

## Association for Information Systems AIS Electronic Library (AISeL)

---

ECIS 2011 Proceedings

European Conference on Information Systems  
(ECIS)

---

Summer 10-6-2011

# ATTENUATING PERCEIVED PRIVACY RISK OF LOCATION-BASED MOBILE SERVICES

L. G. Pee

Follow this and additional works at: <http://aisel.aisnet.org/ecis2011>

---

### Recommended Citation

Pee, L. G., "ATTENUATING PERCEIVED PRIVACY RISK OF LOCATION-BASED MOBILE SERVICES" (2011). *ECIS 2011 Proceedings*. 238.  
<http://aisel.aisnet.org/ecis2011/238>

This material is brought to you by the European Conference on Information Systems (ECIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ECIS 2011 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

# ATTENUATING PERCEIVED PRIVACY RISK OF LOCATION-BASED MOBILE SERVICES

L. G. Pee, Tokyo Institute of Technology, 2-12-1-W9-120 Ookayama, Meguro-ku, Tokyo, Japan, 152-8552, peelg.aa@m.titech.ac.jp

## Abstract

*The rapid diffusion of mobile devices has spurred the development and use of location-based mobile services (LBMS). LBMS have the potential to add value to businesses through sale of LBMS applications and targeted marketing of products and services. However, studies have shown that individuals' intention to use LBMS is plagued by the perceived privacy risks of disclosing location and personal information. This study examines how various consumption values may weaken the negative influence of perceived privacy risk on individuals' intention to use LBMS based on the multi-dimensional concept of privacy risk, theory of consumption values, and privacy calculus. The attenuating effects of conditional, emotional, epistemic, functional, and social values are studied. Results of a survey of 194 potential users of a LBMS show that conditional, functional, and social values have significant attenuating effects. This study contributes to research by looking beyond the separate and direct effects of perceived privacy risk and consumption values to provide new insights on their joint influences. For practitioners such as LBMS providers and businesses' marketing managers, the findings highlight the type of values that should be emphasized in designing and promoting LBMS.*

*Keywords: Perceived privacy risk, theory of consumption values, location-based mobile services, intention to use.*

# 1 Introduction

Location-based mobile services (LBMS) use the geographical position of a mobile device (e.g., smart phone) to provide value-added information and services to users (Xu et al., 2009). With the rapid diffusion of mobile devices and deployment of high-capacity information network, LBMS are increasingly being developed and used. Common LBMS include emergency assistance, maps and navigation, business directory, friend finder, and location-based marketing and advertising (Pura, 2005). It is predicted that the number of European LBMS users will grow at a compound annual growth rate of nearly 37% to 130 million in 2014 (Berg Insight, 2009). LBMS also have the potential to add value to businesses (Rao and Minakakis, 2003). They are expected to generate €420 million in revenue through the sale of LBMS applications and targeted marketing of products and services by 2015 (Berg Insight, 2010). It is therefore in the interests of researchers and practitioners to understand how to encourage individuals to use LBMS.

Despite the potential for growth, the use of LBMS by individuals has been plagued by concerns about information privacy (Xu et al., 2009). LBMS require information about users' physical location and sometimes identity and financial information (e.g., for the purpose of billing) to provide relevant information and services. Even when identity is not explicitly revealed, a trace of location information can potentially lead to the identification of individuals (Jonker et al., 2005). Although various user anonymizing techniques have been proposed, the perceived privacy risk of using LBMS remains high. As shown in a recent study, many LBMS users are still concerned about the loss of privacy (Aarkstore, 2010)

Prior research on privacy in the use of LBMS have focused on proposing techniques for preserving privacy (e.g., Jonker et al., 2005), examining the effectiveness of privacy assurance such as privacy notice (e.g., Xu and Teo, 2004) and assessing users' concern for privacy (e.g., Barkhuus and Dey, 2003) and its impact on users' intention to adopt LBMS (e.g., Sheng et al., 2008). Previous studies have shown that perceived privacy risk significantly reduces individuals' intention to use LBMS (e.g., Sheng et al., 2008). However, how the negative influence of perceived privacy risk may be attenuated has not been examined. This study aims to address this gap.

The process through which individuals consider privacy issues to decide whether to disclose personal information to complete a transaction has been conceptualized as a privacy calculus (Dinev and Hart, 2006; Xu et al., 2009). Analogous to risk-benefit analysis, privacy calculus involves the evaluation of privacy risks against benefits (Dinev and Hart, 2006) and "a positive net outcome should mean that people are more likely to accept the loss of privacy that accompanies any disclosure of personal information as long as an acceptable level of risk accompanies benefits" (Culnan and Bies, 2003, p. 327). Further, the privacy calculus perspective implies that personal beliefs are important in influencing behavioral intention (Culnan and Bies, 2003). Espousing this perspective, we focus on perceptions and examine whether perceived privacy risk may be attenuated by perceived benefits. While prior studies have shown that privacy risks are negatively related to individuals' intention and benefits are positively related (e.g., Xu et al., 2009), whether benefits attenuate the effects of perceived privacy risks has not been investigated. This study extends prior research by addressing this gap.

