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FOCUS THEME

The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services

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Abstract Location-Based Services (LBS) use positioning technology to provide individual users the capability of being constantly reachable and accessing network services while 'on the move'. However, privacy concerns associated with the use of LBS may ultimately prevent consumers from gaining the convenience of 'anytime anywhere' personalized services. We examine the adoption of this emerging technology through a privacy lens. Drawing on the privacy literature and theories of technology adoption, we use a survey approach to develop and test a conceptual model to explore the effects of privacy concerns and personal innovativeness on customers' adoption of LBS. In addition, as a number of IS researchers have shown that customers differ in their decision making for continued adoption as compared to initial decision making, we test the research model separately for potential and experienced customers. The results indicate that privacy concerns significantly influence continued adoption as compared to initial adoption. The implications for theory and practice are discussed.

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Introduction

Recently, the growing influence of Location-Based Services (LBS) has attracted significant attention. 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 (Barnes 2003). The growth of LBS to provide nomadic customers with unprecedented mobility and accessibility value has fuelled debate and controversy about potential threats to privacy. While LBS provide mobile consumers the capability of being constantly reachable and accessing network services while "on the move", they also introduce risks for mobile consumers who disclose location information to service providers. Location information often reveals the position of a person in real time, thus rendering the potential intrusion of privacy a more critical and acute concern (Clarke 2001; Danezis et al. 2005). These concerns pertain to the confidentiality of accumulated consumer data and the potential risks that consumers experience over the possible breach of confidentiality (Clarke 2001; Xu and Teo 2004; Xu et al. 2005). To the degree that privacy concerns represent a major inhibiting factor in consumers' adoption of LBS (Clarke 2001; Levy 2004), it is important to study the adoption of LBS through a privacy lens.

Although much theoretical development has occurred in regard to individual adoption behavior with new information technologies (e.g., Venkatesh et al. 2003), this body of work has paid limited attention to privacy issues. Most of the theoretical models (e.g., TAM and TPB) address technology adoption from a positive-utility oriented perspective, while paying limited attention to potential negative consequences (e.g., the risks that consumers may experience with respect to privacy violations in the LBS context) arising from the adoption and use of new technologies. As a consequence, we attempt to develop a research 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.

Moreover, the acceptance of LBS is likely to be moderated by the innate innovativeness of an adopter. As a personal trait, personal innovativeness differs among individuals and is likely to influence their adoption decisions. Although personal innovativeness has a long standing in innovation diffusion research (Rogers 1995), its role as a predictor of technology adoption has been underexplored in current literature (with Agarwal and Prasad 1997; 1998 as notable exceptions). We therefore, attempt to explore its role as a predictor and a moderator to intention to use LBS. Acknowledging the difference between potential and experienced users in relation to technology acceptance (Gefen et al. 2003; Taylor and Todd 1995), we test our model separately for potential and experienced LBS users.

The rest of this paper proceeds as follows. We first describe the theoretical 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 survey. 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.

Theoretical background

UTAUT and privacy concerns

Multiple models have been proposed in previous research to explain the adoption and usage of technology by individuals or organizations. Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating elements across eight major user acceptance models. 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. Venkatesh et al. (2003) demonstrated that their UTAUT 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 adoption literature by specifying a model that directly captures 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* through the construct of privacy concerns. Venkatesh et al. (2003) defined facilitating conditions as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system and remove barriers to use. In the case of LBS, while easing an individual with many location-based services, they also raise issues of privacy particularly of releasing one's personal information to others. Given that privacy concerns are broadly regarded as the major inhibiting factors in the adoption of LBS (Levy 2004), we examine the construct of privacy concerns as a specific aspect of facilitating conditions. Accordingly, we conceptualize *privacy concerns* as the degree to which an individual believes that the organizational and technical infrastructure exists to prevent privacy breach.

Following Smith et al. (1996)'s conceptualization of concerns for information privacy (CFIP), we define this construct with four components: 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 duly authorized to view or work with data. Although privacy concerns have been researched extensively in IS (e.g., Dinev and Hart 2006a; Malhotra et al. 2004), its role in the nomological net of UTAUT has not been investigated. To fill in this gap, current research proposes that privacy concerns will be an anchor exerting a negative influence on the performance expectancy and effort expectancy of using LBS.

