UNDERSTANDING THE USE OF LOCATION-BASED SERVICE APPLICATIONS: DO PRIVACY CONCERNS MATTER?

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ABSTRACT

The popularization of smartphones has brought about substantial changes in location-based services (LBS). Advances in wireless communication technology have allowed affordable data service fees, and current smartphones are equipped with GPS; as a consequence, LBS applications are emerging as next-generation ‘killer apps.’ However, the diffusion of LBS has raised privacy concerns due to the potential abuse of location information. This study aims to validate a research model focusing on privacy concerns as moderators of the post-adoptive behaviors associated with LBS applications. Based on risky shift phenomenon research, the study seeks to test the effects of the major variables of UTAUT on LBS usage intention and actual use, as well as examine how these relationships differ according to the level of an individual’s privacy concerns. We test the hypotheses using a survey with 234 users of LBS applications. The research findings support the hypotheses regarding the effects of performance expectancy and effort expectancy on LBS usage intention but do not support the hypothesis regarding the effect of social influence. In addition, the causal path from usage intention to actual use was significant. Group comparisons showed that the moderating effect of privacy concerns on performance expectancy and continuous usage intension is stronger in conjunction with low-privacy concerns, as shown in previous LBS research; however, the moderating effect on social influence and usage intention is stronger in conjunction with high privacy concerns. This finding can be explained by the risky shift phenomenon. Implications are discussed regarding the dual roles of privacy concerns in the post-adoptive behaviors of LBS users.

Keywords: Location-based service applications; Privacy concerns; Risky shift phenomenon; UTAUT, Post-adoptive behavior

1. Introduction

The popularization of smartphones has led to greater use of various location-based services (LBS). In earlier mobile phones with fewer functions, also known as feature phones, LBS were confined to simple location-tracking services. Smartphones, however, have completely changed LBS with their powerful operating systems and various applications. LBS applications with a wide variety of business models have emerged, and LBS and social networking services (SNS) have been combined. Furthermore, location-based advertisements have appeared, enabling location-based commerce (L-commerce), an enhanced version of mobile commerce. These days, most online/mobile information services, such as portals, maps, SNS, and online yellow pages, provide requested information based on the users’ location information. According to a recent report by Berg Insight [2012], mobile

LBS are already achieving mainstream market acceptance in Europe and North America. Nearly one-third of all mobile subscribers use LBS applications regularly in North America, while 20 percent of users do so in Europe.

Nevertheless, both the growth of the LBS market and advances in LBS technology have raised privacy concerns due to the potential abuse of location information [Junglas & Watson 2008]. The enhanced privacy policies and user-friendly technological features (e.g. opt-in, do-not-track, controllability of GPS) have significantly decreased privacy problems, but the privacy concerns are still a big problem because it becomes very difficult for users to control their location information after the information got collected and stored by the companies. For example, it was alleged recently that Apple regularly recorded the locations of iPhone and iPad users in a hidden file within their devices, raising very serious security and privacy concerns [Allan & Warden 2011]. LBS have continually been associated with privacy concerns, which may serve as a major inhibitor to their expansion. Users show varying degrees of privacy concerns depending on the extent to which their whereabouts are tracked [Junglas et al. 2008]. Several studies have examined and demonstrated the negative impact of privacy concerns or privacy risk on usage intention in the LBS context, although these studies were conducted in the early stages of mobile LBS, before smartphones were popularized [e.g., Keith et al. 2010; Xu & Gupta 2009; Zhou 2011; Zhou 2012].

Therefore, we believe exploratory, but focused, research on the role of privacy concerns in the LBS context is now required to reevaluate earlier perspectives. That is, do privacy concerns actually inhibit the diffusion of LBS in the post-adoptive stages, as previous studies predicted? Notwithstanding the benefits of LBS, will users' privacy concerns actually impede their continuous usage, as past researchers believed?

We utilize two approaches in attempting to understand the relationship between LBS usage and privacy concerns. One adopts the conventional point of view that privacy concerns serve as inhibitors of LBS diffusion. The other approach assumes that privacy concerns may not be a major factor in hindering the spread of LBS applications, as most users are now aware of the benefits of LBS apps and are willing to assume some risks when using LBS. This second view is based on the risky shift phenomenon, which explains when the individuals tend to take more risks [Kogan & Wallach 1967; Wallach et al. 1962]. This phenomenon suggests that LBS users, even those with stronger privacy concerns, will keep using LBS applications if certain factors make them willing to take more risks.

Thus, the primary research question of this study is as follows: Have privacy concerns played a major role in the relatively slow diffusion that has been seen in the post-adoptive stage of LBS? Based on UTAUT (Unified Theory of Acceptance and Use of Technology) with regard to the LBS adoption process, the purposes of this study are as follows: First, the study aims to determine the antecedents of LBS continuous usage intention and actual use. Second, the study sets privacy concerns as a moderating variable among the causal relationships of UTAUT constructs to determine the magnitude and direction of the impact of privacy concerns. More specifically, we want to examine if the traditional antecedents of technology adoption/usage are still significant in the LBS context. If the weak links are found in some of the relationships, privacy concerns can be keys to explain the weak link as a moderator.

The remainder of this paper is structured as follows: First, the concepts of LBS, risky shift, and privacy concerns, along with literature relevant to UTAUT, are reviewed. The research model and hypotheses are then introduced, and the research methods are explained. Next, the research findings are presented. Finally, theoretical and practical implications are discussed.

2. Conceptual Background

2.1. Location-Based Services and Privacy Concerns

Broadly, LBS can be defined as network-based services that integrate a mobile device's location or position with other information in order to provide added value to the user [Barnes 2003; Xu & Gupta 2009]. Supported by advances in wireless communication technology and the popularization of mobile phones, LBS have become a global phenomenon [Rao & Minakakis 2003]. Contrary to initial expectations, however, LBS applications did not emerge as 'killer apps' until recently. With the growth in the popularity of smartphones, more attention is being paid to the LBS industry [Ryu 2010]. According to ABI Research, the size of the global LBS market, which was $515 million at the end of 2007, is expected to increase more than 250-fold, to $135 billion, by the end of 2013 [Ryu 2011].

