce context). As a consequence, we attempt to develop an adoption model to simultaneously consider both positive and negative outcomes of adopting and using a new technology that raises a new set of concerns related to individual privacy.

3. RESEARCH HYPOTHESES

Based on the notion of privacy calculus and UTAUT, we present the research model used in this study as shown in Figure 1. The core of the model is captured by a set of elements in a *calculus* in which users make a delicate balance between 1) negative utility factors such as privacy concerns, and 2) positive utility factors such as performance expectancy and effort expectancy. We further propose that personal innovativeness positively relates to behavioral intention.

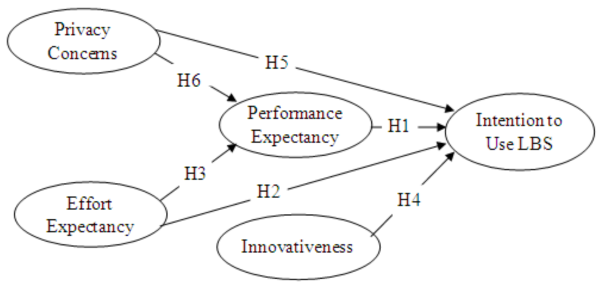

Figure 1. Research Model

3.1. Performance Expectancy, Effort Expectancy, and Behavioral Intention

Venkatesh et al. [55] defined performance expectancy as the degree to which an individual believes that using the system will help him or her in attaining gains in job performance. This construct is similar to perceived usefulness, extrinsic motivation, relative advantage, and outcome expectations that have been discussed in technology acceptance model, job-fit motivational model, model of PC utilization, innovation diffusion theory, and social cognitive theory, respectively. We defined *performance expectancy* in our research context as the degree to which an individual believes that using LBS would reduce his or her time and effort required to search or access the needed information or service.

Performance expectancy captures the notion of the ability of LBS to provide the intended services accurately. Junglas and Watson [30] identify five key characteristics of mobile commerce over and above electronic commerce. These five categories are: portability (physical aspects of mobile devices that enable them to be readily carried for long periods of time), reachability (a person can be in touch with and reached by other people 24 hours per day, 7 days per week, assuming that the mobile network coverage is sufficient and the mobile device is switched on), accessibility (describes the case where a person can access the mobile network at any time from any location, again assuming adequate mobile network coverage), localization (describes the ability to locate the position of a mobile person or entity) and identification (ability of the mobile device to uniquely identify the user). Out of these five features, we believe that reachability, localization and identification are unique aspects fulfilled by LBS. These are the benefits based on which users develop expectations about performance of LBS. To the extent that the anticipation of benefits provides direction for actual behavior through energizing and motivating individuals and enhancing the perceived value of various outcomes, a higher expectation about performance of LBS will amplify the desire to engage in the target behavior. Such a causal mechanism is consistent with UTAUT that includes performance expectations as the important antecedent to use intentions [55]. Therefore, we hypothesize:

> *H1: Performance expectancy is positively related to intention to use LBS.*

Effort expectancy has been defined as the degree or ease associated with the use of the system [55]. The construct captures the essence of perceived ease of use in technology acceptance model, complexity in the model of PC utilization, and ease of use in the innovation diffusion theory. Adapting from Venkatesh et al. [55], we define *effort expectancy* in this research as the degree or ease associated with the use of LBS. In the context of LBS, effort expectancy is about an individual's expectation of using LBS without much effort. If the process of LBS subscription involves tedious documentation, registration, learning about privacy policy, and service terms and conditions, then the mere effort may inhibit an individual to subscribe for such services. Apart from subscription, an individual may need to put effort to learn how to use LBS in the usage process. The more the learning effort required, the more inhibition would be there on the part of the individual to use LBS. In other words, the easier it is to use LBS to obtain desired services, the more an individual would intend to use LBS. This relationship is generally supported by UTAUT, according to which effort expectations influence individual behavioral intention about usage of technology. Hence, we hypothesize that:

> *H2: Effort expectancy is positively related to intention to use LBS.*

Technology acceptance model [15] proposes the relationship between perceived ease of use and perceived usefulness. Given that the construct of effort expectancy is similar to ease of use and that performance expectancy is similar to perceived usefulness [55], effort expectancy should be positively related to performance expectancy. However, such relationship has not been modeled in UTAUT. Effort expectancy has been found to be significant only during the first time period and becomes non-significant over periods of sustained and extended usage [2, 3, 15, 52, 53]. Since LBS are still considered as new technologies at the initial diffusion stage, we attempt to predict LBS adoption among potential users who do not yet have credible information about or affective bonds with the LBS. Thus we include the relationship between effort expectancy and performance expectancy in this study to test if there is any indirect influence on behavioral intention through performance expectancy. Hence, we hypothesize:

> *H3: Effort expectancy is positively related to performance expectancy.*

3.2. The Role of Personal Innovativeness

Although not specifically included in UTAUT, we attempt to explore the role of personal innovativeness in the research model. This is because LBS are in early adoption stage whereby many early innovative adopters simply adopt or try out technologies without a detailed value-based analysis. Personal innovativeness has been examined in innovation diffusion research [46], and in the domain of marketing [e.g., 22, 39]. In the field of information systems, Agrawal and Prasad [3] define personal innovativeness as willingness of an individual to try out new technology.