The role of personal innovativeness

Although personal innovativeness is 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 new technologies without a detailed value-based analysis. Personal innovativeness has been examined in innovation diffusion research (Rogers 1995), and in the domain of marketing (e.g., Flynn and Goldsmith 1999; Midgley and Dowling 1978). In the field of information systems, Agarwal and Prasad (1998) 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 (Agarwal and Prasad 1998). This conceptualization (which implies that innovation has already been adopted) was criticized later because using *time of adoption* as a surrogate for measuring personal innovativeness obscures its definition (Agarwal and Prasad 1998; Flynn and Goldsmith 1999; Midgley and Dowling 1978). Later, marketing researchers conceptually and operationally drew a distinction between global innovativeness and domain specific innovativeness (Flynn and Goldsmith 1999). However, empirical studies found that global innovativeness exhibits low predictive power (Goldsmith and Hofacker 1991; Leonard-Barton and Deschamps 1988). Domain-specific innovativeness, on the other hand, was found to exhibit significant influence on behavior within a narrow domain of activity (Agarwal and Prasad 1998; Goldsmith and Hofacker 1991). Agarwal and Prasad (1998) used the domain-specific innovativeness in the domain of IT for characterizing adoption. Since the nature of this study pertains to a specific technology domain (i.e. LBS), we follow Agarwal and Prasad (1998) to use domain-specific conceptualization of personal innovativeness in the context of LBS. Accordingly, we define *personal innovativeness* as an individual's willingness to try out LBS.

Research model and hypothesis

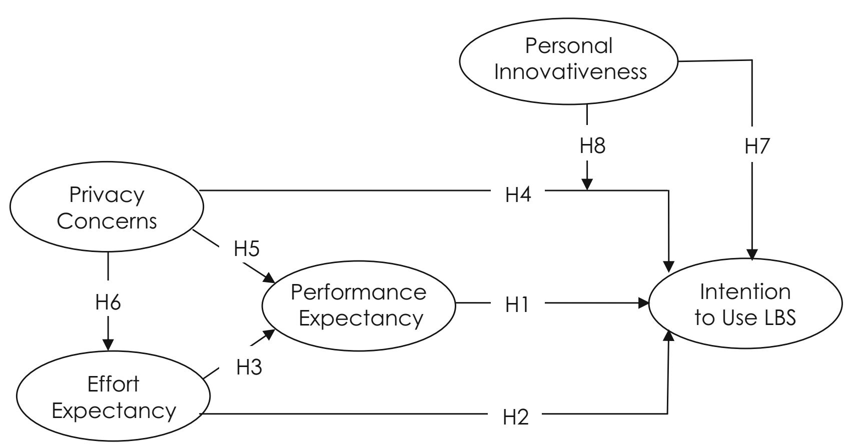
Based on the above discussions on UTAUT, privacy concerns and personal innovativeness, we present the research model in this study (Fig. 1).

Performance expectancy, effort expectancy and behavioral intention

Venkatesh et al. (2003) 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. We adapt this definition in our research context and define *performance expectancy* 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. Prior research has suggested that primary motivations for using LBS are the accessibility and mobility enabled by positioning and timeliness (Barnes 2003; Bellavista et al. 2008; Junglas and Watson 2006). LBS provide nomadic consumers flexible and timely access to information/services that would otherwise not be available in the conventional commercial realm (Junglas and Watson 2006; Rao and Minakakis 2003). Indeed, positioning and timeliness are the key dimensions of the value propositions of LBS. Through LBS, consumers can lower search costs and time for whereabouts information, easily access the needed information/services anytime and anywhere, and be

Fig. 1 Research model



provided relevant information/services at the right time in the right place. Therefore, accessibility and mobility, enabled by positioning and timeliness, are the key advantages used to entice consumers to exchange their personal information for gaining flexible access to needed information or services at the right time in the right place. 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 (Venkatesh et al. 2003). The relationship between performance expectancy and behavioral intention is likely to be true in the LBS context (Taylor and Todd 1995). Therefore, we hypothesize:

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

Adapting from Venkatesh et al. (2003), 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 (Davis et al. 1989) 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 (Venkatesh et al. 2003), effort expectancy should be positively related to performance expectancy. However, such relationship has not been modeled in UTAUT. To fill in this gap, 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.

