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Abstract

The continuance of use is an important topic of IS research. However, in the past, many researchers have focused on adoption rather than IS continuance. Studying continuance is of equal importance, because if use does not persist, this may limit the revenues of the provider. This is particularly true for consumer-oriented services, which rely on advertising, or subscription-based revenue models. In this paper, we investigate the determinants of location-based services (LBS) continuance as a relevant case study for the examination of IS continuance generally. A research model is developed and empirically tested through a survey of a representative sample in Germany. The proposed model builds on and extends the Limayem et al. model of IS continuance. Our analysis highlights the importance of habit and emotion in LBS continuance. The results indicate that habit has a stronger predictive power than continuance intentions for LBS continuance and that emotions are an important driver for user satisfaction with LBS.

Keywords: Post-Adoption, IS Continuance, Habit, Emotions, Location-based Services

1 Introduction

The determinants of information systems (IS) acceptance and use have been studied intensively over the last two decades. Various studies have applied the diffusion of innovation theory, the technology acceptance model (TAM), the theory of reasoned action (TRA) and the theory of planned behavior (TPB) to investigate IS adoption. However, adoption is only the first step towards a successful implementation and deployment of a system. Equally important is the continued use of a system (Bhattacherjee 2001; Limayem et al. 2007). IS continuance refers to the post-adoption stage when "IS use transcends conscious behavior and becomes part of normal routine activity" (Bhattacherjee 2001, p. 352), ending only with a user's decision to discontinue use (Bhattacherjee 2001). IS continuance is important both for the successful implementation of a system in an organizational as well as in a consumer context (Limayem et al. 2007). In this research we focus on the latter.

In a consumer context, continuance of service use is an important revenue source (Parthasarathy and Bhattacherjee 1998). Online retailers and agencies generate revenues based on the number and/or size of transactions they process. Online content providers (e.g., web portals, online newspapers) often apply advertising or subscription-based revenue models. Further, acquiring new customers is generally more expensive than retaining existing customers (Parthasarathy and Bhattacherjee 1998). In an environment in which users can easily switch from one service provider to another at low cost, customer retention becomes a challenging issue. Continuance of service use implies that customers remain with the chosen service provider, alleviating the burden of heavily investing in retention strategies.

Despite the relevance of post-adoption usage for businesses, the phenomenon has not been extensively studied in the IS field. While a large body of research on IS acceptance exists, the area of IS continuance has not enjoyed a comparable level of attention (Larsen et al. 2009). Accordingly, researchers are calling for studies on the topic (e.g., de Guinea and Markus 2009).

This study aims to understand continuance of mobile location-based services (LBS) use. LBS are defined as services that use the current geographic position of a mobile user to provide personalized services (Perusco and Michael 2005). LBS encompass a broad range of applications, including maps and navigation services, city guides, traffic updates, tracking services, friend finders and many other innovative services. LBS are praised as a promising revenue source for mobile service providers, but in order to generate revenues from LBS, mobile service providers must maintain users' interest in and regular use of them. A particular challenge faced by providers is that many mobile services are adopted but abandoned after a short while (Franz 2010).

LBS have been available for quite some time, but not to private users. More recently, LBS have become highly popular due to various technical advances and new marketing strategies (May et al. 2007). A key driver of this popularity is the profusion of new mobile devices, especially smartphones offering high resolution color screens, increased processing power, new functionalities, and inbuilt high-performance positioning technologies such as GPS. Additionally, the widespread availability of broadband wireless infrastructure facilitates the use of mobile data services. Operators have also changed their pricing models, offering new and attractive plans for fast data connections (e.g., flat rates for mobile internet instead of users paying by the megabyte).

In the recent years, the adoption of LBS has received considerable attention from both IS researchers and practitioners, but few studies have investigated the post-adoption usage of LBS. Rather, the low adoption rates of LBS motivated researchers and practitioners to investigate the reasons behind it. Costs, security and privacy issues, quality of LBS information (e.g., information accuracy and update), and lack of cognition of LBS were all identified as the main barriers to LBS adoption (e.g., Chang et al. 2007; May et al. 2007). Users' privacy concerns have been studied as well (e.g., Sheng et al. 2008). LBS use was investigated by Pura (2005), who found that conditional value (i.e., related to the use context), commitment, and monetary value had the strongest influence on behavioral intentions to use LBS.