Personal innovativeness has been conceptualized in terms of its operational definition, i.e., individuals are characterized as 'innovative' if they are early to adopt an innovation [3]. This conceptualization was criticized later as using *time of adoption* as a surrogate for measuring personal innovativeness obscures its definition [22, 39], as this conceptualization implies that the adoption has already been made. Later, marketing researchers felt it important to conceptually and operationally draw a distinction between global innovativeness and domain specific innovativeness [3, 22]. However, empirical studies [27, 33] found that global innovativeness exhibits low predictive power when applied to any specific innovation adoption decision. Domain-specific innovativeness, on the other hand, was found to exhibit significant influence on behaviors within a narrow domain of activity [27]. Agarwal and Prasad [3] used the domain-specific innovativeness in the domain of IT for characterizing adoption. Consistent with their research, we use domain-specific conceptualization of innovativeness in the context of LBS. Adapting Agrawal and Prasad's [3] definition, we define personal innovativeness as *an individual's willingness to try out LBS*. As personal innovativeness in an individual-specific trait, those who are more innovative are likely to adopt LBS more readily than others and vice-versa. Rogers [46] noted that innovators exhibit certain characteristics behaviors such as active information seeking, greater exposure to mass-media, and less reliance on subjective evaluation of other members in their social circle about the innovation. This implies that innovators' decision to adopt is independent of other antecedents of intention to use LBS. Hence, we hypothesize:

> *H4: Personal innovativeness is positively related to intention to use LBS.*

3.3. The Role of Privacy Concerns

Prior privacy research has focused on understanding what motivates or inhibits the disclosure of personal information. Among these investigations, the construct of privacy concerns is one of the most widely used in MIS research and it is often used as a proxy for the concept of privacy. Several studies have conceptualized and operationalized privacy concerns in more detail: the Concern for Information Privacy (CFIP) instrument was developed by Smith et al. [48] which identified four dimensions of information privacy concerns: 1) *collection* reflected the concern that extensive amounts of personally identifiable data are being collected and stored in databases; 2) *unauthorized secondary use* reflected the concern that information is collected from individuals for one purpose but is used for another secondary purposes without consent; 3) *errors* reflected the concern that protections against deliberate and accidental errors in personal data are inadequate; and 4) *improper access* reflected the concern that data about individuals are readily available to people not properly authorized view or work with data. These dimensions have since served as some of the most reliable scales for measuring individuals' concerns toward organizational privacy practices. Recently, Malhotra et al. [38] operationalized a multidimensional notion of Internet Users Information Privacy Concerns (IUIPC) which adapted the CFIP into the Internet context.

According to UTAUT, facilitating conditions influence the usage of technology. Privacy concerns, as a specific aspect of facilitating conditions, reflect a user's subjective views of service providers' information practices to prevent misuse of personal information. Numerous extant studies have treated the construct of privacy concerns as an antecedent to various behavior-related variables, e.g., willingness to disclose personal information [9], intention to transact [17], and information disclosure behavior [7]. Privacy concerns are generally considered as a cost of adopting new technology [17]. The negative impact of privacy concerns on behavioral intention has been empirically supported in the e-commerce context [9, 16, 38]. Similarly, we expect a negative relationship between privacy concerns and behavioral intention in the context of LBS. Hence, we hypothesize:

> *H5: Privacy concerns are negatively related to intention to use LBS.*

As discussed earlier, individuals are concerned about loss of privacy in using LBS whereby their whereabouts and other personal identifiable information may be tracked by service providers. Moreover, this information can be used for nefarious purposes thus encroaching into a person's personal life. Especially, in this day and time of widespread terrorism using mobile devices, individuals are more fearful about disclosing personal information. The fear of losing control over personal information reduces their expectancy about the performance of the technology. In other words, in the wake of privacy invasion, the technology becomes unattractive. Therefore, LBS that are perceived as being privacy intrusive may also be perceived as being plagued with performance problems and usage uncertainties. Conversely, individuals who perceive service providers responsible and reliable in terms of using personal information may increasingly believe they will perform well, evaluate them highly and potentially adopt them. Hence, we hypothesize:

> *H6: Privacy concerns are negatively related to performance expectancy.*

4. METHOD

4.1. Pull-Based vs. Push-Based LBS

We conducted a scenario-based survey to test the proposed model. At present, most of the available LBS are delivered to mobile users over different underlying technology platforms such as Wireless Application Protocol-based (WAP-based) mobile Internet and Short Messaging Service (SMS) [58]. Since most mobile phones support the SMS[1] functionality, LBS in our study was introduced as the service offered to mobile phone users via SMS based on the Cell-Identification (Cell-ID)[2] technique employed by the network of telecom operators. Acknowledging that LBS differentiated by different information delivery mechanisms could yield distinct benefits and privacy costs for individuals (Gidari 2000; Levijoki 2001; Wallace et al. 2002), we test our model using two types of LBS that represent different information delivery mechanisms. The information delivery and acquisition in the LBS context could be either *pull* or *push* [6, 29, 35, 54]. In pull-based LBS, users request some information or use some service based on their location on a one-time basis [6, 54]. This type of LBS may be seen in some 'on demand' services where the individual dials or signals a service provider for specific information/service such as the nearest auto-teller machine (ATM) or Starbucks store. In these services, location

[1] SMS allows the sending of text messages of up to 160 characters via a mobile phone.