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 IS 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. (1996) which identified four dimensions of information privacy concerns: collection, unauthorized secondary use, errors and improper access. These dimensions have since served as some of the most reliable scales for measuring individuals' concerns toward organizational privacy practices. Recently, Malhotra et al. (2004) 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 the degree to which an individual believes that the organizational practices and infrastructure exist to prevent privacy breach. 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 (Chellappa and Sin 2005), intention to transact (Dinev and Hart 2006b), and information disclosure behavior (Buchanan et al. 2007). The negative impact of privacy concerns on behavioral intention has been empirically supported in the e-commerce context (Chellappa and Sin 2005; Dinev and Hart 2006a; Malhotra et al. 2004). Hence, we hypothesize:

H4: Privacy concerns are negatively related to intention to use LBS.

As discussed earlier, consumers 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 today's world, both private corporations and government agencies take advantage of the powerful surveillance means to track and profile consumers and citizens through mobile devices (Dinev et al. 2008; Levy 2004). Consumers are more fearful about disclosing personal information in the seamless electronic environment (Dinev et al. 2008). 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, consumers 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:

H5: Privacy concerns are negatively related to performance expectancy.

We propose that privacy concerns will be an anchor exerting a negative influence on the performance expectancy. The theoretical underpinning for such a link is drawn from privacy literature that suggests that the consequences of privacy concerns include a negative impact on cognitive responses, particularly process expectations. It has been suggested that, privacy, as control over private information, provides the opportunities for self-assessment and experimentation, development of individuality, and protection of personal autonomy (Margulis 2003; Westin 1967). Conversely, privacy failures include costs arising from failures of control over personal information, such as doubts about personal competence, stress, depression and anxiety (Johnson 1974; Margulis 2003). Johnson (1974) further indicated that privacy concerns are more likely than many other control concerns, to create conditions for stress. Accordingly, we believe that privacy concerns, viewed as the fear of losing control over personal information, should negatively impact an individual's process expectancy — i.e., effort expectancy. Further evidence for the impact of privacy concerns on effort expectancy comes from prior research demonstrating the "anxiety—ease of use" link by Venkatesh (2000). Drawing on attentional resource allocation theory, Venkatesh (2000) argued that "some of the attentional resources will be directed to the off-task activity of anxiety reduction, thus increasing the effort required to accomplish tasks" (p.350). Similarly, we argue that higher levels of concerns over information privacy are expected to cause lowering of judgements about the effort expectancy. Hence, we hypothesize:

H6: Privacy Concerns are negatively related to effort expectancy.

The influences of personal innovativeness

Agarwal and Prasad (1998) hypothesized and empirically tested the effects of personal innovativeness on the antecedents as well as the consequences of individual perceptions about a new information technology among potential users. Rogers (1995) noted that innovators exhibit certain characteristics behavior, such as active information seeking and less reliance on subjective evaluation of other members in their social circle about the innovation. We believe that effects of personal innovativeness would also be present in adoption of 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. This implies that a more innovative individual should be more likely to develop positive attitudes toward the information disclosure to use the innovation (e.g., LBS) as compared to a less innovative individual. Hence, we hypothesize:

H7: Personal innovativeness is positively related to intention to use LBS.

Apart from the main effects, we also propose the moderating effect of personal innovativeness on the relationship between privacy concerns and behavioral intention. It has been suggested in the literature that any innovation is associated with greater risk, uncertainty, and imprecision (Agarwal and Prasad 1997; Kirton 1976; Thiesse 2007). Thus it is reasonable to argue that personal innovativeness characterizes the risk-taking propensity that exists in certain individuals and not in others. The risks in using LBS, particularly pertains to privacy whereby one's personal information may be shared to other parties without permission or be used for some other nefarious purposes. Rogers (1995) argue that innovators and early adopters are able to cope with higher level of uncertainty. Therefore, a more innovative individual should be more likely to cope with higher privacy risks inherent in using LBS. Hence, we hypothesize:

H8: Personal Innovativeness will moderate the relationship between privacy concerns and intention to use LBS.