Unlike earlier feature phones, smartphones have strong and reliable operating systems and evolving tools that have made the development of various applications relatively easy. With such applications, smartphones have become powerful tools that allow the completion of many tasks on just one device. For instance, although Park et al. [2007] classified mobile devices into such disparate tools as PDAs, wireless notebooks, portable GPS, auto navigators, and cell phones, current smartphones can support all of these functions through embedded or installed applications.

Smartphones with built-in GPS are able to provide users with novel experiences through a variety of LBS applications. The benefits of installing LBS applications on smartphones are numerous. Previously, due to the technological limitations of feature phones, LBS were confined to relatively simple services such as tracking the location of employees and goods; searching for specific places; identifying one's current location; and checking weather or traffic conditions. Moreover, the accuracy of such location information was rather low, as the cell-ID method was used. However, smartphone-based LBS using GPS or Wi-Fi show high levels of accuracy and are applicable in many business areas. LBS-based target advertising can be performed by connecting to 'searching' or 'call connecting' functions, and commerce functions such as automatic payments are also enabled [Ryu 2010]. Recently, SNS have combined with LBS to offer what are known as location-based social network (LBSN) services [Zhao et al. 2012]; therefore, practical benefits and hedonic value can be achieved at the same time through 'check-in' services [Ryu 2011].

Despite such benefits, LBS may also involve a high risk of privacy violations, as users' location information must be disclosed [Nam & Rah 2009]. According to Samuelson [2008], there are four types of privacy: location privacy, electronic communication privacy, individual information privacy, and public place privacy. This study focuses on location privacy—the right to limit how much information about one's current and past location(s) is tracked and shared with others [Keith et al. 2010]. The study addresses location privacy concerns, which are emerging as a significant issue for the viability of LBS.

A number of prior studies found a negative correlation between LBS adoption and privacy concerns. Zhou [2011] noted four variables related to privacy concerns—collection, improper access, errors, and secondary use—as Smith et al. [1996] suggested, and then examined the effects of each variable on perceived risk and trust. In a more recent study, Zhou [2012] tested the direct influence of privacy concerns on usage intention, although this causal path was not significant. Several studies examined the effects of privacy risk on behavioral intention, such as willingness to pay for and intention to adopt LBS [e.g., Keith et al. 2010; Nam & Rah 2009; Xu & Teo 2004; Xu et al. 2005]. Additionally, Xu and Gupta [2009] identified the impact of privacy concerns on performance expectancy and effort expectancy in groups of potential and experienced users.

Some previous studies in other contexts tested the moderating effect of privacy concerns; McCole et al. [2010] incorporated the level of privacy and security concerns as a moderator in the relationship between trust and attitude towards online purchasing. Another study examined electronic health records and showed that the attitudes of users, even those with high privacy concerns, can be changed positively through positive and credible messages [Angst & Agarwal 2009]. However, no studies have examined how the level of LBS users' privacy concerns acts as a moderator in the relationship between predictor variables and usage intention or usage behavior.

The empirical study to test moderating effects of privacy concerns is urgently required at this moment. The direct negative effects of privacy risks/concerns might have been decreasing thanks to enhanced privacy policies and technological advances. However, the users' privacy concerns that the companies might exploit their location information can still inhibit the further diffusion of LBS apps by weakening the link between LBS benefits and continuous usage.

2.2. The Risky Shift Phenomenon and Privacy Concerns

McCole et al. [2010] noted that "fears" surrounding the Internet as a business setting hinder its use for commercial purposes. As most smartphones are equipped with LBS, this technology is becoming increasingly ubiquitous, pervasive, and personalized [Lyytinen et al. 2004]. The ability to track a person's location anywhere and anytime is the most important benefit of LBS, but this location information also generates risk that his or her privacy will be compromised [Junglas et al. 2008]. From this standpoint, concerns over privacy can be regarded as psychological risks [Forsythe & Shi 2003], and using LBS apps despite strong privacy concerns can be regarded as risk-taking behavior.

A risky shift refers to the phenomenon whereby people tend to take more risks when part of a group than they normally would take by themselves [Kogan & Wallach 1967; Reynolds 2009; Wallach et al. 1962]. In the LBS context, we assume that the growing user base of LBS applications causes some users to consider themselves as part of a group. Moreover, for people with higher privacy concerns, the continuous use of LBS is a risk-taking behavior, while hesitation about using LBS is a risk-averse behavior. Many previous studies have found evidence of a risky shift and/or a cautious (conservative) shift in various group contexts [Viscusi et al. 2011], but to the best of our knowledge, these phenomena have not been examined in the LBS context.

The risky shift phenomenon can arise due to social comparisons with other group members [Hill & Buss 2010], interactions with others [Heath & Gonzalez 1995; Kogan & Wallach 1967], and familiarization to the situation [Flanders & Thistlethwaite 1967]. According to Sitkin and Pablo [1992], individual differences are important determinants of risky behaviors. Risk propensity that results in risky behavior is determined by an individual's risk preferences, inertia, and history of past outcomes after risky decisions. In addition, the effects of gender [Ronay &

Kim 2006; Siegrist et al. 2002] and cultural diversity/homogeneity [Watson & Kumar 1992] on risky and/or cautious shifts have been examined in group settings.

In a recent study, Viscusi et al. [2011] proved that the risky shift phenomenon could be generated through merely observing others' behaviors, without personal interaction or discussion within the group. This finding supports the idea that LBS users will consider themselves part of a group when observing others using LBS.