Based on the relevance for both researchers and practitioners, this study focuses on the post-adoption behavior of LBS use. Specifically, we seek to answer the following research question:

- *What are the prominent factors determining LBS continuance?*

We address this question by adopting a model of IS continuance by Limayem et al. (2007), enhancing it with two constructs of emotions, positive and negative. The proposed model is empirically tested via a large scale quantitative survey with a representative sample of mobile internet users.

The contribution of this research is twofold. First, this study contributes to IS continuance research by extending our current knowledge of continuance of consumer services, such as LBS. We highlight the importance of emotions generated from the service use as well as the influence of habitual behaviors. We adopt a complementary approach to existing research and shed some light on the affective and intuitive aspects of IS continuance, in contrast to the perceptual perspective underlined by existing theories such as expectation-confirmation theory. Second, the research provides insights for market players into how to retain LBS users by focusing on their emotional reactions after service use as well as supporting the development of habitual behaviors. These insights are useful to service providers competing for customers' retention in a market of low switching costs.

The paper proceeds as follows. The next section reviews the theories of IS continuance, which constitute the theoretical background for our research. In the subsequent sections, a theoretical model for explaining LBS continuance and the corresponding hypotheses are developed. This is followed by empirical testing of the model and the presentation of results. After discussing the theoretical and practical implications of our research, we conclude by presenting some limitations and describing an agenda for further research.

2 Literature Review

Research on IS continuance has largely emerged from the acceptance literature. However, early post-adoption studies have already found that many of the salient antecedents that explain the adoption intention of potential adopters add little explanatory value in the case of experienced users (e.g., Taylor and Todd 1995; Karahanna et al. 1999). This suggests that adoption and continuance are theoretically distinct concepts driven by different factors. While an adoption decision occurs only once, continuance involves repetitive use decisions. Further, an adoption decision is driven by individual perceptions and expectations of service performance, usefulness and other characteristics. Recurring use decisions, on the other hand, are influenced by a user's personal experiences with the service, subjective assessment of service's value, habitual behavior etc.

To overcome the explanatory shortcomings of acceptance models, Bhattacherjee (2001) turned to theory from consumer behavior research, specifically expectation-confirmation theory (ECT) (Oliver 1980). ECT takes into account that users gain experience with a system over time and theorizes that a consumer's repurchase or continuance intentions are primarily based on their satisfaction with their previous use of a product or service (Oliver 1980). In turn, the consumer's post-purchase satisfaction is jointly determined by initial expectations (pre-purchase expectations), perceived performance, and expectancy confirmation (Oliver 1980).

Based on ECT, Bhattacherjee (2001) proposes a model of IS continuance that links satisfaction and perceived usefulness (from TAM) to the intention of a user to continue using a system. In conformance with ECT, satisfaction is central to Bhattacherjee's model and is seen as being influenced by the (ex-post) perceived usefulness of the service use and confirmation. Confirmation describes a user's perception of the congruity between expectations and the actual service performance. The better a user's expectations are met, the more satisfied he will be and the more likely he is to continue using the service in question. In contrast, disconfirmation causes dissatisfaction, which in turn negatively influences the continuance intention (Bhattacherjee 2001). In recent years, Bhattacherjee's IS continuance model has been partially extended and was applied to a wide range of systems, including online banking (Bhattacherjee 2001), web portals (e.g., Lin et al. 2005), E-Learning systems (e.g., Limayem and Cheung 2008) and online services (Limayem et al. 2007; Liao et al. 2007; Kang et al. 2009). Only very few studies have investigated the mobile internet services continuance (e.g., Hong et al. 2006; Thong et al. 2006; Kim et al. 2007). To our knowledge no study has investigated LBS continuance yet.

Building upon Bhattacherjee's IS continuance model, recent studies have investigated how and why user cognitive beliefs (i.e., perceived usefulness) and attitude toward IT use change over time. Bhattacherjee and Premkumar (2004) argue that the change in perception is mainly driven by disconfirmation and satisfaction resulting from actual usage experience (Bhattacherjee and Premkumar 2004). However, the model has also been criticized for relying too heavily on cognitive reasoning for explaining post-adoption decisions. Based on research in psychology, Limayem et al. (2007) proposed the consideration of non-cognitive aspects, such as habit, as factors in continuance, suggesting that with long-term continued use of a system reflective cognitive processing attenuates and IT use becomes a habitual and automated process (Limayem et al. 2007; Kim 2009). A first attempt to develop an integrative model for IS users' continued usage was made by Hong et al. (2008).