In this study, the benefits of using LBMS are conceptualized based on the theory of consumption values (Sheth et al., 1991). The theory identifies various benefits that influence individuals' consumption of products and services and has been shown to be relevant for conceptualizing the benefits of LBMS (Pura, 2005). Specifically, this study seeks to address the following research question: *How do perceived consumption values attenuate the perceived privacy risk of using location-based mobile services?*

This study contributes to research by empirically examining the attenuating effects of perceived consumption values on individuals' perceived privacy risk (modeled as interactions). This is the first study to assess their interaction effects, and, as we will show, our findings indicate that the interaction effects significantly improve the explanatory power of the model consisting of only direct effects. For

practitioners such as LBMS providers and businesses' marketing managers, our findings highlight the types of value that should be emphasized in designing and promoting LBMS.

## 2 Conceptual Background

### 2.1 Perceived Privacy Risk and Privacy Calculus

Privacy risk has been identified as a key factor inhibiting individuals' acceptance of Internet-delivered electronic services (Featherman and Pavlou, 2003) and LBMS (Xu et al., 2009). In this study, we focus on perceived privacy risk since privacy risk is unlikely to influence individuals' behavioral intention if it is not perceived or believed to be present (Culnan and Bies, 2003). *Perceived privacy risk* refers to individuals' belief about the potential for loss associated with the release of personal information to a firm (Featherman and Pavlou, 2003; Malhotra et al., 2004; Xu et al., 2009). Privacy breaches may occur through unauthorized collection, access, and secondary use of personal information and errors in information (Smith et al., 1996). Concern about unauthorized *collection* refers to the concern that extensive amount of personally identifiable data are being collected and stored in databases (Smith et al., 1996). Concern about unauthorized *access* refers to the apprehension that data about individuals may be available to people not properly authorized to view or work with the data (Smith et al., 1996). Concern about unauthorized *secondary use* relates to the possibility that the information collected for one purpose may be used for another purpose by the collecting organization or disclosed to and used by an external party without authorization (Smith et al., 1996). Concern about *errors* relates to whether protections against deliberate and accidental errors in personal data are adequate (Smith et al., 1996). Accordingly, we consider perceived privacy risk as a multidimensional construct encompassing these aspects.

While perceived privacy risk reduces individuals' willingness to disclose personal information, prior research suggests that individuals may be willing to disclose personal information in exchange for certain benefits (Laufer and Wolfe, 1977). This risk-benefit analysis of factors related to a particular situation to decide whether to disclose personal information is referred to as *privacy calculus* (Dinev and Hart, 2006; Laufer and Wolfe, 1977). The perspective of privacy calculus is relevant in understanding the intention to use LBMS because the service requires information about users' location to work and can potentially be used to track users' movements (Beresford and Stajano, 2003). This information is valuable and may be collected, accessed, and used for secondary purposes without users' authorization or contain undesirable errors. This is likely to evoke evaluations of privacy risks and benefits of disclosing location information to use the service. Recent studies have begun to adopt the privacy calculus perspective to examine the *separate* influences of privacy risks and benefits (e.g. personalization of information and services) in the use of LBMS (e.g., Xu et al., 2009). However, it has also been proposed that the influence of one belief might override another to the extent that the resulting probability favours one behavioural intention over another (Dinev and Hart, 2006). This study extends prior research by examining whether perceived benefits attenuate the effect of perceived privacy risk. We conceptualize perceived benefits based on the theory of consumption values (Sheth et al., 1991) to identify the *type* of benefits that feature most prominently in individuals' privacy calculus related to the use of LBMS. The theory of consumption values is discussed next.

### 2.2 Theory of Consumption Values

The theory of consumption values posits that the choice of whether to purchase a product or use a service is a function of conditional value, emotional value, epistemic value, functional value, and social value (Sheth et al., 1991). In this study, we focus on the use of a service (i.e., LBMS) rather than a product. *Conditional value* refers to the perceived utility of a service as the result of a specific situation or a set of circumstances facing the consumer (Sheth et al., 1991). LBMS are likely to have conditional value for users who often need to access location-specific information and services. *Emotional value* refers to the perceived utility acquired from a service's capacity to arouse positive feelings or affective states (Sheth et al., 1991). Feelings such as enjoyment have been found to be associated with the use of LBMS (Hong and Tam, 2006). *Epistemic value* refers to the perceived

utility acquired from a service’s capacity to arouse curiosity, provide novelty, and/or satisfy the desire for knowledge (Sheth et al., 1991). A recent survey found that while LBMS are poised for growth, only a small percentage of mobile device users have utilized the services (Zickuhr and Smith, 2010). This suggests that LBMS have the potential to arouse curiosity and provide novelty to users. In support of this, a study found that individuals’ curiosity, intellect, and propensity to try new things and experience new situations have significant influences in the use of LBMS (Junglas et al., 2008). *Functional value* refers to the perceived utility acquired from a service’s capacity for functional, utilitarian, or physical performance. A service may derive functional value from its reliability and price (Sheth et al., 1991). LBMS have been found to be perceived as offering functional value such as convenience and value for money (Pura, 2005). *Social value* refers to the perceived utility acquired from a service’s association with one or more positively stereotyped social groups such as demographic, socioeconomic, and cultural-ethnic groups (Sheth et al., 1991). The use of mobile devices has been found to have symbolic meanings (Sarker and Wells, 2003). Mobile devices are often viewed as “young”, “rich”, or “cool” things and may enhance the users’ perception of self importance. These images may be associated with the use of LBMS as well.