2.3. UTAUT to Explain Technology Adoption

The Technology Acceptance Model (TAM) [Davis 1989] has been used in many studies in the academic IS field. However, TAM has limitations, as it is not able to support the validity of the relationships among various external variables. Therefore, many studies have employed modified versions tailored to their specific research contexts. To address this issue, Venkatesh et al. [2003] proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), an enhanced, more comprehensive model. The variance of usage intention explained by TAM was about 40 percent, whereas that explained by UTAUT was about 70 percent, indicating that UTAUT had achieved advances in statistical power.

The key variables of UTAUT include three that affect the intention to use and one that influences usage behavior. First, performance expectancy refers to the degree of perceived usefulness of a technology for improving performance. Second, effort expectancy refers to the level of a certain technology's ease of use. Third, social influence refers to the degree to which an individual believes that he or she is expected to use a new technology by significant others. Lastly, facilitating conditions refer to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a certain technology. In addition, Venkatesh et al. [2003] added gender, age, experience, and voluntariness of use to the model as moderating variables.

UTAUT provides a very solid theoretical basis, supported by numerous examples of empirical evidence in various contexts. Many studies have used UTAUT or TAM in predicting the intention to use an emerging technology, but as mobile technologies such as smartphones and tablet computers become more prevalent, technology adoption studies are increasingly choosing UTAUT [e.g., Park et al. 2007; Yu 2012]. Several UTAUT-based studies have been conducted in the LBS context. Junglas and Watson [2008] compared mobile devices with an LBS function to those without an LBS function in terms of perceived usefulness and ease of use. Their results revealed that mobile devices with LBS showed significantly higher levels of perceived usefulness in location-tracking tasks and location-aware tasks, while ease of use was significantly higher only in location-tracking tasks. Keith et al. [2010] reported that the usefulness of LBS had significant effects on willingness to pay for and intention to use LBS, while ease of use only affected usefulness and not behavioral intentions. Recent studies employing UTAUT have attempted to verify significant influences of all or some of the UTAUT independent variables on the intention to use LBS [Xu & Gupta 2009; Zhou 2012]. As these studies were conducted before the emergence of LBS smartphone applications, most of them used experimental or quasi-experimental methods [e.g., Junglas & Watson 2008; Keith et al. 2010; Xu et al. 2005] or focused on the usage intentions of potential users instead of actual users; [e.g., Xu & Gupta 2009; Xu & Teo 2004; Xu et al. 2005; Zhou 2011; Zhou 2012].

3. Research Model and Hypotheses

This study aims to test the research model shown in Figure 1 based on the perceptions of actual users of LBS smartphone applications in order to understand their post-adoptive behaviors according to their level of privacy concerns. The research model was designed to verify the impact of the major variables of UTAUT—performance expectancy, effort expectancy, and social influence—on the continuous usage intention of LBS.

Other independent variables of UTAUT—such as facilitating the resources and knowledge necessary for LBS use and compatibility with other technologies—are not considered in this study because we assume this condition in our research samples by default. Because we investigate the post-adoptive behaviors of actual LBS users, it can be assumed that they already have the required resources and knowledge; furthermore, pre-equipped LBS smartphone applications are compatible with other technologies.

A causal relationship between continuous usage intention and actual use as measured by a surrogate variable, usage frequency, is also assessed. Finally, privacy concerns, which are very important in the LBS context, are included in the research model as a moderating variable. Here, all of the paths in the suggested research model are tested with the overall sample first, and the samples are then divided into two groups according to their level of privacy concerns to determine the structural differences between the two sub-models.

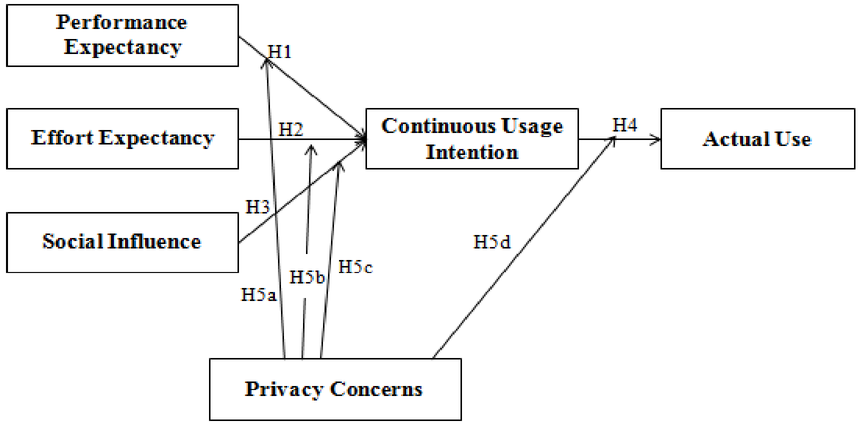


Figure 1: Research Model

3.1. Operational Definition and Survey Items of the Research Constructs

The research constructs used in this study were measured using survey item scales with confirmed reliability and validity from previous studies. These measures were modified to fit the LBS context, if needed, and were translated into Korean from English. Table 1 shows the operational definitions, survey items, and sources. All of the variables except for actual use were measured using a 7-point Likert scale.

In a recent study on the actual use of mobile web browsing services, correlation analyses among variables related to usage behavior were conducted, proving that usage frequency represents usage behavior very well [Yun et al. 2011]. Therefore, actual usage behavior is measured as the usage frequency of LBS in this study.

3.2. Antecedents of LBS Use Based on UTAUT

Performance expectancy is defined as the degree to which one believes that the use of a certain technology will be useful for enhancing task performance. This is similar to the perceived usefulness of TAM [Venkatesh et al. 2003]. In the LBS context, performance expectancy captures the notion of the ability of LBS to provide the intended outcomes appropriately; in other words, it is the instrumental value of using LBS [Xu & Gupta 2009].