3 Theoretical Framework and Hypotheses Development

This study employs the model of Limayem et al. (2007) which explains IS continuance as the result of intentions towards continuance and habit. The model shows that habit moderates the relationship between intentions and IS continuance and that when introduced in the model habit may limit the explanatory power of intentions. We find these results interesting and wish to further investigate them in relation to LBS. However, we argue that in order to adequately capture the continuous behavior of mobile LBS we must also consider emotions, which represent the affective aspects of post-adoption behavior, as well as elaborate on the measurement of habit. These extensions may provide further insights into LBS continuance. Below, we present our theoretical framework.

Confirmation

Confirmation is a central construct in IS continuance models based on ECT. It describes users' perception of the discrepancy between their expectations of service use and actual service performance (Bhattacherjee 2001). Expectations are formed based on past experience and knowledge available and refer to the level of performance that the user anticipates receiving. Expectations function as an anchor level against which the service performance is compared (Bhattacherjee 2001) and are positively confirmed when a service performs at least as well as expected and are disconfirmed when it performs worse than expected. Confirmation is positively related to satisfaction with IS use because it indicates that the user has obtained the expected benefits of service use. Disconfirmation, on the other hand, indicates failure to fulfill expectations and results in dissatisfaction (Bhattacherjee 2001). Thus, in the case of LBS we can expect that users will be satisfied when their expectations concerning, for example, response time of the service, accuracy and completeness of the content are met, and dissatisfied otherwise. Confirmation is also positively associated with perceived usefulness, suggesting that the better the users' expectations are met, the higher the perceived utilitarian value of the LBS will be.

H1: A higher level of confirmation positively affects satisfaction with LBS use.

H2: A higher level of confirmation positively affects perceived usefulness.

Perceived Usefulness

Perceived usefulness originates from the TAM and was included in the IS continuance model because of its consistent predictive power of usage behavior in both adoption and post-adoption phases (Bhattacherjee 2001). In the TAM, perceived usefulness is an indicator of the degree to which the use of a particular system will enhance a user's job performance (Davis 1989). In the context of LBS it seems more appropriate to define perceived usefulness as the utilitarian value a user perceives obtaining from service use (Limayem et al. 2007), as LBS are mainly used for private rather than work purposes. As previous research has shown, perceived usefulness is a salient predictor of users' satisfaction and intention to continue service use. Perceived usefulness in the case of LBS may be a strong reason for continuance of use, since it provides the user with value related arguments of LBS importance.

H3: Perceived usefulness positively affects satisfaction with LBS use.

H4: Perceived usefulness positively affects LBS continuance intention.

Satisfaction

In the marketing literature, satisfaction has been identified as the major reason for consumers' intention to repurchase a product or continue using a service (Oliver 1993), indicating that it is central to building and retaining a loyal base of long-term customers (Bhattacherjee 2001). In the IS context, satisfaction is regarded as an important determinant of users' intention to continue using a service. In accordance with ECT, satisfaction is perceived as a psychological or affective state primarily resulting from the level of confirmation and secondarily from perceived usefulness (Bhattacherjee 2001; Limayem et al. 2007). Consistent with the conceptualization of satisfaction as an emotional response, a high level of satisfaction is often measured empirically with emotional connotations such as "pleased", "contented", "delighted" and the evaluative element "satisfied" (Bhattacherjee 2001; Limayem et al. 2007).

However, this aggregate measure of satisfaction does not allow us to investigate the influence of emotions on satisfaction in a comprehensive manner. Thus, we treat emotions as separate theoretical constructs. By doing so, we are able to investigate the interrelationships between the two constructs. Consequently, we define satisfaction as a post-adoption evaluative judgment concerning LBS use (Westbrook and Oliver 1991). Rather than being an emotional state itself, satisfaction incorporates an evaluation of the emotions elicited by service use, such as whether a use experience was pleasurable or frustrating (Hunt 1977). Satisfaction is understood as a unidimensional concept which can vary from dissatisfied to satisfied (Westbrook and Oliver 1991).

Satisfaction has been intensively investigated in previous IS studies, which confirmed a significant relationship between satisfaction and continuance intention (e.g., Bhattacherjee 2001; Limayem et al. 2007). We expect the same relationship in the case of LBS.