### 3 Research Model and Hypotheses

The proposed research model and hypotheses based on the multi-dimensional concept of perceived privacy risk and theory of consumption values are shown in Figure 1. In line with findings of previous studies, we hypothesize that perceived privacy risk decreases individuals’ intention to use location-based mobile services. However, based on the privacy calculus perspective, we expect the negative impact of perceived privacy risk to be attenuated by perceptions about the services’ conditional, emotional, epistemic, functional, and social values. We also control for the effects of individuals’ age, experience with Facebook (i.e., the website hosting the LBMS examined in this study, as detailed later), experience with the Internet, gender, and level of education. The hypotheses are further detailed next.

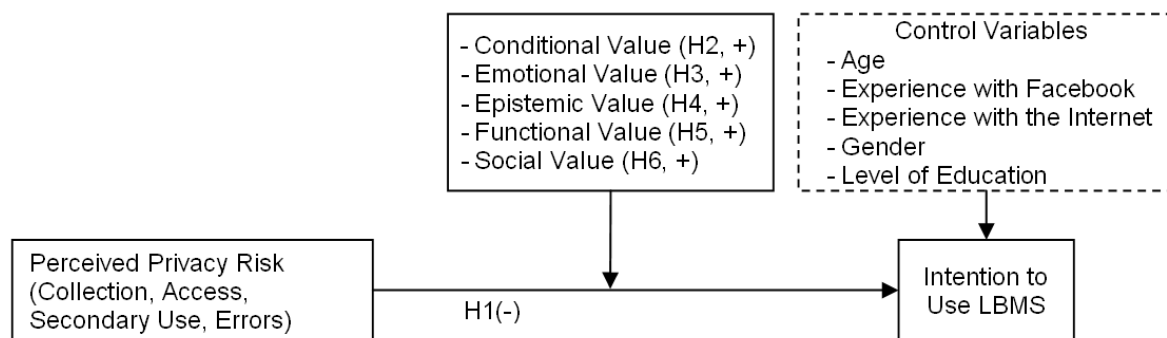


Figure 1. Research Model and Hypotheses

*Perceived privacy risk* refers to individuals’ belief about the potential for loss associated with the release of personal information to a firm (Featherman and Pavlou, 2003; Malhotra et al., 2004; Xu et al., 2009). When perceived privacy risk is high, users are likely to reduce the potential for loss by avoiding personal information disclosure (Xu et al., 2009). Consequently, they are less likely to use LBMS, which work by requiring users to disclose their location information. In line with this, in an experiment study of a location-based mobile service, Xu et al. (2005) found that perceived privacy risk is negatively related to the subjects’ intention to use the service. In another study of ubiquitous commerce applications (where location is used to personalize services), Sheng et al. (2008) found that privacy concerns are negatively related to intention to adopt the applications. Accordingly, we hypothesize that:

*H1: Perceived privacy risk is negatively related to individual’s intention to use LBMS.*

*Conditional value* refers to the perceived utility of a service as the result of a specific situation or a set of circumstances facing the consumer (Sheth et al., 1991). Figge (2004) suggests that mobile services have strong situation dependency where the perceived value of a service depends on the extent to which the service can meet a user's needs in a situation characterized by the user's identity, position, and time. LBMS have high potential to generate conditional value for users since they can provide personalized services anytime, anywhere based on information about the users' identity, position, and time (Xu et al., 2009). While prior studies have shown that conditional value is positively related to individuals' intention to use LBMS (Pura, 2005), the extent to which it attenuates the negative influence of perceived privacy risk has not been examined. We expect that conditional value may entice individuals to use LBMS, even when they perceive significant privacy risk. In other words, the negative influence of perceived privacy risk on individuals' intention to use LBMS may be weakened when conditional value is high. Therefore, we hypothesize that:

*H2: Conditional value weakens the negative relationship between perceived privacy risk and intention to use LBMS.*

*Emotional value* refers to the perceived utility acquired from a service's capacity to arouse positive feelings or affective states (Sheth et al., 1991). Prior studies have shown that emotional value increases individuals' intention to use LBMS (Pura, 2005). Emotions have an important role in motivating behavioural decisions because they may influence individuals' assessment of risks and benefits (Slovic et al., 2002). This process is referred to as *affect heuristic* and suggests that emotions may override rational decision making (Loewenstein, 2000). Considering the effect of emotions have helped to explain otherwise anomalous risk-taking behaviors such as smoking (Loewenstein, 2000). Accordingly, we expect that the negative influence of perceived privacy risk on intention to use LBMS is likely to be weaker when individuals perceive LBMS as having positive emotional value because their judgment in behavioral decision making is swayed by their emotions.