If one can achieve an aim using location information through LBS applications (e.g., finding the accurate location and other useful information about the nearest restaurant, subway station, or hospital), the performance expectancy of LBS will be fulfilled. That is, the usefulness of LBS applications in providing ubiquitous and instant accessibility as well as accurate and valuable information will affect its continuous usage. Several previous studies confirmed the impact of performance expectancy on intention to use LBS [Xu & Gupta 2009; Zhou 2012]. Therefore, we hypothesize that the anticipation of the benefits of using LBS will have an effect on continuous usage intention:

H1: Performance expectancy will positively affect the continuous usage intention of LBS.

Effort expectancy refers to the degree of perceived effort when using a system [Venkatesh et al. 2003]. The perceived ease of use of an information system consists of users' evaluations of the interface in terms of ease of use of the input and output function, ease of use of the searching and analyzing processes, and the degree of complexity [Davis 1989]. Furthermore, prior studies commonly revealed that this construct is a significant antecedent of behavioral intention [e.g., Agarwal & Prasad 1997; Davis 1989; Venkatesh & Morris 2000; Venkatesh et al. 2003], indicating how strongly the effort expectancy variable stands out in the early stages of a new technology, in particular.

In the LBS context, effort expectancy relates to an individual's expectation of being able to use LBS to obtain necessary information or services without exerting much effort or encountering much difficulty [Xu & Gupta 2009]. Prior studies tested the causal path from effort expectancy to usage intention [Xu & 2009; Zhou 2012], but the results were inconsistent. Only in Xu and Gupta's [2009] study was this relationship significant in an experienced LBS user group. Therefore, we hypothesize that continuous usage intention is expected to increase if not much effort is required to learn about or use LBS:

H2: Effort expectancy will positively affect the continuous usage intention of LBS.

Social influence can be defined as the degree to which an individual believes that he or she is expected to use the technology by significant others; it is similar to the social norm construct in other technology adoption theories [Venkatesh et al. 2003]. Prior studies reported that an individual will be more likely to behave corresponding to others' expectations, especially when he or she will gain a reward for carrying out the expected behaviors or receive a punishment for not doing so [Venkatesh & Morris 2000; Venkatesh et al. 2003]. In a recent study on mobile web browsing services, subjective norms were shown to be a significant driver of the actual use of the service [Yun et al. 2011]. Previous studies using UTAUT in various contexts, including mobile technologies [Park et al. 2007], mobile banking [Yu 2012; Zhou et al. 2010], and LBS [Zhou 2012], demonstrated that social influence is a significant antecedent of usage intention.

Table 1: Operational Definitions and Survey Items

Construct	Operational Definition	Survey Items	References
Performance Expectancy	The degree to which people believe that their using LBS can help them accomplish their goals	PE1. I find that LBS are useful. PE2. Using LBS increases my living and working productivity. PE3. Using LBS improves my living and working efficiency. PE4. LBS are useful for achieving my personal goals.	[Venkatesh et al. 2003] [Zhou 2012]
Effort Expectancy	The degree of users' perceived ease of LBS use	EE1. Learning to use LBS is easy for me. EE2. Skillfully using LBS is easy for me. EE3. I found it easy to learn to use LBS. EE4. For me, using LBS is an easy task.	[Venkatesh et al. 2003] [Zhou 2012]
Social Influence	The degree to which people that are important to them think they should use LBS	SI1. People who influence me think that I should use LBS. SI2. People who are important to me think that I should use LBS. SI3. People around me help me use LBS. SI4. My family and friends support my use of LBS.	[Venkatesh et al. 2003] [Zhou 2012]
Continuous usage intention	The degree to which LBS are planned to be used continuously in the future	CUI1. I will be using LBS frequently. CUI2. I will be using LBS regularly. CUI3. I intend to use LBS continuously. CUI4. I will continue to use LBS in the future.	[Baek et al. 2011]
Actual use	The degree to which LBS are actually used	AU1. How many times do you use LBS in a month? [1: Less than one time, 2: More than 5 times, 3: More than 20 times, 4: As frequently as possible]	[Yun et al. 2011]
Privacy concerns	The degree to which an individual is concerned about the collection, improper access, errors, and secondary use of their personal location information	PC1. I am concerned that the company is collecting too much location information about me. PC2. I am concerned that the company may not take measures to prevent unauthorized access to my location information. PC3. I am concerned that the company may keep my location information in an inaccurate manner in their database. PC4. I am concerned that the company may share my location information with other parties without obtaining my authorization. PC5. Overall, I feel unsafe about providing location information to the company through the use of LBS.	[Xu 2007]

Although the choice of whether to use LBS continuously is a voluntary and individual decision, normative pressure from peers or acquaintances can influence individual intentions and behaviors, as Venkatesh and Morris [2000] suggested. Because LBS providers are increasingly concentrating on providing SNS rather than just location-tracking services [Zhao et al. 2012], LBS users may feel social pressure to use LBS applications more frequently and continuously due to significant others' postings on social networking sites. This is stated in the following hypothesis:

H3: Social influence will positively affect the continuous usage intention of LBS.

The impact of behavioral intention on usage behavior has been suggested in many technology adoption theories, such as TAM [Davis 1989] and UTAUT [Venkatesh et al. 2003], but this relationship has rarely been tested in studies about the adoption of new technologies owing to the difficulty of collecting valid user responses. Furthermore, this causal link may have been omitted in some studies because there are already numerous examples of empirical support for this relationship [Venkatesh & Davis 2000]. However, with the number of LBS applications and LBS users increasing sharply [Zhao et al. 2012], it is now feasible to study the post-adoptive behaviors of LBS users and to test empirically the relationship between the levels of continuous usage intention and the actual usage behaviors of LBS. Thus, the following hypothesis was formulated:

H4: Continuous usage intention will positively affect the actual use of LBS.