[2] Cell-ID, or Cell of Origin (COO), works by identifying the cell of the network in which the handset is operating (Barnes 2003). Such technique is the main technology that is widely deployed in mobile communication networks today. It requires no modification to handsets or networks since it uses the mobile network base station as the location of the caller (Barnes 2003).

information is ephemeral and useful only for users to receive real-time navigational requests (e.g., informing the user of the nearest ATM or Starbucks store). The other type of information delivery mechanism is push-based LBS where the service provider sends the user relevant information/service based on her known proximity to a store or service center via a wireless device [6, 54]. In the push-based approach, location information is used to target the user and she is sent the related advertisements when she gets within the vicinity of the merchants.

One specific pull-based LBS application and one push-based LBS application, i.e., the pull-based *SEND-A-TAXI service and push-based Mobile Coupon (M-Coupon) service, were utilized as the scenarios in the survey. In the scenario of **SEND-A-TAXI service*, when the individuals wanted to book a taxi, they could dial a certain number and their location would be detected automatically via their mobile phones. A list of taxi stands or landmarks near to their location will be transmitted to them via a text message. Individuals can select the pick-up point from the list and confirm their booking by replying to the text message. The *M-Coupon service* would involve recruiting individuals by service registration and interest subscription: Individuals could register their mobile phone numbers and subscribe to a list of merchants that provided M-Coupon services, based on their interests and preferred period of time for receiving coupons. Profiling information would then be used to target the subscribers, and their mobile phones would be sent related promotional information when they came within the vicinity of merchants.

4.2. Scale Development

To the extent possible, we adapted constructs from measurement scales used in prior studies to fit the LBS context. Drawing on technology adoption literature [55], *intention to use LBS* was measured with questions on whether the respondents were likely to use the particular type of LBS, whether they intended to use it, and whether they would consider using it. *Performance expectancy* was measured with four questions to capture the instrumental value of using the LBS [55]; *effort expectancy* was measured with questions on whether using LBS would be clear, understandable, and easy to use [55]. *Personal innovativeness* was assessed with three questions taken from Agarwal and Prasad [3]. *Privacy concerns* were measured by seven-point Likert scale items that integrated more tightly the CFIP's [48] four dimensions collection of personal information, unauthorized secondary use of personal information, errors in personal information, and improper access to personal information. Language was adapted to capture perceptions of specific service provider’s privacy practices. All items in the questionnaire were anchored to appropriately labeled seven-point Likert scales (see Appendix A).

4.3. Data Collection

Data for the study were collected through a scenario-based survey. The subjects were asked to assume the role of a potential LBS user and to evaluate some services that would be soon introduced in the local market. They were presented with two scenarios: a pull-based LBS scenario and a push-based LBS one. Next, they were asked to complete a questionnaire regarding their intention to use LBS, performance expectancy, effort expectancy, personal innovativeness, and privacy concerns in each specific scenario. Scenarios of two different types of LBS applications – *SEND-A-TAXI service (pull-based) and M-coupon service (push-based) were described to subjects. To control for order effects, half of the subjects in each scenario were asked to complete the pull-based scenario followed by the push-based scenario and vice versa. A dummy variable created for order effects had no significant influence on any of the endogenous variables in a MANOVA analysis ($F(4,171) = 0.912$, $p = ns$).

A total of 176 undergraduate students at a large university were recruited via an online registration system participated in the survey (83 females, 93 males). As an incentive for their participation, each subject received $5 upon completion of the task. All the subjects owned mobile phones and were familiar with text messages. While the use of undergraduate students as potential LBS users might limit the generalizability of the results, we believe that this should not be a major concern because research indicates that younger individuals are among the most avid users of mobile technologies [44], and arguably, represent the next generation of mobile individuals.

5. DATA ANALYSIS AND RESULTS

A second-generation causal modeling statistical technique – Partial least squares (PLS), was used for data analysis in this research for three reasons. First, PLS is widely accepted as a method for testing theory in early stages, while LISREL is usually used for theory confirmation [23]. Similar to the cases in prior research [e.g., 37], we chose PLS as the statistical technique because this study is an early attempt at advancing a theoretical model in a new context of LBS. Second, PLS is well suited for highly complex predictive models [10]. Prior research that applied PLS [e.g., 31] has claimed that PLS is best suited for testing complex relationships by avoiding inadmissible solutions and factor indeterminacy. This makes PLS suitable for accommodating the relatively complex relationships among various constructs in current research. Third, PLS has the ability to assess the measurement model within the context of the structural model, which allows a more complete analysis of inter-relationships in the model.

Since it has been noted that pull-based LBS and push-based LBS provide different instrumental values and induce different privacy concerns for individuals [34, 58], we split the dataset into two subsets according to the type of LBS to assess the different effects of pull- and push-based LBS on the theoretical constructs. Thus, the measurement and the structural models were tested separately for the pull- and push-based LBS subsets.