Satisfaction was also found to be a determinant of habit (Limayem et al. 2007; Lankton et al. 2010). Satisfactory experiences are a key condition for habit formation because they enhance the tendency to repeat the same course of action repeatedly: habit strength increases as a result of repetition with positive reinforcements (Aarts et al. 1997). In this research, we hypothesize that satisfactory experience with prior LBS use has a positive effect on habit strength and a users' intention to continue to use LBS.

H5: Satisfaction with LBS use positively affects LBS continuance intention.

H6: Satisfaction with LBS use positively affects habit.

Continuance Intention

According to the theory of reasoned action, research models in the area of IS continuance follow the assumption that a user's behavioral intention (i.e., the intention to continue using a system) is a good predictor of future behavior (i.e., actual continued IS usage). We investigate this relationship in the case of LBS. Hence, we hypothesize:

H7: LBS continuance intention positively affects actual LBS continuance.

Habit

Habit is an important construct that has been introduced to IS continuance research recently. In psychology, habit is commonly understood as "learned sequences of acts that become automatic responses to specific situations, which may be functional in obtaining certain goals or end states" (Verplanken et al. 1997, p. 540). Behavior may become habitual, when it has been repeated frequently in a satisfactory manner and a mental association between a goal and an action is established (Verplanken and Orbell 2003). Once a habit is formed, the cognitive processing that initiates and controls the behavior becomes automatic and can be performed quickly with minimal mental effort (Ouellette and Wood 1998). However, habits are not mindless courses of action, but are directed to achieve a certain goal. For example, when confronted with a specific travel goal (e.g., going shopping), people may choose a certain travel mode alternative (e.g., bicycle) out of habit without going through an elaborate choice process (Aarts and Dijksterhuis 2000).

In the context of IS usage, habit has been defined as "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem et al. 2007, p. 709). While individuals are likely to engage in active cognitive processing during the initial adoption phase when forming adoption intentions, cognitive processing is likely to attenuate, once a system is adopted and used regularly. Behavior (i.e., IS use) is more likely to be driven by non-reflective, routinized cognitive processes (Ouellette and Wood 1998). Habitual behavior may be altered when the individual deliberates his actions (Louis and Sutton 1991) or when interventions occur to disrupt these deep, non-reflective mental scripts (Jasperson et al. 2005). Previous post-adoption studies in IS have identified diverse factors that intensify habit, including satisfaction with the IS use experience, prior IS use frequency, comprehensiveness of usage and task importance (Limayem et al. 2007; Wu and Kuo 2008; Lankton et al. 2010).

We believe that habit can play a significant role in LBS continuance. In contrast to Limayem et al. (2007), who argue that habit has a moderating effect on the relationship between IS continuance intention and the actual continuance behavior, we believe that habit directly influences continuance. We build on the notion that two relatively autonomous cognitive modes exist, which guide interpretation and behavior, i.e., a conscious mode and an automatic mode (Louis and Sutton 1991). The conscious mode is

characterized by deliberate and thorough information processing resulting in intentions, which in turn guide behavior. In the automatic mode, however, the individual follows mental schemas and scripts with minimal awareness and attention to incoming information. Behavior is triggered automatically without a preceding formation of evaluations and intentions. Depending on the task at hand, the individual decides in a constructive manner, which cognitive mode to use, acting as an "adaptive decision maker" (Payne et al. 1993). However, because the conscious processing demands more cognitive effort, there is a general predisposition toward the automatic mode in everyday's situations, such as LBS use (e.g., Aarts and Dijksterhuis 2000). Conscious thinking and decision-making is likely in novel or discrepant situations or as a reaction to an internal or external request for consciousness (Louis and Sutton 1991).
Furthermore, we elaborate on the measurement of habit by applying a habit scale developed in psychology. The Self-Report Habit Index (SRHI) by Verplanken and Orbell (2003) takes into account the multiple features of this psychological construct: history of repetition of behavior, automaticity (which is described by low awareness, mental efficiency, difficulty to control behavior and lack of conscious intention) and expression of identity. Consequently, we hypothesize:

H8: Habitual use of LBS positively affects actual LBS continuance.