3.3. Privacy Concerns as a Moderating Variable

The negative impact of privacy concerns on behavioral intention has been empirically confirmed in many e-commerce studies [e.g., Chellappa & Sin 2005; Dinev & Hart 2006; Malhotra et al. 2004]. In addition, many studies in the LBS context have demonstrated the negative effects of privacy concerns on the usage intention of LBS [e.g., Keith et al. 2010; Xu & Teo 2004; Xu et al. 2005] and on the intention to disclose location-based information [Zhao et al. 2012]. It has also been shown that privacy concerns increase perceived risk and decrease trust in the LBS context [Zhou 2011; 2012]. One UTAUT-based study referred to privacy concerns as an inhibitor of performance expectancy and effort expectancy [Xu & Gupta 2009].

Although concern for privacy is one of the most influential inhibitors of LBS adoption, research has not examined the moderating effect of privacy concerns. The potential for an invasion of location privacy and users' privacy concerns have both increased recently due to the increase in LBS use, and there is an urgent need to increase our understanding of how and where privacy concerns influence post-adoptive behaviors pertaining to LBS usage. In order to understand the moderating effect of privacy concerns, we adapted the risky shift phenomenon suggested in two early studies [Kogan & Wallach 1967; Wallach et al. 1962].

In the LBS context, we can regard continuous usage of LBS as a risk-taking behavior for people with higher privacy concerns, while hesitation toward the use of LBS can be regarded as a risk-averse behavior. On the other hand, such use is neither a risk-taking nor risk-averse action for individuals who have lower levels of privacy concerns. Taking this into consideration, the relationship between risky shifts and privacy concerns can be summarized as follows: First, neither a risky shift nor cautious shift effect exists if there are no differences between groups with high versus low levels of privacy concerns. Second, cautious shifts, or being more risk-averse, appear to occur in the LBS context if stronger paths exist in groups with lower privacy concerns as compared to those with higher levels of concern. Third, we can assume that the risky shift effect acts in the LBS context if stronger paths exist in a group with stronger privacy concerns. Therefore, it is hypothesized that users' privacy concerns will play a moderating role in the relationships between UTAUT variables and the continuous usage intention of LBS.

Performance expectancy is associated with the core purpose of using LBS. The effect of performance expectancy of LBS on continuous usage may work differently according to the level of privacy concerns. Applying risky shifts phenomenon in this situation, LBS users with relatively strong privacy concerns will show greater levels of continuous usage intention as well if risky shifts are true. In contrast, in the case of cautious shifts, LBS users with stronger privacy concerns will use LBS less even though they may have high expectations about the performance of LBS. The first assumption can also be explained by the personalization-privacy paradox, in which customers must surrender some of their personal information in order to receive useful personalized services [Sheng et al. 2008; Xu et al. 2011]. The second is related to the traditional belief that privacy concerns negatively affect LBS usage by increasing perceived risk and uncertainty. Thus, the following hypothesis is formulated:

H5a: The positive impact of performance expectancy on the continuous usage intention of LBS will differ depending on the level of concern over privacy held by LBS users.

The effect of effort expectancy on continuous usage intention can also differ according to the level of privacy concerns. Familiarity with problematic situations leads to a risky shift [Dion & Miller 1971; Flanders & Thistlethwaite 1967]. We expect that perceived ease of use leads to familiarity with LBS; accordingly, risky shifts may occur when the LBS app is easy-to-use by minimizing the moderating effect of privacy concerns on continuous usage. On the contrary, the positive impact of effort expectancy on the continuous usage intention of LBS may decrease with high levels of privacy concerns if privacy concerns hinder LBS usage intention. This leads to the following hypothesis:

H5b: The positive impact of effort expectancy on the continuous usage intention of LBS will differ according to the level of privacy concerns held by LBS users.

People tend to take more risks when they are in a group compared with when they are alone [Kogan & Wallach 1967; Reynolds et al. 2009; Wallach et al. 1962], and peer pressure results in risky decisions [Gardner & Steinberg 2012]. In an opposite way, however, the effect of social influence on continuous usage may become stronger in the groups of low privacy concerns because high privacy concerns weaken the other effects. From this point of view, we formulate the following hypothesis in order to test whether a risky shift or a cautious shift effect exists in the LBS context.

H5c: The positive impact of social influence on the continuous usage intention of LBS will differ according to the level of privacy concerns held by LBS users.

The relationship between behavioral intention and actual behavior in the LBS context can be moderated by privacy concerns, and the result of a group comparison will vary accordingly, as there are risky shifts or cautious shifts in a group with stronger privacy concerns. Therefore, we suggest the following hypothesis:

H5d: The positive impact of continuous usage intention on the actual use of LBS will differ according to the level of privacy concerns held by LBS users.

4. Data Collection and Sample Characteristics

This study aims to validate the research model shown Figure 1 based on the perception of actual users of LBS applications. An online survey based on Google Docs was conducted. The URL link was sent by e-mail or by instant messenger to 300 Korean smartphone users, and replies were gained from 234 actual or experienced users of LBS applications installed on their smartphones; thus, respondents had already adopted LBS. To determine whether the respondents were users of LBS applications, they were initially asked to note all of the different types of smartphone applications that they had downloaded. As a result, data from 66 people who did not check LBS applications as downloaded were excluded from the final analysis. Examples of LBS applications were specified in the instructions given to respondents. We limited LBS applications to those that disclose the user's current location information; that is, LBS applications that simply track locations without disclosing users' location information were not considered. The demographic characteristics of the sample are shown in Table 2.