The role of customer experience

Gefen et al. (2003) defines *potential customers* as those who have not yet conducted the transaction and *experienced customers* as those who have conducted the transaction with the vendor at least once. Potential customers are also variously mentioned as new customers or inexperienced customers and experienced customers are also referred to as repeat customers in previous studies. The subject of difference between potential and repeat customers has been the subject of study in detail mainly in marketing studies. In IS studies, however, there have been a lacuna on this subject (see Table 1).

Table 1 shows the research that compares potential and experienced customers. It is clear from Table 1 that

Table 1 IS studies that compare potential and experienced customers

Author(s)	Significant findings
Thompson et al. (1994)	Influence of social norms and affect on usage were greater for inexperienced than for experienced users. Ease of use had a greater influence on utilization for inexperienced users.
Taylor and Todd (1995)	Inexperienced users' intentions were better predicted by the antecedent variables in the model than were the intentions of experienced users. Inexperienced users tend to discount control information in the formation of intentions, relying instead primarily on perceived usefulness.
Karahanna et al. (1999)	The attitude is a stronger predictor of behavioural intention for users than for adopters. Normative beliefs (subjective norms) are stronger predictor of behavioural intention for adopters than for users.
Gefen et al. (2003)	Perceived usefulness is not a crucial determinant of purchase intention for potential customers, whereas it is a crucial determinant of purchase intention for repeat customers. The effect of trust on customers purchase intention decreases from potential customers to repeat customers.
Kim et al. (2004)	Perceived price has a stronger effect on purchase intention for repeat customers as compared to potential customers; however its effect reduces over transaction experience for repeat customers.
Gupta and Kim (2007)	In online purchase, the effects of perceived convenience and perceived price on repurchase intention change over the transaction experience, whereas the effects of perceived value and pleasure do not.

differences do exist between the adoption intention of potential and experienced customers. Accordingly, in this study, we look into the differences between the two groups of customers in relation to the adoption of LBS.

Research methodology

*SEND-A-TAXI service

We conducted a survey to test the proposed model in Singapore. "What's around me?"[1] service provided by SingTel (the largest telecom operator in Singapore), can locate the nearest public library, community center, hospital, ATM, Café, cinema, horse betting outlet, Fast Food and Food Court, Petrol Station, taxi stands, Post Office, and Supermarkets. In Singapore, these location-based services were offered to mobile phone users via Short Messaging Service (SMS) based on the Cell-Identification (Cell-ID)[2] technique employed by the network of telecom operators. One specific pull-based LBS application — *SEND-A-TAXI service, was introduced with more details in the survey[3]. In the scenario of this service, when the consumers wanted to book a taxi, they could dial a certain number (*654) and their location would be detected automatically. A list of taxi stands or landmarks near to their current location will be sent to them via text messages. Consumers can select the pick-up point from the list and confirm their booking by replying to the text messages.

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 (Venkatesh et al. 2003), *intention to use LBS* was measured with questions on whether the respondents were likely to use the LBS. *Performance expectancy* was measured with four questions to capture the extent to which an individual would believe that using LBS would reduce his or her time and effort required to search or access the needed information or service (Venkatesh et al. 2003); *effort expectancy* was measured with questions on whether using LBS would be clear, understandable, and easy to use (Venkatesh et al. 2003). *Personal innovativeness* was assessed with three questions taken from Agarwal and Prasad (1998). *Privacy concerns* were measured by seven-point Likert scale items that integrated more tightly with Smith et al.'s (1996) CFIP instrument including four dimensions of privacy concerns: 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 labelled seven-point Likert scales (see Appendix A).

Data collection

Email addresses of 1000 undergraduate students were randomly collected from an online learning system at a large university in Singapore. Invitation emails explained

[1] More details: http://www.ideas.singtel.com/ideas/ideasvp.jsp?t=s&p=2&i=43&v=43.

[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).