5.1. Evaluating Measurement Model

We evaluated the measurement model by examining the convergent validity and discriminant validity of the research instrument. Convergent validity is the degree to which different attempts to measure the same construct agree [12]. In PLS, three tests are used to determine the convergent validity of measured reflective constructs in a single instrument: reliability of items, composite reliability of constructs, and average variance extracted by constructs. Table 1 presents the assessment of the measurement model. We assessed item reliability by examining the loading of each item on the construct, and found the reliability score for all the items exceeded the criterion of 0.707. Thus, the questions measuring each construct in our experiment had adequate item reliability. Composite reliabilities of constructs with multiple indicators exceeded Nunnally’s [42] criterion of 0.7. The average variances extracted for the constructs were all above 50 percent, and the Cronbach’s alphas were also all higher than 0.7. These results support the convergent validity of the measurement model.

Discriminant validity is the degree to which measures of different constructs are distinct [8]. To test discriminant validity, the square root of the variance shared between a construct and its measures should be greater than the correlations between the construct and any other construct in the model. Tables 2 report the results of discriminant validity which may be seen by comparing the diagonal to the non-diagonal elements. All items in our experiment fulfilled the requirement of discriminant validity.

Table 1. Psychometric Properties of Constructs

	Pull-Based LBS				Push-Based LBS			
Construct Indicators	Factor Loadings	Composite Reliability	Cronbach's Alpha	Variance Extracted	Factor Loadings	Composite Reliability	Cronbach's Alpha	Variance Extracted
Behavioral Intention (INT)								
INT1	0.870	0.893	0.821	0.737	0.881	0.900	0.834	0.751
INT2	0.881				0.897			
INT3	0.824				0.821			
Performance Expectancy (PEPT)								
PEPT1	0.902	0.948	0.927	0.819	0.921	0.940	0.917	0.796
PEPT2	0.918				0.889			
PEPT3	0.909				0.888			
PEPT4	0.891				0.871			
Effort Expectancy (EEPT)								
EEPT1	0.876	0.899	0.814	0.752	0.802	0.909	0.845	0.771
EEPT2	0.787				0.819			
EEPT2	0.946				0.939			
Privacy Concerns (PCON)								
PCON1	0.818	0.935	0.849	0.783	0.871	0.940	0.911	0.796
PCON2	0.923				0.888			
PCON3	0.855				0.887			
PCON4	0.936				0.921			
Innovativeness (INNO)								
INNO1	0.835	0.929	0.861	0.815	0.862	0.852	0.831	0.658
INNO2	0.884				0.728			
INNO3	0.962				0.838			

Table 2. Correlation between Latent Variables

ITEMS	PULL-BASED LBS					PUSH-BASED LBS				
	INT	INNO	PCON	PEPT	EEPT	INT	INNO	PCON	PEPT	EEPT
INT	**0.858**					**0.867**				
INNO	0.224	**0.903**				0.187	**0.811**			
PCON	-0.130	-0.026	**0.885**			-0.386	-0.035	**0.892**		
PEPT	0.549	0.124	-0.178	**0.905**		0.292	0.021	-0.071	**0.892**	
EEPT	0.352	0.185	-0.146	0.357	**0.867**	0.307	0.191	-0.229	0.225	**0.878**

Note: The diagonal line shows the square root of variance extracted of each construct

5.2. Testing Structural Model

After establishing the validity of the measures, we tested the structural paths in the research model using PLS. We conducted hypothesis tests by examining the sign and significance of the path coefficients. Additionally, we inspected the weights of the dimensions of the constructs and the explanatory power of the structural model. A bootstrapping technique was applied to estimate the significance of the path coefficients. Since PLS does not generate any overall goodness of fit indices, predictive validity is assessed primarily through an examination of the explanatory power and significance of the hypothesized paths. The explanatory power of the structural model is assessed based on the amount of variance explained in the endogenous construct (i.e., behavioral intention). The structural models for the pull and push mechanisms explained 41.9% and 47.6%, respectively, of the variance in behavioral intention. These greatly exceeded 10%, which was suggested by Falk and Miller [21] as an indication of substantive explanatory power. Figures 2a and 2b show a graphical display of the results of hypothesis testing.

Our findings indicate that performance expectancy, effort expectancy, and personal innovativeness were positively related to behavioral intention, i.e., H1, H2, and H4 were supported. Effort expectancy was found positively related to performance expectancy and thus H3 was supported. However, privacy concerns was negatively related to behavioral intention only for push-based LBS (H5 was partially supported). Also, privacy concerns was negatively related to performance expectancy only for pull-based LBS (H6 was partially supported). Table 3 summarizes the hypothesis testing.