Table 2: Demographic Characteristics of the Respondents

Attributes		Frequency	Percentage
Gender	Male	158	68%
	Female	76	32%
Age	20-29	77	33%
	30-39	128	55%
	Over 40	29	12%
Job	Student	24	10%
	Employed	210	90%
Type of Smartphone	iPhone [Apple]	119	51%
	Galaxy [Samsung]	63	27%
	Others	52	22%
Main purpose of using LBS	Information search	182	78%
	Location-based social network [LBSN]	44	19%
	Others	8	3%

5. Data Analysis and Results

5.1. Statistical Analysis

SmartPLS 2.0 [Ringle et al. 2005] was used to test the measurement model and the structural model. The component-based SEM (structural equation modeling) like PLS does not assume normal distribution of samples and can conduct statistical analyses with relatively small size of samples while covariance-based SEM, such as LISREL or Amos, assumes normal distribution and requires large size of samples [Gefen et al. 2000]; therefore, PLS technique is more appropriate for exploratory studies like ours than for rigorous and confirmatory studies.

5.2. Measurement Model

Before testing the psychometric validity of the measurement model, Harman's one-factor test was performed to assess the level of common method bias. Following Podsakoff et al. [2003], all of the measurement items of every construct—performance expectancy, effort expectancy, social influence, continuous usage intention, and usage frequency—were entered into an exploratory factor analysis (maximum likelihood) without any rotation. Evidence of common method bias exists when a single factor emerges from the analysis or when one general factor accounts for the majority of the covariance. As a result of the analysis, three factors each showing eigenvalues of more than 1.0 and one factor with an eigenvalue of 0.93 emerged. The first factor accounted for 50.8 percent of the total variance, and 80 percent of the total variance was explained by these four factors.

We performed the additional analysis by including the common method factor into the research model suggested by Podsakoff et al. [2003] and followed the analytical procedures done by Liang et al. [2007] and Park et al. [2012]. The R^2 values explained by the principal construct and by the method factor were calculated after associating all the indicators of every construct reflectively with the common method factor. As shown in Appendix A, only 3 out of the 17 common method loadings are significant, and the average substantively explained variance for the indicators is 0.843 while the common method factor only explained 0.004 of the variance. The ratio of substantive variance to method variance is 189:1. Considering the insignificance and the small magnitude of method factors, we believe that common method variance was not a major issue in this study.

Convergent validity is evaluated by factor loadings, AVE (average variance extracted), and composite reliability in structural equation modeling using PLS [Chin 1998]. According to existing rules of thumb, if the factor loadings and AVE values are higher than 0.5 and if the composite reliability and Cronbach's α values are higher than 0.7, convergent validity and internal consistency are confirmed [Gefen et al. 2000]. Discriminant validity generally requires that each item-latent construct loading is higher than the cross-loadings and that the square root of AVE of each construct is larger than the correlation coefficients with other variables [Chin 1998; Gefen et al. 2000].

As a result of confirmatory factor analysis (CFA) using SmartPLS 2.0, all items showed factor loadings higher than 0.7, as shown in Appendix B. As shown in Table 3, the AVE values of all of the latent variables are over 0.5, and the composite reliability values exceed 0.7; therefore, convergent validity and reliability are ensured. The discriminant validity of all of the latent constructs is also confirmed by comparing the item-latent construct loadings to the cross-loadings and the square roots of AVE to the correlation coefficients of the other variables (Table 3).

Due to the high correlation found between performance expectancy and effort expectancy (0.72), a multicollinearity test was conducted. A linear regression analysis was conducted with four other variables as independent variables and usage frequency as the dependent variable. As a result of the test, all of the variance inflation factors (VIF) showed a value of less than 2.45, and every condition index was less than 17.93. These findings indicate that multicollinearity does not exist among the constructs according to Mason and Perreault's rule [1991], which claims that multicollinearity exists when the VIF is greater than 10 and with condition indices greater than 30.

Table 3: Descriptive Statistics, Reliability and Validity of Research Constructs

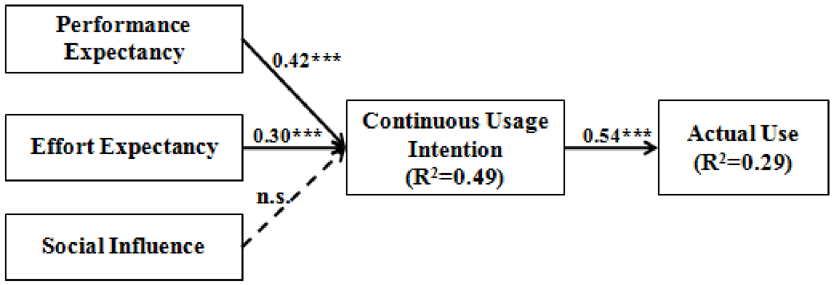
	Mean	S.D.	C.R.	PE	EE	SI	CUI	AU
Performance Expectancy (PE)	5.22	1.22	0.951	**0.911**				
Effort Expectancy (EE)	5.04	1.27	0.940	0.723	**0.893**			
Social Influence (SI)	3.91	1.21	0.922	0.530	0.463	**0.865**		
Continuous Usage Intention (CUI)	4.59	1.54	0.972	0.667	0.629	0.424	**0.947**	
Actual Use (AU)	2.32	1.06	N.A.	0.489	0.440	0.266	0.535	1.000
AVE				**0.829**	**0.797**	**0.747**	**0.896**	**N.A.**

[Note: S.D.=standard deviation, C.R.=composite reliability, Diagonals are the square roots of AVE]

5.3. Structural Model

PLS uses a bootstrapping method to test the significance of path coefficients. In this study, 500 sub-samples were created to test the suggested hypotheses. The results are summarized in Figure 2 and Table 4. Because the PLS method does not provide model fit indices, it is generally acceptable to measure the statistical power with R^2 values of endogenous variables using at least 0.10 as the reference value [Chin 1998; Falk & Miller 1992]. The R^2 value of continuous usage intention is 0.49 and that of usage frequency is 0.29, both of which are desirable.

As a result of hypotheses testing, all of the suggested hypotheses except for H3 (social influence→continuous usage intention) are supported. Performance expectancy and effort expectancy significantly increase intention to use LBS continuously (H1, H2), and continuous usage intention leads to actual usage behavior of LBS (H4).