[3] *SEND-A-TAXI was selected based on the subjects' interest indications in the pilot study (n=51): the participants were asked to choose three of their interested 'what's around me?' services. *SEND-A-TAXI service was ranked as the top one.

the purpose of the study and also included the URL link to the web-based survey questionnaire. The respondents were told that their anonymity would be assured and the results would be reported only in aggregate format. A total of 176 subjects participated in the survey (83 females, 93 males). In the survey, the subjects were first asked to browse the Web site of "What's around me?" service provided by SingTel. Next, they were introduced with the usage scenario of one specific service — *SEND-A-TAXI, and then asked to complete a questionnaire regarding their behavioral intention, performance expectancy, effort expectancy, personal innovativeness, and concerns for information privacy (CFIP). All the subjects owned mobile phones and were familiar with SMS (with 80% reportedly sending more than 100 messages per month). While the use of undergraduate students 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 (Pedersen 2005), and arguably, represent the next generation of mobile consumers.

Data analysis and results

Partial least squares (PLS), a second-generation causal modeling statistical technique developed by Wold (1982), was used for data analysis. This technique has the ability to simultaneously test the measurement model and the structural model, which allows a more complete analysis of inter-relationships in the model. Although LISREL usually requires sound theory base and only supports confirmatory research; PLS can support both exploratory and confirmatory research (Gefen et al. 2000). Thus PLS is suitable for this confirmatory research that is based on an existing model (UTAUT). Also, this technique does not require multivariate normal distribution or a large sample size (Fornell and Bookstein 1982). Given that our sample size is relatively small, PLS appears more suitable to perform data analysis, which allows us to split the dataset into two subsets to explore the differences between potential and experienced customers.

We split the dataset into two subsets based on participants' experiences of using LBS: the participants having no experience were grouped as potential customers and the participants having usage experience of location-based services were grouped as experienced customers. Therefore, the measurement and the structural models were tested separately for two subsets for the potential (n=101) and experienced LBS users (n=75).

Evaluating the 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 (Cook and Campbell 1979). 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 2 presents the assessment of the measurement model. We assessed item reliability by examining the loading of each item, and found the reliability score for all the items exceeded the criterion of 0.707. Thus, the questions measuring each construct in our study had adequate item reliability. Composite reliabilities of constructs with multiple indicators exceeded Nunnally's (1978) criterion of 0.7. The average variances extracted for the constructs were all above 50%, 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 (Campbell and Fiske 1959). 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 3 report the results of discriminant validity which can be seen by comparing the diagonal to the non-diagonal elements. All items in our study fulfilled the requirement of discriminant validity.

Except the construct of CFIP (second-order reflective construct), we modelled the rest constructs as first-order reflective constructs that were measured using multiple indicators. Following the approach adopted by Agarwal and Karahanna (2000), we treated the construct of CFIP in the structural model by using summated scales, which were represented by factor scores derived from the confirmatory factor analysis.

Testing the 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. A jack-knife resampling 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 hypothesis (H8) related to the moderating effects of personal innovativeness was tested in PLS, with the approach used by Bock et al. (2006). 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 struc-

Table 2 Psychometric properties of constructs

Construct indicators	Potential users (n=101) Factor loadings	Composite reliability	Cronbach's alpha	Variance extracted	Experienced users (n=75) Factor loadings	Composite reliability	Cronbach's alpha	Variance extracted
Behavioral Intention (INT)								
INT1	0.862	0.901	0.836	0.753	0.879	0.874	0.821	0.698
INT2	0.896				0.828			
INT3	0.844				0.797			
Performance Expectancy (PEPT)								
PEPT1	0.916	0.861	0.930	0.826	0.873	0.872	0.920	0.632
PEPT2	0.929				0.892			
PEPT3	0.904				0.919			
PEPT4	0.886				0.913			
Effort Expectancy (EEPT)								
EEPT1	0.804	0.909	0.930	0.772	0.709	0.884	0.800	0.721
EEPT2	0.818				0.839			
EEPT2	0.939				0.931			
Privacy Concerns — Collection (CLCT)								
CLCT1	0.744	0.851	0.734	0.658	0.892	0.900	0.832	0.750
CLCT2	0.894				0.886			
CLCT3	0.787				0.819			
Privacy Concerns — Unauthorized Access (ACES)								
ACES1	0.879	0.929	0.886	0.814	0.844	0.917	0.860	0.786
ACES2	0.934				0.919			
ACES3	0.893				0.895			
Privacy Concerns — Error (ERR)								
ERR1	0.899	0.898	0.927	0.790	0.890	0.912	0.854	0.775
ERR2	0.855				0.836			
ERR3	0.912				0.913			
Privacy Concerns — Secondary Use (USE)								
USE1	0.925	0.965	0.945	0.902	0.981	0.987	0.980	0.961
USE2	0.964				0.982			
USE3	0.959				0.979			
Innovativeness (INNO)								
INNO1	0.814	0.928	0.883	0.811	0.777	0.853	0.867	0.659
INNO2	0.907				0.826			
INNO3	0.967				0.828			