Actual continuance

Theories of IS continuance and most empirical studies rely on users' behavioral intention as the final dependent variable without exploring the relationship between continuance intention and actual behavior (Bhattacherjee et al. 2008). We argue that a comprehensive understanding of IS continuance should be based on the actual behavior and not solely on intentions. This is particularly important as there is empirical evidence that intention may not always accurately predict future behavior, for example in the presence of habit (Limayem et al. 2007). In the literature, IS continuance is most often measured as the frequency of use, the duration of use, and/or the diversity of applications used (e.g., Limayem et al. 2007; Bhattacherjee et al. 2008; Kim et al. 2005). However, the construction of a single use measure from frequency, duration and/or comprehensiveness measures raises the problem that the interpretation of the measure becomes more difficult. Thus, we have chosen to define LBS continuance by frequency of use alone. This decision is supported by the nature of accessing LBS, which generally involves using the service for only one or two minutes per unique session. Thus, usage is differentiated primarily on frequency, with relatively little spread in the amounts of time spent per use session.

The present study builds upon Limayem et al.'s model (2007) to investigate LBS continuance. However, we argue that their model does not fully capture the relevant concepts which can explain LBS continuance. In order to improve the model's relevance and to enhance our understanding of LBS continuance we incorporate two additional constructs, addressing positive and negative emotions separately. We believe that emotions are an important determinant of users' satisfaction and consequently influence LBS continuance.

Emotions

Following the expectation confirmation paradigm, Limayem et al. conceptualize user satisfaction as the result of a cognitive comparison process (i.e., confirmation) in which a user actively processes the perceived performance of system and compares it with expectations. Additionally, satisfaction is determined by the user's perception of the service's usefulness. While this rational perspective on satisfaction was dominant in consumer research until the eighties (Westbrook 1987), recent studies have underlined that emotions also play a powerful role in influencing satisfaction (e.g., Westbrook 1987; Oliver 1993; Phillips and Baumgartner 2002), complementing cognitive-based approaches.
While the comparison processes in disconfirmation judgments require deliberate processing of information, the emotional processes are thought to be partly outside the customer's conscious control (Liljander and Strandvik 1997). Cognitive and emotional responses are assumed to simultaneously influence satisfaction (Oliver 1993; Mano and Oliver 1993). According to Westbrook and Oliver (1991) "consumption emotion refers to the set of emotional responses elicited specifically during product usage or consumption experiences" (p. 85) such as joy, anger, and fear. Emotions must be distinguished from the related but distinct concept of mood. Mood is usually conceived as being longer lasting and lower in

intensity, whereas emotions have a relatively greater psychological urgency, motivational potency, and situational specificity (Westbrook and Oliver 1991).

Technological artifacts such as LBS can trigger emotional reactions during service consumption, for example frustration or anger when the LBS does not fulfill a user's expectations (e.g., with regard to response time or completeness and accuracy of content). Delight or joy may also arise when the service exceeds a user's expectations (e.g., finds a target quicker than expected or shows highly relevant search results). These experienced emotions are stored in the user's memory and are retrieved when an evaluation of the relevant consumption experience is required (Westbrook and Oliver 1991).

Most studies in marketing apply a dimensional (or valence-based) approach and classify emotions into two groups, positive and negative, by means of a factor analysis (e.g., Westbrook 1987; Westbrook and Oliver 1991; Oliver 1993; Mano and Oliver 1993; Liljander and Strandvik 1997). The influence of both factors on satisfaction is then investigated, with positive emotions found to be positively and negative emotions to be negatively related to satisfaction. Emotion specific approaches, on the other hand, investigate the individual effects of specific emotions (e.g., regret, disappointment) on satisfaction (e.g., Bougie et al. 2003; Zeelenberg and Pieters 2004). In this study we follow the dimensional approach.

In the IS context, emotions have not been investigated with the same intensity as in marketing research. Most previous research on IS adoption and continuance has extended existing cognitive models by including either perceived enjoyment/playfulness to investigate the influence of positive emotions or anxiety to investigate negative emotions. However, these are rather narrow conceptualizations as they only capture very specific types of emotions. A broader measurement of emotion is used by Kim et al. (2007) to measure emotions along the two basic dimensions pleasure and arousal.