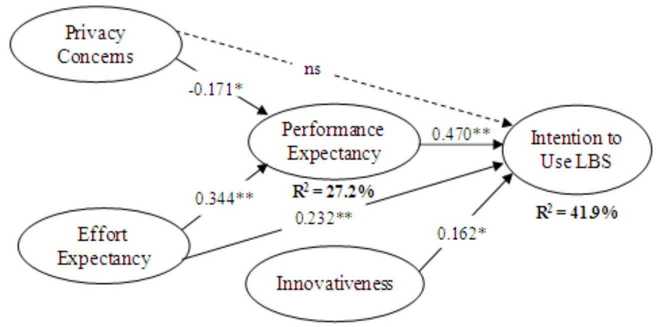

Figure 2a. Graphical Display of Results (Pull)

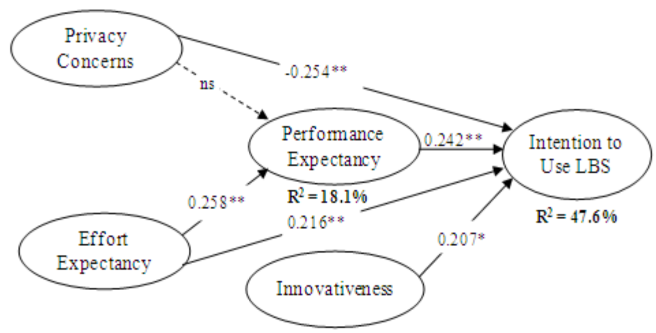

Figure 2b. Graphical Display of Results (Push)

Table 3. Results of Hypotheses Testing

Hypotheses	Coefficient		Supported
	Pull	Push	
H1: Performance Expectancy → Intention	0.470**	0.242**	Yes
H2: Effort Expectancy → Intention	0.232**	0.216**	Yes
H3: Effort Expectancy → Performance Expectancy	0.344**	0.258**	Yes
H4: Personal Innovativeness → Intention	0.162*	0.207*	Yes
H5: Privacy Concerns → Intention	0.043	-0.254**	Partially supported for push-based LBS
H6: Privacy Concerns → Performance Expectancy	-0.171*	-0.015	Partially supported for pull-based LBS

**Significant at 5% level of significance; **Significant at 1% level of significance*

6. DISCUSSIONS AND CONCLUSIONS

The goal of this study was to integrate theories and research from privacy, and technology acceptance in order to construct a conceptual model of LBS adoption that includes contrary factors capturing the delicate balance between privacy concerns, learning costs, and instrumental values that influence behavioral intentions to adopt LBS. The results reveal that performance expectancy, effort expectancy and personal innovativeness have significant influences on intention to use LBS for both pull-based and push-based services. However, the influence of privacy concerns on behavioral intention and performance expectancy varies under different types of LBS. On one hand, privacy concern influences intention to use LBS only in case of push-based LBS (and not in case of pull-based LBS). On the other hand, privacy concern has an impact on influencing performance expectancy only in case of pull-based LBS (and not in case of push-based LBS).

A plausible explanation for this finding is that individuals' privacy concerns are affected by the level of *control* inherent in the delivery mechanisms of location content (i.e., pull or push). In pull-based LBS, the individual exercises greater control over the interaction – the decision to initiate contact with the merchant is volitional, and location information is provided only to complete the requested transaction (e.g., inform the individual of the location of the nearest taxi). In contrast, in push-based LBS, the location information is tacked to target individuals who will likely be sent unsolicited information/services when they appear within the vicinity of the merchants. Accordingly, it appears that push mechanism is more controversial in terms of individuals' perceptions of privacy and authentication. The current research has shown that privacy concern has a direct negative impact on intention to use LBS in push-based LBS; but it influences behavioral intention indirectly through performance expectancy in pull-based LBS.

6.1. Limitations and Future Research

Although the data generally supported the proposed model, we need to mention some characteristics of our study that may limit the ability to generalize from these results. First, the scenarios used in the study represent a simplification of all pull-based and push-based LBS, which may limit the generalizability of our findings. Future work could also be directed to look into the applicability of our findings to different LBS applications. Second, actual adoption behavior was not measured, rather, we assumed, based on a significant body of prior work in information systems [51], organizational behavior [56] and psychology [47], that intention is a good predictor of actual behavior. However, some researchers [e.g., 50] have expressed concerns about the predictive ability of intention for actual behavior. Therefore, future research could examine the findings of this study in a context where adoption can be measured for added validation of the model. However, to the extent that LBS is still in an early stage of diffusion, examining adoption intention is appropriate and could potentially yield more meaningful and fruitful lessons for privacy advocates, individuals and providers of LBS alike. Finally, although the subjects in this study may fall in the target market for LBS, the generalizability of this research to the general population is likely to be affected. Future research should be conducted with a more diverse sample.

6.2. Implications

The investigation of individual adoption issues in LBS reported here represents one of the first attempts at developing and testing a model in LBS, with considerations of balancing privacy concerns and capturing individual difference in terms of personal innovativeness. Through the causal modeling of antecedents affecting adoption intentions of LBS, our findings provide preliminary theoretical and empirical insight into the dynamic structural relationships of these factors under two different mechanisms of content delivery. Several theoretical implications follow from our findings. For researchers, our study underscores the importance of explicitly incorporating both positive and negative consequences inherent in technological developments such as LBS. Our posited predictors explain between 40 percent and 50 percent of the variance in the intention to use LBS in the pull- and push-based models, suggesting that our model is a useful conceptualization of the phenomenon. Given that information privacy continues to be eroded as a result of technology innovations [49], and that there is sufficient evidence regarding the role of negative utility in the evaluation and adoption of LBS, researchers need to pay attention to the placement of negative utility constructs in their theoretical models. Other important examples of negative utility constructs that could enrich models of LBS adoption are those of data quality, service dependability, service cost and risks.