*H3: Emotional value weakens the negative relationship between perceived privacy risk and intention to use LBMS.*

*Epistemic value* refers to the perceived utility acquired from a service's capacity to arouse curiosity, provide novelty, and/or satisfy the desire for knowledge (Sheth et al., 1991). Research on psychology has suggested that individuals' behaviour may be motivated by the prospect of novel experiences, the desire for variation and change, and the urge to satisfy one's curiosity (Berlyne, 1978). It has been shown that individuals may even engage in risky behaviours to satisfy their need for novelty and curiosity (Zuckerman and Kuhlman, 2000). Accordingly, we expect that when individuals perceive that LBMS have epistemic value, they may be less influenced by or even ignore perceived privacy risk.

*H4: Epistemic value weakens the negative relationship between perceived privacy risk and intention to use LBMS.*

*Functional value* refers to the perceived utility acquired from a service's capacity for functional, utilitarian, or physical performance (Sheth et al., 1991). LBMS have been found to offer functional value in terms of information and service personalization, convenience, time savings, and cost savings (Pura, 2005; Xu et al., 2009). These benefits may outweigh the potential costs associated with privacy risks, thereby weakening the influence of perceived privacy risk on individuals' intention to use LBMS. Therefore, we hypothesize that:

*H5: Functional value weakens the negative relationship between perceived privacy risk and intention to use LBMS.*

*Social value* refers to the perceived utility acquired from a service's association with one or more positively stereotyped social groups such as demographic, socioeconomic, and cultural-ethnic groups (Sheth et al., 1991). It has been shown that the use of mobile services is motivated by the expression of personal style and image (Nysveen et al., 2005). The extent to which using an innovative mobile service is perceived to enhance individuals' image or social status is significantly related to their intention to use the service (Hsu et al., 2007). Further, the theory of social representation of risk

suggests that when risks are encountered, individuals may go beyond individual information processing and place greater emphasis on their social identity (Joffe, 2003). This suggests that when LBMS are perceived to have social value, individuals may be less influenced by perceived privacy risk:

*H6: Social value weakens the negative relationship between perceived privacy risk and intention to use LBMS.*

## 4 Research Method

Data for assessing the proposed model was collected in a survey. The survey questionnaire was developed following the procedure suggested by Moore and Benbasat (1991). Potential items for measuring each construct were first identified from existing instruments. New items were also developed to measure aspects of constructs that have no suitable existing measures. The operationalization of constructs was guided by their definitions. To accurately specify the measurement model, we clearly distinguished between reflective and formative constructs. Reflective constructs have indicators that are affected by an underlying latent construct and dropping an indicator should not alter the conceptual domain of the construct (Jarvis et al., 2003). On the other hand, formative constructs are composites of multiple indicators and dropping an indicator may alter the conceptual domain of the construct (Jarvis et al. 2003). In this study, the formative constructs are perceived privacy risk and functional value because these constructs' items tap into different themes and the items are not interchangeable. For example, functional value (FT) was measured by the extent to which a LBMS offers good value for money, provides personalized information and services, and improves convenience. These indicators are defining characteristics of the construct and excluding an indicator is likely to change the conceptual domain of the construct. The construct is therefore considered to be formative.

The other constructs were measured as follows. *Perceived privacy risk* (PR) was measured by the extent to which individuals believed that unauthorized collection, access, and secondary use of personal information and errors in information might occur. *Conditional value* (CD) was measured by the extent to which individuals' lifestyle and work required them to access location-specific information and services. *Emotional value* (EM) was measured by the extent to which individuals perceived LBMS to be fun, entertaining, and exciting. *Epistemic value* (EP) was measured by the extent to which individuals perceived that LBMS would allow them to experience new technologies, learn new knowledge, and try new ways of doing things. *Social value* (SC) was measured by the extent to which individuals believed that they would be perceived as highly educated, information technology-savvy, cool, and fashionable for using LBMS. *Intention to use LBMS* (IN) was measured by the extent to which individuals intend to use LBMS regularly. All constructs were measured with at least three items.

To assess the influence of perceived privacy risk and consumption values on individuals' intention to use LBMS, we collected data from potential users of a LBMS named Facebook® Places. The service was launched in August 2010 by Facebook, a popular social networking website with more than 500 million users, 70% of which were outside the United States. The new LBMS allows users to share their physical locations, connect with friends nearby, and find special deals offered by businesses near their locations. At the time of the survey, the service was only available in Australia, France, Italy, Japan, United Kingdom, and United States. We collected data from Facebook users in Malaysia and Singapore, where the LBMS had not been launched. We posted the request for survey participation on the top three public discussion forums in each country for two weeks. Individuals who chose to participate followed a link to the survey website that contained an introduction and the survey questionnaire. The introduction explained the purpose of the survey and functions of Facebook® Places. Screenshots of the LBMS were also provided. Multiple responses from the same IP address were blocked.

We received 194 complete responses. Among the respondents, 35.1 percent were from Malaysia and 64.9 percent were from Singapore. The majority of the respondents was male (66.0 percent) between 21-25 years old (44.3 percent) and held a professional certificate or bachelor's degree (64.9 percent). Most respondents had used the Internet for more than five years (95.9 percent) and had used Facebook for more than a year (96.9 percent).