tural models explained 38.9% and 49.8% for potential users and experienced users respectively, of the variance in behavioral intention. Table 4 summarizes the hypothesis testing.

Our findings indicate that performance expectancy was positively related to behavioral intention and thus H1was supported. Privacy concerns were found negatively related to effort expectancy and thus H6 was supported. Effort expectancy was found positively related to performance expectancy only for potential users (H3 was partially supported). Privacy concerns were negatively related to performance expectancy only for experienced users (H5 was partially supported). However, privacy concerns was not related to behavioral intention (H4 was not supported). Also, the moderating effect of personal innovativeness on the relationship between privacy concerns and behavioral intention was found insignificant (H8 was not supported).

Since the sample size for both groups was relatively small, we conducted further tests for statistical power of the two models using G*Power software that is based on the F-test for multiple regression (Faul et al. 2007). The statistical power of a research design is defined as the capacity of a design to detect the effect of the independent variable on the dependent variable, if one truly exists in the population. The higher the statistical power, the lower are the chances of committing Type II error (β). The acceptable minimum level for Type II error is four times that of Type I error (α=0.05), i.e., β=4*0.05=0.20 in the field of Information Systems. This implies that the minimum acceptable statistical power of the model should be 0.80 (80%).

Table 3 Correlation between latent variables

	Potential customers								Experienced customers							
	INT	PEPT	EEPT	CLCT	ACES	ERR	USE	INNO	INT	PEPT	EEPT	CLCT	ACES	ERR	USE	INNO
INT	0.87								0.84							
PEPT	0.53	0.91							0.64	0.80						
EEPT	0.32	0.43	0.88						0.33	0.17	0.85					
CLCT	−0.04	−0.09	−0.43	0.81					−0.23	−0.24	−0.53	0.87				
ACES	−0.11	−0.12	−0.13	0.28	0.90				−0.15	−0.31	−0.33	0.48	0.89			
ERR	−0.11	−0.15	−0.16	0.32	0.72	0.89			−0.11	−0.28	−0.19	0.46	0.70	0.88		
USE	−0.10	−0.10	−0.11	0.33	0.68	0.71	0.95		−0.23	−0.31	−0.16	0.43	0.68	0.71	0.98	
INNO	0.23	0.19	0.13	−0.01	−0.14	−0.09	−0.07	0.90	0.35	−0.11	0.27	0.07	0.08	0.16	0.14	0.81

According to Cohen (1988), the statistical power depends on the sample size, the error probability (<5%), and the expected effect size (size of the path coefficients), and the number of predictors of the most complex construct. The calculations for statistical power are shown in Table 5. Results reveal that the calculated statistical power for potential users is 93.6% and that for experienced users is 91.6%, which are acceptable.

Thus, our model is statistically sound for the marginal supported hypothesis H7 (for potential users) and H2 (for experienced users). For the minimum acceptable statistical power (80%), the sample size in this study is able to capture effect size (lowest path coefficient) of 0.124 and above for potential users and 0.170 and above for experienced users. In summary, the statistical power confirms that the results of this study are statistically valid.