In our research, we wish to capture the full range of emotional reactions of users and thus draw on the work of Beaudry and Pinsonneault (2010), who developed a framework that classifies emotions into four distinct types: challenge, achievement, loss, and deterrence emotions. These categories are based on two dimensions: first, whether an IT event is perceived as an opportunity or a threat and, second, the perceived control over the realization of expected consequences of an IT event. *Challenge emotions* are triggered by the perception of an IT event as being an opportunity likely to result in positive consequences and over which the individual feels he has some control. In this case, emotions like excitement, eagerness or playfulness are likely to be experienced. LBS users may experience challenge emotions when, for example, they discover and explore new features and are excited about the potential benefits of the service. *Achievement emotions* result when an IT event is perceived as an opportunity that will generate positive outcomes, but where the individual lacks control over expected consequences. This may trigger happiness and joy. LBS use may trigger achievement emotions when the user is fully satisfied with the service and the outcome, e.g., because he has achieved a goal quicker than expected. *Loss emotions* reflect the perception of an IT event as a threat and the perception of a lack of control over its consequences, which may lead to anger and disappointment. Loss emotions may be triggered by LBS when the service misleads the user or shows inaccurate content. *Deterrence emotions* such as anxiety and irritation may occur when an IT event is perceived as a threat and the individual feels that he has some control over its consequences. Anxiety and irritation may occur during LBS use when the service shows confusing results or is unreliable. We hypothesize that challenge and achievement emotions (i.e., positive emotions) will positively influence overall satisfaction while loss and deterrence emotions (i.e., negative emotions) will negatively affect it:

> H9: Positive emotions from LBS use positively affect satisfaction with LBS use.
>
> H10: Negative emotions from LBS use negatively affect satisfaction with LBS use.

Furthermore, confirmation may evoke positive emotional reactions in the user and reduce the occurrence of negative reactions. These reactions may mediate the impact of confirmation in the user's satisfaction.

> H11: A higher level of confirmation positively affects the occurrence of positive emotions.
>
> H12: A higher level of confirmation negatively affects the occurrence of negative emotions.

Having described the proposed research model, Figure 1 provides a graphical presentation.

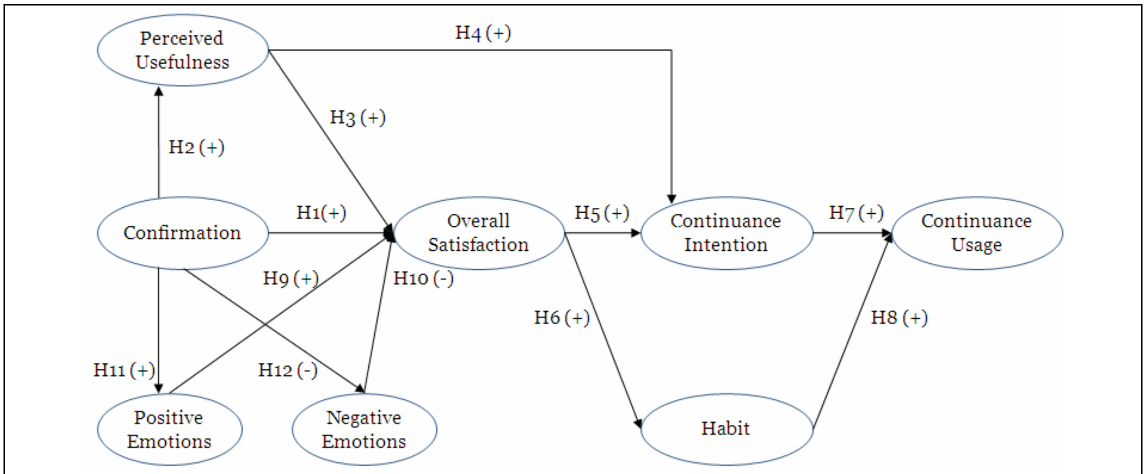

Figure 1. Research Model

4 Research Method

A survey instrument was developed to test the research model. We drew a representative sample of German mobile internet users and conducted a survey at two points in time. This section presents the measures used in the survey instrument and details the data collection process.