[Note: ***p<0.001, n.s.=not significant at the 5% level]

Figure 2: Structural Model Testing (Main Effect)

Table 4: Hypotheses Testing

	Path	Path Coefficient	t-value	p-value	Result
H1	Performance Expectancy → Continuous Usage Intention	0.42	4.95	0.000	**Supported**
H2	Effort Expectancy → Continuous Usage Intention	0.30	3.92	0.000	**Supported**
H3	Social Influence → Continuous Usage Intention	0.07	1.00	0.319	Rejected
H4	Continuous Usage Intention → Usage Frequency	0.53	10.52	0.000	**Supported**

5.4. Multi-Group Analysis According to the Level of Privacy Concern

In order to examine the moderating effects of privacy concerns, the equation for testing the difference between path coefficients suggested by Chin [2004][1] is used. In this new equation, $(m-1)^2$ and $(n-1)^2$ are included instead of (m-1) and (n-1), as PLS uses a bootstrapping method for its path analysis. Due to these changes, we can expect more rigorous results when testing path differences.

To verify H5a to H5d, the samples are divided into two groups according to the median (5.20) of the mean variables of the five privacy concerns items. One is the group of LBS users who have a low privacy concern level (N=112, mean=3.98, S.D.=0.86), and the other is the group with a high level of privacy concern (N=110, mean=6.09, S.D.=0.50). Twelve subjects who had the exact median score of 5.20 were excluded. Multi-group analyses using Chin's equation were then conducted. The results are shown in Table 5.

Group comparisons are possible regardless of the significance of each group's path coefficients [Chin & Dibbern 2010]; hence, group comparisons were done for all suggested paths. In support of H5a, the relationship between performance expectancy and continuous usage intention was stronger in groups with low levels of privacy concerns. However, the impact of social influence on continuous usage intention was stronger in groups with a high level of privacy concerns (H5c). H5b and H5d did now show significant results. In sum, in the relationship between performance expectancy and continuous usage intention, privacy concerns act as a moderator, and this effect is well explained by cautious shifts. On the other hand, the risky shift phenomenon makes sense for the path from social influence to continuous usage intention in the presence of stronger privacy concerns.

1 $$t = \frac{Path_{sample\_1} - Path_{sample\_2}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * S.E.^2_{sample1} + \frac{(n-1)^2}{(m+n-2)} * S.E.^2_{sample2}}\right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

(m: sample size of sample 1, n: sample size of sample 2, S.E.: standard error, m+n-2: degree of freedom)

Table 5: Results of the Multi-Group Analysis

	Paths	Coefficients	Low privacy concerns (N=112)	High privacy concerns (N=110)	Results
H5a	Performance Expectancy →Continuous Usage Intention	Path coefficients	0.62	0.34	**Low > High**
		Standard error	0.09	0.11	
		t-value	**2.06***		
H5b	Effort Expectancy →Continuous Usage Intention	Path coefficients	0.26	0.30	n.s
		Standard error	0.10	0.09	
		t-value	-0.35		
H5c	Social Influence →Continuous Usage Intention	Path coefficients	-0.11	0.13	**Low < High**
		Standard error	0.10	0.08	
		t-value	**-1.87†**		
H5d	Continuous Usage Intention →Actual Use	Path coefficients	0.53	0.52	n.s
		Standard error	0.07	0.07	
		t-value	0.07		

[Note: *p<0.05, †p<0.1, n.s.=not significant at the 10% level]

6. Discussion and Implications

The findings of this study can be summarized as follows. First, all of the relationships suggested in the original UTAUT were supported except for the impact of social influence on continuous usage intention. Second, continuous usage intention and actual usage were shown to be significant. Finally, our main inquiry, the moderation effect of privacy concerns, was also tested through the group comparison method suggested by Chin [2004]. The positive impact of performance expectancy on the continuous usage intention of LBS is stronger in groups with low levels of privacy concerns compared to those with high levels. In contrast, the impact of social influence on continuous usage intention is stronger in high-privacy groups than in low-privacy groups.

In this research, we attempt to provide a snapshot of the post-adoptive behaviors of LBS users shortly after the widespread growth of smartphones. We do so using UTAUT, a very solid model to explain technology adoption. The current study examines actual users' behaviors towards LBS applications; therefore, we believe that the results of this study have significant implications, which are different from those of previous studies that used UTAUT or TAM before widespread LBS adoption took place.

In particular, the current study makes a valuable theoretical contribution to the field of information privacy through its use of the risky shift phenomenon as a meta-theory to explain the relationship between privacy concerns and continuous usage. The continuous usage of LBS is a risk-taking behavior if the individual possesses higher privacy concerns; that is, we can say that risky shift phenomenon exists in this circumstance. On the contrary, the users' hesitant behavior toward the continuous use of LBS, when they have high privacy concerns, shows no sign of risky shifts. In sum, this research attempted to examine whether the risky shifts phenomenon is valid in the LBS context and successfully found out which condition generates risky shifts.

The research findings revealed that when an individual has the intention to use LBS due to social influences, the risky shift phenomenon occurs due to significant others. Meanwhile, when LBS usage intention stems from performance expectancy, cautious shifts occur instead of risky shifts. In other words, in contrast to the findings of previous research, our findings show that privacy concerns may not always be the main causes of slow LBS diffusion. Rather, the effects of privacy concerns on LBS show different patterns depending on what originally motivated the individuals to use their LBS applications. Our findings also indicate that it is necessary to investigate the effects of privacy concerns on a better contingent basis, examining how effects vary according to the types of LBS as well as their objectives and popularity.