We viewed the adoption of LBS through a *rational* lens (a calculus of contrary factors) because the objective of this study was to predict its adoption among potential users who do not yet have credible, meaningful information about, or have affective bonds with the service providers at the initial adoption / usage stage. Future research could move beyond the domain of initial adoption / usage stage to the domain of continuance / discontinuance of usage whereby individuals already have a long ongoing relationship with service providers. In this context, *social* theoretical perspectives such as integrative social contract theory [19] and trust theories [24] may be particularly relevant. Indeed, these theories tend to view the sustenance of an ongoing relationship (i.e., the continuance and discontinuance of LBS usage) as dependent on individual parties' assessment and forecast of the benefits / costs tradeoff of *past, present,* and *future* interactions. Hence, whether individuals will continue to participate in this relational contract depends largely on their estimation of the probability of the service provider's departure from the expected pattern of behavior [18]. Further longitudinal research could be especially useful in investigating how individuals could be motivated to adopt and continue with LBS usage.

Consistent with Agarwal and Prasad (1998), we also included the role of individual trait (personal innovativeness) in predicting their intention to use LBS. While Agarwal and Prasad (1998) addressed the moderating role of personal innovativeness in predicting intention to adopt, we tested its direct role in predicting intention to adopt. Our findings confirm its importance by revealing that personal innovativeness has a significant influence behavioral intention for both pull-based and push-based LBS. Table 2 also reveals that personal innovativeness do not correlate highly with any of the other latent variables thus ruling out any possibility of multicollinearity. In other words, our study highlights the importance of personal innovativeness for studying adoption intention particularly for studying technologies that are in the stage of early adoption.

From a practical perspective, this study has implications for LBS service providers and privacy advocates. Our findings further suggest that service providers and privacy advocates need not tar all types of LBS with the same brush. Although privacy protection is a fundamental concern which must be addressed, "one size fits all" regulations on privacy are ill equipped to accommodate the interests of broader groups of users and the full gamut of players in the LBS industry.

In conclusion, this study attempted to integrate theories and research from privacy, and technology acceptance and constructed a conceptual model of LBS adoption that included contrary factors capturing the delicate balance between privacy concerns, learning costs, and instrumental values that influence behavioral intentions to adopt LBS. We also included the role of personal innovativeness as the study was on a technology, which is relatively in the early stages of adoption. Our initial findings that the influences of privacy concerns depend on the type of LBS suggest the need for future studies to understand these effects more fully. Using the groundwork laid in this study, future research along various possible directions could contribute to extending our theoretical understanding and practical ability to foster the acceptance of LBS.

7. REFERENCES

[1] ABI, Mobile Location-Based Services: Market Development, Revenue Opportunities, LBS Applications, and Key Industry Players in ABI Research. 2008, Allied Business Intelligence Inc.

[2] R. Agarwal and J. Prasad, "The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies," *Decision Sciences*, vol. 28, no. 3, 1997, pp. 557-582.

[3] R. Agarwal and J. Prasad, "A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology," *Information Systems Research*, vol. 9, no. 2, 1998, pp. 204-215.

[4] J.S. Barnes, "Known by the Network: The Emergence of Location-Based Mobile Commerce," in E-P. Lim and K. Siau, ed., *Advances in Mobile Commerce Technologies*, Hershey, PA: Idea Group Publishing, 2003, pp. 171-189.

[5] E. Beinat, "Privacy and Location-based Services: Stating the Policies Clearly," *GeoInformatics*, vol. 4, 2001, pp. 14-17.

[6] C.G. Bruner II and A. Kumar, Attitude toward Location-Based Advertising. 2007, Journal of Interactive Advertising (7:2):

[7] T.P. Buchanan, A.; Reips, J.U., "Development of measures of online privacy concern and protection for use on the Internet," *Journal of the American Society for Information Science and Technology*, vol. 58, no. 2, 2007, pp. 157-165.

[8] D.T. Campbell and D.W. Fiske, "Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix," *Psychological Bulletin*, vol. 56, no. 1, 1959, pp. 81-105.

[9] R.K. Chellappa and R. Sin, "Personalization versus Privacy: An Empirical Examination of the Online Consumer's Dilemma," *Information Technology and Management*, vol. 6, no. 2, 2005, pp. 181-202.

[10] W.W. Chin, "The Partial Least Squares Approach to Structural Equation Modeling," in G.A. Marcoulides, ed., *Modern Methods for Business Research*, London: 1998b, pp. 295-336.

[11] R. Clarke, "Person location and person tracking: Technologies, risks and policy implications," *Information Technology & People*, vol. 14, no. 2, 2001, pp. 206.

[12] M. Cook and D.T. Campbell, *Quasi-Experimentation: Design and Analysis Issues for Field Settings*, Boston: Houghton Mifflin, 1979.