4.1 Measures

We used validated scales to measure the constructs of the proposed model, with the wording of the items adapted to the LBS context. In order to minimize the response-set artifacts, the order of the items was randomized. The Appendix includes a table presenting details about the constructs and the items used.
Confirmation, overall satisfaction and IS continuance intention were adapted from Bhattacherjee (2001). To measure perceived usefulness we used the items from Limayem et al. (2007), which were adapted from Davis (1989). Habit was operationalized by an adapted scale from Verplanken and Orbell (2003). This scale offers a comprehensive tool to measure habitual behavior. Continuous use was measured as the frequency with which a user actively interacts with LBS. Respondents were asked to indicate, in an open question, how often they had used a particular LBS in a given period of time (i.e., during the last three weeks) (Limayem et al. 2007). Thus, we measured continuance with an interval variable, rather than a categorical two-value variable (continue vs. discontinue). To measure the emotional response to LBS use, we adapted the approach of Beaudry and Pinsonneault (2010) and included those emotions that might be experienced while using LBS. Respondents were asked to think about their previous LBS usage and indicate the frequency with which they had felt each of the following emotions related to the IS service encounter: anger, anxiety, disappointment, irritation, eagerness, happiness, joy, surprise. A 7-point Likert scale ranging from 1 (never) to 7 (always) was used. A factor analysis showed that the emotions split into two distinct groups based on positive and negative affect.
A pre-test was administered to examine and validate the survey instrument. 76 students possessing smartphones and using LBS were recruited. During the pre-tests we realised that our initial choice of Izard's (1977) Differential Emotions Scale was not appropriate for measuring emotional response in the case of LBS, leading us to adapt the approach of Beaudry and Pinsonneault (2010).

4.2 Data Collection

Data collection was conducted in cooperation with a German market research institute and involved two rounds. In the first round, data about the theoretical constructs were gathered, while actual LBS use was measured in the second round. An online questionnaire was distributed via email to a representative sample of German mobile internet users with respect to age, gender and education. In the data collection process, respondents were first asked questions about their general mobile phone usage (e.g., brand of mobile phone, mobile and mobile internet subscription). They were then given a definition of LBS and a list of LBS categories and were asked which type of services they knew and used. Respondents who had tried at least one or more service categories were then asked to state, in an open question, the LBS they had used most recently. Next, respondents received personalized survey questions that integrated the name of the service stated by the participant in each question. Data from participants who did not possess a mobile phone, did not use mobile internet, or had never tried an LBS were not collected. The questionnaire ended with questions about demographics and involvement with LBS in general.

After three weeks, in round two, respondents who had successfully completed the survey in round one were contacted again and asked to fill in a very short questionnaire about their frequency of use of the LBS named in round one within the last three weeks. To ensure that people answered in relation to the LBS stated in round one, we matched the user ID with the service stated in round one and integrated it into each question.

A total of 700 respondents successfully completed the first questionnaire. 459 respondents (65%) also participated in the second round. However, some of these responses had to be excluded from the sample because of missing or inconsistent data. The main reasons for inconsistency were that participants did not name a location-based service but a service from a different category, as the service used most recently, they filled in the survey in an unrealistic time for thorough completion (i.e., less than 4 minutes at an average completion duration of 12 minutes) or they showed inconsistency of the responses in the reversed items. Further, in order to prevent the use of unreliable data we excluded those participants who had indicated a high frequency of use in the first round of the survey (i.e., at least once per week), but when we measured their actual use behavior they did not use the service at all. As a result, 371 usable responses formed the final sample, including 31% women and 69% men. The age of respondents ranged from 14 to over 60 years. Nearly equal amounts of participants were in their 20s (22%), 30s (22%), 40s (26%), and 50s (20%). Only 4% were between 14 and 19 years old and 6% over 60. The reported level of education was 44% with a secondary education qualification, 28% with a high school degree, and 28% with a university or college degree. The majority of participants were employed (63%), while the others were pupils, students or apprentices (14%), self-employed or freelancers (12%), and retired or unemployed (11%). A report by the Arbeitsgemeinschaft Online Forschung (AGOF) [Working Group for Online Media Research] (AGOF 2010) confirms that our sample is representative of German mobile internet users. We tested for nonresponse bias by comparing the demographics of participants who did not respond in the second round with the final sample. As we found no significant difference between the two groups, we believe that the nonresponse bias does not constitute a problem in our study.