The practical implications of these findings are as follows. First, as most previous LBS studies suggested, LBS service providers should make every effort to minimize users' concerns over their location privacy; this study demonstrated that privacy concerns actually hinder the continuous usage of LBS when the level of performance expectancy is an important motivator behind their use. For example, to enhance the usage of productivity-oriented LBS applications such as search engines, maps, or even taxi services with a LBS function, it is important to convince customers that the company is adhering well to privacy regulations. At the moment of LBS application download, not only the core functions but also detailed privacy policies should be provided in order to allay users' concerns over their location information privacy. Moreover, to lower privacy concerns, pull-based LBS appear to be more appropriate than their push-based counterparts. In the pull-based mechanism, users send their location information to service providers only when they choose, whereas push-based service providers automatically collect users' location information upon the initial agreement [Xu et al 2009].

Second, social influence from significant others does not directly increase continuous usage intention, but the effect of social influence on continuous usage can differ according to the level of privacy concerns; this finding can be explained by the risky shift phenomenon. Social influence showed stronger effects in conjunction with high levels of privacy concern, indicating that groups with a high degree of privacy concern may be more active LBS users than low-concern groups. This result implies that users who are highly sensitive with regard to privacy and are under social pressure to use LBS are willing to assume some risk and thus use LBS. Considering the current trend of integrating LBS and SNS, managing the level of social influence is one of the most effective and controllable ways to expand LBS markets. LBS providers should focus more on promoting LBS through various marketing activities, such as mass media advertising, personalized advertising, and social marketing through blogs by IT-savvy people and SNS postings by celebrities.

In sum, service providers, designers, and marketing managers of LBS applications should remember that the weight on each function differs according to the main objectives of these applications. For example, when developing productivity-oriented LBS applications, performance qualities as well as privacy aspects must be equally ensured. Meanwhile, functions that can maximize the social influence of existing users on reluctant/potential users (e.g. invitations) are very important for LBS applications embedded in SNS.

This study has several limitations. First, the sample is mainly composed of people in their 20s and 30s, but it is generally believed that members of the younger generation (i.e., digital natives) have lower levels of concern over privacy compared with older people. Further studies should include various age groups in the sample. Secondly, there are numerous types of LBS, but the types are not distinguished in this study. Typically, LBS can be divided into pull-based and push-based forms based on the information delivery mechanism [Xu et al. 2009]. The type of LBS could be an interesting moderator in further studies, as the levels of privacy concerns may vary according to the LBS type. For instance, we only measured privacy concerns towards companies in this study, but interpersonal privacy concerns centered on other users may be a problem in the LBS-plus-SNS context.

7. Concluding Remarks

Owing to the proliferation of smartphones and mobile Internet service, LBS applications may finally become 'killer apps.' However, the 'whenever and wherever' and 'always-on' nature of LBS can pose a threat to users' location privacy. In this context, this study attempted to understand the post-adoptive behaviors of LBS application users by concentrating on the moderating effects of users' privacy concerns. The study revealed that cautious shifts are still a factor in the relationship between performance expectancy and continuous usage intention of LBS, a finding that is consistent with traditional views. Meanwhile, risky shifts occur due to the effect of social influences in the presence of stronger privacy concerns. The results of this study have practical implications for interested parties, including LBS application developers and service providers.

Acknowledgment

An earlier version of this research was presented and published in *ICIS 2011 Proceedings* as research-in-progress. The authors sincerely thank to the two anonymous reviewers for their insightful comments. This work was supported (in part) by the Yonsei University Research Grant of 2013.

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Appendix A. Common Method Bias Analysis

Constructs	Items	Substantive Factor Loading (R1)	$R1^2$	Common Method Factor Loading (R2)	$R2^2$
Performance Expectancy	PE1	0.917	0.841	0.104	0.001
	PE2	0.945	0.893	-0.072	0.001
	PE3	0.947	0.896	-0.190*	0.004
	PE4	0.906	0.822	0.165	0.003
Effort Expectancy	EE1	0.935	0.874	-0.089	0.002
	EE2	0.880	0.775	0.421**	0.036
	EE3	0.919	0.845	-0.251*	0.013
	EE4	0.850	0.723	-0.075	0.001
Social Influence	SI1	0.885	0.783	-0.053	0.002
	SI2	0.891	0.795	-0.077	0.003
	SI3	0.828	0.685	0.008	0.000
	SI4	0.852	0.726	0.125	0.008
Continuous Usage Intention	CUI1	0.949	0.900	-0.072	0.001
	CUI2	0.961	0.923	-0.013	0.000
	CUI3	0.963	0.928	0.055	0.001
	CUI4	0.960	0.922	0.028	0.000
Actual Use	UF	1.000	1.000	0.000	0.000
Average		**0.917**	**0.843**	**0.106**	**0.004**

Appendix B. Factor Loadings and Cross-Loadings of the Latent Constructs

	Performance Expectancy	Effort Expectancy	Social Influence	Continuous Usage Intention	Usage Frequency
PE1	**0.90**	0.66	0.44	0.62	0.43
PE2	**0.94**	0.66	0.52	0.64	0.49
PE3	**0.93**	0.68	0.50	0.57	0.42
PE4	**0.87**	0.64	0.47	0.60	0.43
EE1	0.65	**0.90**	0.39	0.60	0.41
EE2	0.75	**0.89**	0.50	0.62	0.41
EE3	0.57	**0.90**	0.36	0.50	0.37
EE4	0.60	**0.87**	0.39	0.51	0.39
SI1	0.44	0.41	**0.89**	0.33	0.20
SI2	0.44	0.38	**0.88**	0.31	0.22
SI3	0.41	0.36	**0.82**	0.33	0.22
SI4	0.52	0.44	**0.87**	0.46	0.26
CUI1	0.64	0.60	0.38	**0.92**	0.48
CUI2	0.63	0.58	0.38	**0.96**	0.50
CUI3	0.65	0.62	0.42	**0.96**	0.52
CUI4	0.62	0.58	0.42	**0.95**	0.52
UF	0.49	0.44	0.27	0.53	**1.00**