[13] M.J. Culnan, "Consumer Awareness of Name Removal Procedures: Implication for Direct Marketing," *Journal of Interactive Marketing*, vol. 9, 1995, pp. 10-19.

[14] M.J. Culnan and J.R. Bies, "Consumer Privacy: Balancing Economic and Justice Considerations," *Journal of Social Issues*, vol. 59, no. 2, 2003, pp. 323-342.

[15] F.D. Davis, R.P. Bagozzi, and P.R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *Management Science*, vol. 35, 1989, pp. 982-1003.

[16] T. Dinev and P. Hart, "An Extended Privacy Calculus Model for E-Commerce Transactions," *Information Systems Research*, vol. 17, no. 1, 2006, pp. 61-80.

[17] T. Dinev and P. Hart, "Internet privacy concerns and social awareness as determinants of intention to transact," *International Journal of Electronic Commerce*, vol. 10, no. 2, 2006, pp. 7-29.

[18] T. Donaldson and W.T. Dunfee, *Ties that Bind: A Social Contracts Approach to Business Ethics*, Cambridge, MA: Harvard Business School Press, 1999.

[19] W.T. Dunfee, N.C. Smith, and T.W.J. Ross, "Social Contracts and Marketing Ethics," *Journal of Marketing*, vol. 63, 1999, pp. 14-32.

[20] J. Easton, "Going Wireless: Transform Your Business with Mobile Technology," New York: HarperBusiness, 2002, pp. 24-33.

[21] R.F. Falk and N.B. Miller, *A Primer for Soft Modeling*, Akron, Ohio: University of Akron Press, 1992.

[22] L.R. Flynn and R.E. Goldsmith, "A Short, Reliable Measure of Subjective Knowledge," *Journal of Business Research*, vol. 46, no. 1, 1999, pp. 57-66.

[23] C. Fornell and F.L. Bookstein, "Two Structrual Equation Models: LISREL and PLS Applied to Customer Exit-Voice Theory," *Journal of Marketing Research*, vol. 19, no. 11, 1982, pp. 440-452.

[24] D. Gefen, E. Karahanna, and D.W. Straub, "Trust and TAM in online shopping: an integrated model," *MIS Quarterly*, vol. 27, no. 1, 2003, pp. 51-90.

[25] M.G. Giaglis, P. Kourouthanassis, and A. Tsamakos, "Towards a Classification Framework for Mobile Location Services," in B.E. Mennecke and T.J. Strader, ed., *Mobile Commerce: Technology, Theory, and Applications*, Hershey, PA: Idea Group Publishing, 2002, pp. 64-81.

[26] A. Gidari, No 'L-Commerce' Without 'L-Privacy': Fair Location Information Practices for Mobile Commerce, in paper presented at L-Commerce 2000-The Location Services & GPS Technology Summit. 2000, Washington, D.C.

[27] R.E. Goldsmith and C.F. Hofacker, "Measuring consumer innovativeness," *Journal of the Academy of Marketing Science*, vol. 19, no. 3, 1991, pp. 209-221.

[28] C. Goodwin, "Privacy: Recognition of a Consumer Right," *JOURNAL OF PUBLIC POLICY AND MARKETING*, vol. 10, no. 1, 1991, pp. 149-166.

[29] H.-A. Jacobsen, "Middleware for Location-Based Services," in J. H. Schiller and A. Voisard, ed., *Location-based Services*, Morgan Kaufmann: Elsevier, 2004, pp. 84-110.

[30] I. Junglas and R.T. Watson, "The U-Constructs: Four Information Drives," *Communications of AIS*, vol. 17, 2006, pp. 569-592.

[31] D. Kim and I. Benbasat, "The Effects of Trust-Assuring Arguments on Consumer Trust in Internet Stores: Application of Toulmin's Model of Argumentation," *Information Systems Research*, vol. 17, no. 3, 2006, pp. 286-300.

[32] P.H. Klopfer and D.I. Rubenstein, "The Concept Privacy and Its Biological Basis," *Journal of Social Issues*, vol. 33, no. 3, 1977, pp. 52-65.

[33] D. Leonard-Barton and I. Deschamps, "Managerial influence in the implementation of new technology," *Management Science*, vol. 34, no. 10, 1988, pp. 1252-1265.

[34] S. Levijoki, Privacy vs Location Awareness. 2001, Working Paper, Helsinki University of Technology:

[35] S. Levijoki, Privacy vs Location Awareness. 2001, Helsinki University of Technology:

[36] S. Levy, A Future With Nowhere to Hide? 2004, Newsweek

[37] M. Ma and R. Agarwal, "Through a Glass Darkly: Information Technology Design, Identity Verification, and Knowledge Contribution in Online Communities," *Information Systems Research*, vol. 18, no. 1, 2007, pp. 42-67.

[38] N.K. Malhotra, S.S. Kim, and J. Agarwal, "Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model," *Information Systems Research*, vol. 15, no. 4, 2004, pp. 336-355.

[39] D.F. Midgley and G.R. Dowling, "Innovativeness: The Concept and Its Measurement," *Journal of Consumer Research*, vol. 4, no. 4, 1978, pp. 229-242.