## 5 Data Analysis

We analyzed the data using Partial Least Squares (PLS), a structural equation modeling (SEM) technique that concurrently tests the measurement model and structural model (Chin et al., 2003). PLS was chosen because it is able to account for formative and reflective constructs jointly occurring in a single structural model. The SmartPLS program (Ringle et al., 2005) and Bootstrap resampling method were used.

### 5.1 Tests of Measurement Model

Psychometric properties of the measurement model were evaluated by examining the internal consistency, convergent validity, and discriminant validity of reflective constructs and the item weights of formative constructs (Chin et al., 2003). Since the data was collected in a cross-sectional survey, multicollinearity among constructs and common method bias were also assessed.

For reflective constructs, internal consistency was assessed with Cronbach's alpha coefficient and composite reliability (see Table 1). All reflective constructs in our model achieved scores above the recommended 0.70 (Nunnally and Bernstein, 1993). Convergent validity was assessed with item loadings and average variance extracted (AVE) by each construct. All item loadings were above the recommended level of 0.70 and all AVEs were above 0.5 (Chin et al., 2003), indicating that convergent validity of the instrument was satisfactory.

Construct	Mean	SD	PR	IN	CD	EM	EP	FT	SC	PR*CD	PR*EM	PR*EP	PR*FT	PR*SC
PR#	4.79	1.27	N.A.											
IN ( $\alpha=0.94$ , CR=0.96)	5.38	1.34	0.28	<b>0.94</b>										
CD ( $\alpha=0.80$ , CR=0.88)	4.85	1.24	0.04	0.44	<b>0.85</b>									
EM ( $\alpha=0.88$ , CR=0.92)	5.58	1.14	0.01	0.53	0.24	<b>0.86</b>								
EP ( $\alpha=0.88$ , CR=0.92)	5.40	1.07	0.03	0.59	0.41	0.49	<b>0.86</b>							
FT#	5.18	1.28	0.14	0.65	0.46	0.44	0.49	N.A.						
SC ( $\alpha=0.90$ , CR=0.93)	4.78	1.35	0.05	0.63	0.40	0.43	0.40	0.44	<b>0.88</b>					
PR*CD#			0.15	0.28	0.10	0.05	0.06	0.06	0.13	N.A.				
PR*EM			0.09	0.16	0.08	0.14	0.31	0.20	0.17	0.02	N.A.			
PR*EP			0.10	0.20	0.06	0.19	0.24	0.12	0.12	0.00	0.41	N.A.		
PR*FT			0.03	0.24	0.06	0.04	0.05	0.01	0.15	0.47	0.42	0.25	N.A.	
PR*SC			0.17	0.21	0.17	0.02	0.13	0.15	0.01	0.47	0.39	0.33	0.41	N.A.

a: Cronbach's Alpha; CR: Composite Reliability; SD: Standard deviation;  
 #Cronbach's alpha and composite reliability were not calculated for formative constructs and interaction terms.

Table 1. Results of Measurement Model

Discriminant validity was assessed with factor analysis and comparing AVEs and construct correlations (Gefen and Straub, 2005). Results of factor analysis were favorable as all items loaded highly on their stipulated constructs but not highly on other constructs. The correlation matrix (see Table 1) shows that all the non-diagonal entries (construct correlations) did not exceed the bold diagonal entries (square root of AVEs), indicating that the items of each construct correlated more highly with their own items than with items measuring other constructs (Fornell and Larcker, 1981). Overall, the reliability and validity of the reflective constructs were adequate.

For formative constructs, significance of item weight was examined to determine the relative contribution of items constituting each construct. All items were significant at  $p < 0.05$ , indicating that the formative constructs had satisfactory content validity.



To assess the extent of multicollinearity, variance inflation factor (VIF) was calculated. The resultant values of VIF ranged from 1.15 for perceived privacy risk to 2.28 for functional value and intention to use LBMS. They were well below the threshold value of 3.3, indicating that multicollinearity was unlikely (Diamantopoulos and Winklhofer, 2001). The extent of common method bias was examined with Harman's one-factor test. The test involves entering all constructs into an unrotated principal components factor analysis and examining the resultant variance (Podsakoff and Organ, 1986). None of the constructs accounted for more than 50 percent of the variance and we therefore concluded that common method bias was unlikely (Mattila and Enz, 2002).

## 5.2 Tests of Structural Model

The PLS latent variable modelling approach for analyzing interaction effects (Chin et al., 2003) was used to test the moderating relationships. The procedure involves computing interaction terms by multiplying the predicting and moderating constructs. For interaction terms involving formative constructs, the construct score procedure suggested by Chin et al. (2003) was used to create underlying construct scores before creating the interaction terms.