Discussions and conclusions

The goal of this study was to integrate theories and research from information privacy and technology acceptance in order to construct a conceptual model of LBS adoption. Privacy concerns were found to be negatively related to effort expectancy for both potential and experienced users. Interestingly, personal innovativeness did not moderate the relationship between privacy concerns and behavioral intention for this sample and the specific context of LBS. Privacy concerns did not have a direct impact on behavioral intention (as shown in H4), but influenced behavioral intention indirectly through effort expectancy. A plausible explanation for these findings is that, when consumers are aware of privacy risks, their attentional resources are directed to the off-task activity of privacy concern reduction, thus increasing the effort required to accomplish the task. Our findings also suggest that privacy concerns, viewed as the fear of losing control over personal information, have a larger negative impact on an individual's process expectancy (i.e., effort expectancy) and less impact on outcomes of using LBS (i.e., performance expectancy and behavioral intention). This is consistent with findings of Venkatesh (2000) who empirically validated the indirect relationship between computer anxiety and behavioral intention through process expectancy (effort expectancy).

An interesting finding of this study is that while for potential customers, only effort expectancy (and not privacy concerns) had a significant influence on performance expectancy; for experienced customers, only privacy concerns (and not effort expectancy) had a significant influence on performance expectancy. This implies that privacy concerns hold more clout in determining instrumental value of the LBS use for experienced customers.

Table 4 Results of hypothesis testing

Hypotheses	Coefficient		Supported
	Potential users	Experienced users	
H1: PEPT → INT	**0.456**[b]	**0.663**[b]	**Yes**
H2: EEPT → INT	**0.211**[b]	**0.232**[a]	**Yes** (marginally supported for experienced users)
H3: EEPT → PEPT	**0.425**[b]	0.037	**Partially** (only supported for potential users)
H4: CFIP → INT	−0.027	−0.078	**No**
H5: CFIP → PEPT	−0.004	**−0.341**[b]	**Partially** (only supported for experienced users)
H6: CFIP → EEPT	**−0.345**[b]	**−0.417**[b]	**Yes**
H7: INNO → INT	**0.182**[a]	**0.297**[b]	**Yes** (marginally supported for potential users)
H8: CFIP * INNO → INT	0.008	0.103	**No**
R-square	**38.9%**	**49.8%**	

[a] Significant at 5% level of significance; [b] Significant at 1% level of significance.

One of the reasons could be that customers become directly aware of the negative consequences of information disclosure (i.e., customer privacy) after using LBS. Thus, privacy concerns become the focal point of their continued adoption of LBS. Intuitively also, we find that many service providers spam the mobile devices of their subscribers with unwanted messages unless a customer specifically opts out of receiving the messages.

The results reveal that the performance expectancy, effort expectancy and personal innovativeness contribute predominantly to the intention to use LBS for both potential and experienced users. Among the factors that were hypothesized to directly influence behavioral intention: performance expectancy had a stronger positive effect (b=0.663) for experienced users compared to potential users (b=0.456); effort expectancy had a stronger positive effect (b=0.232) for experienced users compared to potential users (b=0.211); innovativeness had a stronger positive effect (b=0.297) for experienced users compared to potential users (b=0.182). These results suggest that experienced users placed relatively higher importance on these aspects compared to potential users, which may contribute to the R^2 difference in two structural models for potential users and experienced users (49.8% vs. 38.9%).

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 LBS, which may limit the generalizability of our findings. Future work could be directed to look into the applicability of our findings to different types of LBS applications (Kaasinen 2003). For example, Barkhuus and Dey (2003) found that the level of concerns for privacy varied in different types of LBS: privacy concerns are more higher for location-tracking based services than for position-aware based services. Second, actual adoption behavior was not measured, rather, we assumed, based on a significant body of prior work in IS (Taylor and Todd 1995), organizational behavior (Venkatesh and Speier 1999) and psychology (Sheppard et al. 1988), that intention is a good predictor of actual behavior. However, some researchers (e.g., Straub et al. 1995) have expressed concerns about the predictive ability of intention for actual behavior. Therefore, for added validation of the model, 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

Table 5 Test for statistical power using G*Power Software

Parameters	Potential users	Experienced users
Sample size	101	75
Error probability (α)<5%	0.05	0.05
Most complex construct	Intention (INT)	Intention (INT)
No. of predictors for most complex construct	4	4
Effect size (Lowest Path Coefficient)	INNO→INT=0.182	EEPT→INT=0.232
Calculated statistical power	93.6%	91.6%

intention is appropriate and could potentially yield more meaningful and fruitful lessons for privacy advocates, consumers and providers of LBS alike. Third, this study was conducted in Singapore, care must be taken when generalizing these findings to consumers in other social, economic, and cultural environments, and future research should attempt to replicate this study in other countries to further validate the research model.