[40] G.R. Milne and E.M. Gordon, "Direct Mail Privacy-Efficiency Trade-Offs Within an Implied Social Contract Framework," *Journal of Public Policy and Marketing*, vol. 12, no. 2, 1993, pp. 206-215.

[41] P.R. Minch, "Privacy Issues in Location-Aware Mobile Devices," in *Proceedings of Proceedings of the 37th Hawaii International Conference on System Sciences*, Big Island, Hawaii, 2004, IEEE Computing Society Press, pp. 127-136.

[42] J.C. Nunnally, *Psychometric Theory*, 2nd ed., New York: McGraw-Hill, 1978.

[43] G. Orwell, *1984, San Diego: Harcourt Brace Jovanovich Publishers, 1984. Originally published as Nineteen Eighty-Four*, London: Martin Secker & Warburg, 1949.

[44] E.P. Pedersen, "Adoption of Mobile Internet Services: An Exploratory Study of Mobile Commerce Early Adopters," *Journal of Organizational Computing and Electronic Commerce*, vol. 15, no. 2, 2005, pp. 203 - 222.

[45] B. Rao and L. Minakakis, "Evolution of Mobile Location-Based Services," *Communications of ACM*, vol. 46, no. 12, 2003, pp. 61-65.

[46] E.M. Rogers, *Diffusion of Innovations*, 4th ed., New York, NY: Free Press, 1995.

[47] B.H. Sheppard, J. Hartwick, and P.R. Warshaw, "The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research," *Journal of Consumer Research*, vol. 15, no. 3, 1988, pp. 325-343.

[48] H.J. Smith, J.S. Milberg, and J.S. Burke, "Information Privacy: Measuring Individuals' Concerns About Organizational Practices," *MIS Quarterly*, vol. 20, no. 2, 1996, pp. 167-196.

[49] E.F. Stone and D.L. Stone, "Privacy in Organizations: Theoretical Issues, Research Findings, and Protection Mechanisms," *Research in Personnel and Human Resources Management*, vol. 8, no. 3, 1990, pp. 349-411.

[50] D. Straub, M. Limayem, and E. Karahanna-Evaristo, "Measuring System Usage: Implications for IS Theory Testing," *Management Science*, vol. 41, no. 8, 1995, pp. 1328-1342.

[51] S. Taylor and P. Todd, "Assessing IT usage: The role of prior experience," *MIS Quarterly*, vol. 19, no. 4, 1995, pp. 561-570.

[52] R. Thompson, C. Higgins, and J. Howell, "Personal Computing Toward a Conceptual Model of Utilization," *Management Information Systems Quarterly*, vol. 15, no. 1, 1991, pp. 124-143.

[53] R.L. Thompson, C.A. Higgins, and J.M. Howell, "Influence of experience on personal computer utilization: testing a conceptual model," *Journal of Management Information Systems*, vol. 11, no. 1, 1994, pp. 167-187.

[54] R. Unni and R. Harmon, Perceived Effectiveness of Push vs. Pull Mobile Location-Based Advertising. 2007, Journal of Interactive Advertising (7:2):

[55] V. Venkatesh, G.M. Morris, B.G. Davis, and F.D. Davis, "User Acceptance of Information Technology: Toward A Unified View," *MIS Quarterly*, vol. 27, no. 3, 2003, pp. 425-478.

[56] V. Venkatesh and C. Speier, "Computer Technology Training in the Workplace: A Longitudinal Investigations of the Effects of the Mood," *Organizational Behavior and Human Decision Processes*, vol. 79, no. 1, 1999, pp. 1-28.

[57] J. Von Neumann and O. Morgenstern, *Theory of Games and Economic Behavior*, 2nd ed., Princeton: Princeton University Press, 1947.

[58] P. Wallace, A. Hoffmann, D. Scuka, Z. Blut, and K. Barrow, *i-Mode Developer's Guide*, Boston, Mass: Addison-Wesley, 2002.

[59] A.F. Westin, *Privacy and Freedom*, New York: Atheneum, 1967.

Appendix A. Measurement Items (measured on seven-point, Likert-type scale: *1 – Strongly disagree; 7 – Strongly agree*)

Intention to Use LBS (INT)

1. I intend to use the LBS in the next 6 months
2. I predict I would use the LBS in the next 6 months
3. I plan to use the LBS in the next 6 months

Performance Expectancy (PEPT)

1. LBS reduce my searching time to find the information/services that I need
2. LBS reduce my searching efforts to find the information/services I needed
3. With the LBS, I can quickly access the information/services that I need
4. With the LBS, I can easily access the information/services that I need

Effort Expectancy (EEPT)

1. My interaction with the LBS would be clear and understandable
2. I would find the LBS easy to use
3. Learning to use LBS is easy for me

Personal Innovativeness (INNO)

1. If I heard about a new information technology, I would look for ways to experiment with it
2. Among my peers, I am usually the first to try out new information technologies
3. I like to experiment with new information technologies

Privacy Concerns (PCON)

1. Service providers are collecting too much information about me
2. Service providers may not take measures to prevent unauthorized access to my location information
3. Service providers may keep my location information in a non-accurate manner in their database
4. Service providers may share my location information with other companies without notifying me or getting my authorization