Results of the structural model are shown in Table 2. We found that perceived privacy risk negatively influenced individuals' intention to use LBMS (H1). The negative effect was significantly attenuated by conditional (H2), functional (H5), and social (H6) values. Contrary to hypotheses, emotional and epistemic values' attenuating effects were not significant. H3 and H4 were therefore not supported. The model with interaction effects explained 65.1 percent of the variance in individuals' intention to use LBMS while the model without interaction effects explained 59.8 percent (change in  $R^2=0.53$ ,  $p<0.05$ ). Functional value had the strongest mitigating effect since its effect size as indicated by the change in  $R^2$  is the greatest (Carte and Russell, 2003). We also conducted post-hoc analyses for the moderating effects of the control variables. Results indicated that none of the control variables have significant moderating effects.

Control Variable	Path Coefficient	T Value	Change in R <sup>2</sup>	Result
Age	-0.01	0.22		Not Significant
Experience with Facebook	0.06*	2.34		Significant
Experience with the Internet	0.03	1.28	N.A.	Not Significant
Gender	-0.03	1.30		Not Significant
Level of Education	-0.05	1.38		Not Significant
<b>Main Effect</b>				
CD → IN	0.08**	2.94		Significant
EM → IN	0.17***	5.31		Significant
EP → IN	0.10*	1.84	N.A.	Significant
FT → IN	0.21***	4.49		Significant
SC → IN	0.15***	4.28		Significant
<b>Hypothesis</b>				
H1: PR → IN	-0.21***	10.74	N.A.	Supported
H2: CD*PR → IN	0.14**	2.68	0.13	Supported
H3: EM*PR → IN	0.02	0.73	0.05	Not Supported
H4: EP*PR → IN	0.05	0.89	0.03	Not Supported
H5: FT*PR → IN	0.26***	5.27	0.21	Supported
H6: SC*PR → IN	0.07*	1.78	0.11	Supported
* $p<0.05$ ( $T>1.65$ ); ** $p<0.01$ ( $T>2.35$ ); *** $p<0.001$ ( $T>3.14$ )				

Table 2. Results of Structural Model

## 6 Discussion

As hypothesized, we found that conditional, functional, and social values significantly attenuate the negative effect of perceived privacy risk on individuals' intention to use LBMS. In contrast, although emotional and epistemic values have significant direct effects on individuals' intention, their attenuating effects are insignificant. This suggests that while individuals may be encouraged to use LBMS due to their emotional and epistemic values, these values do not effectively mitigate the perceived privacy risk and individuals may still decide not to use LBMS after considering the privacy risk. It is more fruitful to enhance conditional, functional, and social values because they have both direct and attenuating effects that may override individuals' concern for privacy.

It is interesting to note that both emotional and epistemic values are hedonic in nature, which reflects the entertainment and emotional worth of using LBMS and are non-instrumental, experiential, and affective (Sánchez-Fernández and Iniesta-Bonillo, 2007). Respondents in our survey generally agree that LBMS have positive emotional (mean=5.58) and epistemic (mean=5.40) values but these do not induce them to take the risks of using LBMS. One possible reason may be that less risky sources of similar emotional and epistemic values exist. Users might be able to gain similar emotional (i.e., fun, entertainment, excitement) and epistemic (i.e., experience of new technologies, learning of new knowledge, and trial of new ways of doing things) values through using non-location-based mobile services. They were therefore not willing to risk their privacy to gain these values through using LBMS.

This study has several limitations that should be considered when interpreting the results. First, sampling of respondents for the survey was not random since a complete list of Facebook users in Malaysia and Singapore was not available. Second, we focused on a specific LBMS and the findings therefore may not be generalizable. Third, we examined individuals' intention to use LBMS in a cross-sectional survey rather than their actual use of LBMS. Although intention has been found to be strongly correlated with actual technology use (Turner et al., 2010), future studies may consider investigating the interaction effects of perceived privacy risk and consumption values on actual use of LBMS in longitudinal studies. Fourth, PLS tends to underestimate the parameters of the structural model and overestimate those of the measurement model compared to covariance-based SEM (Reinartz et al., 2009). It was chosen in this study to avoid model identification and convergence problems of using covariance-based SEM to analyze formative constructs. More studies are needed to understand the extent to which the parameters are biased.

### 6.1 Implications for Research and Practice

This study contributes to research in several ways. First, this is the first study to empirically examine the attenuating effects of various consumption values on individuals' perceived privacy risk. Based on the multi-dimensional concept of perceived privacy risk, the theory of consumption values, and privacy calculus, we have shown that conditional, functional, and social values significantly reduce the negative influence of perceived privacy risk on individuals' intention to use LBMS. Among them, functional value has the most significant attenuating effect. More studies in different contexts are needed to further ascertain the relative influence of various consumption values.

Second, this is the first study to assess the joint effects of perceived privacy risk and beneficial consumption values through examining their interactions. Prior studies found that each of them has significant influence on individuals' intention to use LBMS (e.g., Sheng et al., 2008; Xu et al., 2009). This study extends prior research by showing that consumption values not only have direct influence on individuals' intention, they also effectively attenuate the negative influence of perceived privacy risk. It is important to consider the interaction effects, as the model with interaction effects explains significantly more variance than the model with only main effects. This suggests that future research should look beyond the direct effects of risks and values when examining privacy calculus.