This study presents many interesting findings that have implications for theory and practice. First, the moderating role of personal innovativeness adds to the findings of Agarwal and Prasad (1997, 1998) which only focused on potential users. Our study shows that personal innovativeness had a direct impact on behavioral intention for both potential and experienced customers. Second, this research is one of the few studies that investigate the role of privacy concerns in the LBS adoption for both potential and experienced customers. The results show that privacy concerns are more significant in case of experienced customers. This means that for continued adoption, LBS service providers should continue to allay customer's privacy concerns. This could be done by assuring customers of their private information, using technological controls (whereby a customer may choose to opt out of the service using technology), developing organizational privacy policy and participating in some privacy certification programs (such as TRUSTe), or by highlighting existing government legislation (see Xu 2009 for a review). Moreover, service providers can ensure information privacy by adopting privacy enhancing technologies, whereby the personally identifiable information is securely stored and processed to prevent unauthorized access.

The advent of mobile and positioning technologies provides new value to consumers and simultaneously creates new vulnerabilities. It is important for researchers, managers, and policy makers to understand how consumers strike a balance between value and risk. This research has provided preliminary evidence toward enriching our understanding in some of these aspects. Using the groundwork laid down in this study, future research along various possible directions could contribute significantly to extending our theoretical understanding and practical ability to foster the acceptance of LBS and other similar technologies.

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Appendix A: Survey instrument

Construct	Item	Question wording	Source
Intention to Use LBS	INT1	I intend to use the LBS in the next 6 months	Venkatesh et al. (2003)
	INT2	I predict I would use the LBS in the next 6 months	
	INT3	I plan to use the LBS in the next 6 months	
Performance Expectancy	PEPT1	LBS reduce my searching time to find the information/services that I need	Chae and Kim (2001); Venkatesh et al. (2003)
	PEPT2	LBS reduce my searching efforts to find the information/services I needed	
	PEPT3	With the LBS, I can quickly access the information/services that I need	
	PEPT4	With the LBS, I can easily access the information/services that I need	
Effort Expectancy	EEPT1	My interaction with the LBS would be clear and understandable	Venkatesh et al. (2003)
	EEPT2	I would find the LBS easy to use	
	EEPT3	Learning to use LBS is easy for me	
Personal Innovativeness	INNV1	If I heard about a new information technology, I would look for ways to experiment with it	Agarwal and Prasad (1998)
	INNV2	Among my peers, I am usually the first to try out new information technologies	
	INNV3	I like to experiment with new information technologies	
Privacy Concerns—Collection	CLCT1	It bothers me to disclose my personal information to service providers	Smith et al. (1996)
	CLCT2	I am concerned that other people may monitor my current location continuously	
	CLCT3	Service providers are collecting too much information about me	
Privacy Concerns—Unauthorized Access	ACES1	Service providers may keep my private information (including my location) in a non-secure manner.	Smith et al. (1996)
	ACES2	Service providers may not take measures to prevent unauthorized access to my personal information.	
	ACES3	Service providers may divulge my personal information to	

		unauthorized parties without my consent	
Privacy Concerns—Errors	ERR1	Service providers may keep my personal information (including my location) in a non-accurate manner in their database	Smith et al. (1996)
	ERR2	Service providers may provide me with inaccurate or wrong information/services due to the error in tracking my location.	
	ERR3	Service providers may not devote time and effort to verifying the accuracy of the personal information in their databases	
Privacy Concerns—Secondary Use	USE1	Service providers may share my personal information (including my location) with other companies without notifying me or getting my authorization	Smith et al. (1996)
	USE2	Service providers may use my personal information for other purposes, e.g., analyzing my daily activities to derive information about me	
	USE3	Service providers may sell my personal information to other companies without notifying me or getting my authorization	

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