Third, the proposed model explains 65.1 percent of the variance in individuals' intention to use LBMS, which is considerable and indicates that the model has high explanatory power. Future studies may enhance the model by examining factors that influence the formation of perceived privacy risk, such as individual (e.g., risk propensity), structural (e.g., legal structure), and social (e.g., media influences) factors.

For practitioners such as LBMS providers and marketing managers, our findings suggest that the conditional, functional, and social values of LBMS should be highlighted when promoting the services to potential users. Conditional values such as LBMS' capacity to support mobile users work and lifestyles may be emphasized. Functional values should also be increased: the costs of using LBMS should be kept at a reasonable level, while the ability of LBMS to provide personalized and relevant information and services should be enhanced. Convenience of use should also be improved through various means such as designing user-friendly interface and minimizing user input. Practitioners may also consider capitalizing on the positive effect of social value by associating the use of LBMS with desirable social images in advertising. It is also important to note that our findings suggest that emotional and epistemic values have insignificant attenuating effects. Although they significantly increase individuals' intention to use LBMS (as indicated by significant main effects), individuals may still choose not to use LBMS due to overriding perceived privacy risk. Therefore, it is more worthwhile to focus on enhancing conditional, functional, and social values.

## 7 Conclusion

The anticipated benefits of LBMS for businesses can only be realized when users are willing to use the services. However, the use of LBMS has been dampened by the perceived privacy risk of disclosing location and personal information. It is therefore important to understand what can effectively attenuate individuals' perceived privacy risk of using LBMS. This study addresses the topic by examining a model developed based on the multi-dimensional concept of privacy risk, theory of consumption values, and privacy calculus. Our findings show that while conditional, emotional, epistemic, functional, and social values all increase individuals' intention to use LBMS, only conditional, functional, and social values have significant attenuating effects. Revealing this subtle yet significant difference improves our understanding of the roles of perceived privacy risk and consumption values in individuals' intention to use LBMS and offers suggestions for fostering the use of LBMS in practice.

## References

- Aarkstore (2010). Location Based Services (LBS) Market in Europe 2008-2012. <http://www.aarkstore.com/reports/Location-Based-Services-LBS-Market-in-Europe-2008-2012-37675.html>.
- Barkhuus, L., and Dey, A. (2003). Location-Based Services for Mobile Telephony: A Study of Users' Privacy Concerns. 9th IFIP TC13 International Conference on Human-Computer interaction, 709-712.
- Beresford, A.R., and Stajano, F. (2003). Location Privacy in Pervasive Computing. *IEEE Pervasive Computing*, 2 (1), 46-55.
- Berg Insight (2009). Berg Insight Forecasts 130 Million Mobile LBS Users in Europe by 2014. [http://www.berginsight.com/News.aspx?m\\_m=6](http://www.berginsight.com/News.aspx?m_m=6).
- Berg Insight (2010). LBS Revenues in Europe to Reach €420 Million by 2015. [http://www.berginsight.com/News.aspx?m\\_m=6](http://www.berginsight.com/News.aspx?m_m=6).
- Berlyne, D.E. (1978). Curiosity and Learning. *Motivation and Emotion*, 2 (1), 97-175.
- Carte, T.A., and Russell, C.J. (2003). In Pursuit of Moderation: Nine Common Errors and Their Solutions. *MIS Quarterly*, 27 (3), 479-501.
- Chin, W.W., Marcolin, B.L., and Newsted, P.R. (2003). A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation

- Study and an Electronic-Mail Emotion/Adoption Study. *Information Systems Research*, 14 (2), 189-217.
- Culnan, M.J., and Bies, R.J. (2003). Consumer Privacy: Balancing Economic and Justice Considerations. *Journal of Social Issues*, 59 (2), 323-342.
- Diamantopoulos, A., and Winklhofer, H.M. (2001). Index Construction with Formative Indicators: An Alternative to Scale Development. *Journal of Marketing Research*, 38 (2), 269-277.
- Dinev, T., and Hart, P. (2006). An Extended Privacy Calculus Model for E-Commerce Transactions. *Information Systems Research*, 17 (1), 61-80.
- Featherman, M.S., and Pavlou, P.A. (2003). Predicting E-Services Adoption: A Perceived Risk Facets Perspective. *International Journal of Human-Computer Studies*, 59 (4), 451-474.
- Figge, S. (2004). Situation-Dependent Services – A Challenge for Mobile Network Operators. *Journal of Business Research*, 57 (12), 1416-1422.
- Fornell, C., and Larcker, D. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18 (1), 39-50.
- Gefen, D., and Straub, D.W. (2005). A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example. *Communications of the Association for Information Systems*, 16 (5), 91-109.
- Hong, S.-J., and Tam, K.Y. (2006). Understanding the Adoption of Multipurpose Information Appliances: The Case of Mobile Data Services. *Information Systems Research*, 17 (2), 162-179.
- Hsu, C., Lu, H., and Hsu, H. (2007). Adoption of the Mobile Internet: An Empirical Study of Multimedia Message Service (MMS). *Omega*, 35 (6), 715-726.
- Jarvis, C.B., MacKenzie, S.B., and Podsakoff, P.M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, 30 (3), 199-218.
- Joffe, H. (2003). Risk: From Perception to Social Representation. *British Journal of Social Psychology*, 42 (1), 55-73.
- Jonker, W., Petkovic, M., Bettini, C., Wang, X., and Jajodia, S. (2005). Protecting Privacy Against Location-Based Personal Identification. in: *Secure Data Management*, Springer Berlin / Heidelberg, 185-199.
- Junglas, I., Johnson, N., and Spitzmüller, C. (2008). Personality Traits and Concern for Privacy: An Empirical Study in the Context of Location-Based Services. *European Journal of Information Systems*, 17 (4), 387-402.
- Laufer, R.S., and Wolfe, M. (1977). Privacy as a Concept and a Social Issue: A Multidimensional Developmental Theory. *Journal of Social Issues*, 33 (3), 22-42.
- Loewenstein, G. (2000). Emotions in Economic Theory and Economic Behavior. *The American Economic Review*, 90 (2), 426-432.
- Malhotra, N.K., Kim, S.S., and Agarwal, J. (2004). Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Information Systems Research*, 15 (4), 336-355.
- Mattila, A.S., and Enz, C.A. (2002). The Role of Emotions in Service Encounters. *Journal of Service Research*, 4 (4), 268-277.
- Moore, G.C., and Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, 2 (3), 192-222.
- Nunnally, J.C., and Bernstein, I. (1993). *Psychometric Theory* (3rd ed.) McGraw-Hill, New York.
- Nysveen, H., Pedersen, P., and Thorbjørnsen, H. (2005). Intentions to Use Mobile Services: Antecedents and Cross-Service Comparisons. *Journal of the Academy of Marketing Science*, 33 (3), 330-346.
- Podsakoff, P., and Organ, M. (1986). Self-Reports in Organizational Research: Problems and Prospects. *Journal of Management*, 12 (4), 531-544.
- Pura, M. (2005). Linking Perceived Value and Loyalty in Location-Based Mobile Services. *Managing Service Quality*, 15 (6), 509-538.
- Rao, B., and Minakakis, L. (2003). Evolution of Mobile Location-Based Services. *Communications of the ACM*, 46 (12), 61-65.

- Reinartz, W., Haenlein, M., and Henseler, J. (2009). An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM. *International Journal of Research in Marketing*, 26 (4), 332-344.
- Ringle, C.M., Wende, S., and Will, A. (2005). *SmartPLS 2.0 (beta)*. University of Hamburg, Hamburg, Germany.
- Sánchez-Fernández, R., and Iniesta-Bonillo, M.A. (2007). The Concept of Perceived Value: A Systematic Review of the Research. *Marketing Theory*, 7 (4), 427-451.
- Sarker, S., and Wells, J.D. (2003). Understanding Mobile Handheld Device Use and Adoption. *Communications of the ACM*, 46 (12), 35-40.
- Sheng, H., Nah, F.F., and Siau, K. (2008). An Experimental Study on Ubiquitous Commerce Adoption: Impact of Personalization and Privacy Concerns. *Journal of the Association for Information Systems*, 9 (6), 344-376.
- Sheth, J.N., Newman, B.I., and Gross, B.L. (1991). Why We Buy What We Buy: A Theory of Consumption Values. *Journal of Business Research*, 22 (2), 159-170.
- Slovic, P., Finucane, M., Peters, E., and MacGregor, D.G. (2002). Rational Actors or Rational Fools: Implications of the Affect Heuristic for Behavioral Economics. *Journal of Socio-Economics*, 31 (4), 329-342.
- Smith, H.J., Milberg, S.J., and Burke, S.J. (1996). Information Privacy: Measuring Individuals' Concerns about Organizational Practices. *MIS Quarterly*, 20 (2), 167-196.
- Turner, M., Kitchenham, B., Brereton, P., Charters, S., and Budgen, D. (2010). Does the Technology Acceptance Model Predict Actual Use? A Systematic Literature Review. *Information and Software Technology*, 52 (5), 463-479.
- Xu, H., and Teo, H.H. (2004). Alleviating Consumers' Privacy Concerns in Location-Based Services: A Psychological Control Perspective. *25th International Conference on Information Systems*, 793-806.
- Xu, H., Teo, H.H., and Tan, B.C.Y. (2005). Predicting the Adoption of Location-Based Services: The Roles of Trust and Privacy Risk. in: *Twenty-Sixth International Conference on Information Systems*, Atlanta, U.S., 897-910.
- Xu, H., Teo, H.-H., Tan, B., and Agarwal, R. (2009). The Role of Push-Pull Technology in Privacy Calculus: The Case of Location-Based Services. *Journal of Management Information Systems*, 26 (3), 135-174.
- Zickuhr, K., and Smith, A. (2010). 4% of Online Americans Use Location-Based Services. 1-10, <http://pewinternet.org/Reports/2010/Location-based-services.aspx>.
- Zuckerman, M., and Kuhlman, D.M. (2000). Personality and Risk-Taking: Common Bisocial Factors. *Journal of Personality*, 68 (6), 999-1029.