Most of the participants had used their current mobile phone for less than one year (58%) and had a subscription to a mobile internet flat rate plan (73%). All the LBS used by the interviewees fell into the category of pull-based infotainment services (Schiller and Voisard 2004), in which the mobile user submits a request to receive information. Push services, which provide information without an active request (e.g., location-based advertising), were not used by the respondents. When asked about the LBS used most recently, nearly half of the participants named maps or navigation services, followed by local weather services, point of interest services and public transportation information services. The remainder were friend finders, traffic jam information providers, sports trackers, radar warnings, event finders and location-based games, in that order. The majority of the participants had been using the LBS stated between one and twelve months, with only a few having merely trial experiences with the particular LBS chosen (i.e., usage less than one month). The use frequency of the LBS was rather high with 16% using the LBS at least once per day on average, 27% several times per week, 14% once per week and 19% several times per month. The rest used the LBS less often.

Within the three weeks between the two survey rounds, respondents indicated they had used the LBS stated in round one an average of 8 times, with use frequency ranging from 1 to 63 times. 60% used the LBS 1-5 times, 20% 6-10 times, and 9% 11-15 times. The remaining 11% were unevenly spread from 15 to 63 times and were summarized in a sixteenth category for data analysis.

5 Data analysis and results

To test the research model and the structural relationships proposed in Figure 1, we used the partial least squares (PLS) data analysis technique. SmartPLS 2.0 (Ringle et al. 2005) was chosen because of its robustness with regard to assumptions and requirements for data analysis.

5.1 Measurement reliability and validity

The investigated model is reflective, so the latent variables are operated by the measurement models and explain the indicators. We estimated the quality of our measurement models with composite reliability and both convergent and discriminant validity.

Convergent validity

Convergent validity is achieved when measurement items exhibit significant loadings on their respective latent constructs. The t-values were estimated using a non-parametric bootstrapping procedure and the results showed that all items have significant loadings (loadings uniformly over 0.7 at a significance level of $\alpha = 0.01$) (Chin 1998). Further, all of our measures fulfill the recommended level concerning average variance extracted (AVE). As shown in Table 1, all the values are well above accepted limits with an average variance extracted at 0.67 or above. The composite reliability (CR) values are at 0.91 or above and thus exceed the 0.70 suggested threshold (Fornell and Larcker 1981).

Table 1: Latent Variables Quality Metrics

Construct	Items	Loading	Standard errors	t-value
Confirmation (EXCON) CR=0.92 AVE=0.80	EXCON1	0.92	0.01	81.14
	EXCON 2	0.89	0.02	55.39
	EXCON 3	0.88	0.01	60.78
Perceived Usefulness (PU) CR=0.93 AVE=0.81	PU1	0.92	0.01	61.55
	PU2	0.85	0.03	29.09
	PU3	0.93	0.01	104.94
Continuance Intention (CINT) CR=0.93 AVE=0.81	CINT1	0.93	0.01	66.93
	CINT2	0.84	0.02	36.60
	CINT3	0.93	0.01	96.97
Habit CR=0.95 AVE=0.67	HABIT1	0.87	0.01	64.49
	HABIT2	0.89	0.01	63.40
	HABIT3	0.82	0.02	37.58
	HABIT4	0.79	0.02	31.70
	HABIT5	0.80	0.02	34.02
	HABIT6	0.81	0.03	31.83
	HABIT7	0.85	0.02	41.53
	HABIT8	0.74	0.03	25.26
	HABIT9	0.82	0.02	35.35
Negative Emotions (NEMOT) CR=0.93 AVE=0.76	NEMOT1	0.90	0.01	76.57
	NEMOT2	0.86	0.02	37.01
	NEMOT3	0.88	0.02	53.32
	NEMOT4	0.84	0.03	26.24
Positive Emotions (PEMOT) CR=0.91 AVE=0.72	PEMOT1	0.81	0.03	29.92
	PEMOT2	0.89	0.01	80.23
	PEMOT3	0.90	0.01	96.98
	PEMOT4	0.78	0.03	23.52

Discriminant validity

Discriminant validity describes whether the items measure the construct in question or other constructs in the model. Discriminant validity is assessed by investigating the latent construct correlations and the square root of their respective AVE. Table 2 displays the square root of the AVE for each construct (boldface on the diagonal) and also the correlation between constructs. The data suggest that the square root of the AVE for each construct is much larger than the correlation of the specific construct with any of the other constructs in the model (Fornell and Larcker 1981). Thus, we can assume discriminant validity of the measures. Furthermore, we assessed discriminant validity of the scales using the cross-loading method (Chin 1998) and found that the item loadings on the corresponding constructs were all much higher than the loadings of the items used to measure the other constructs.

Table 2: Latent Variable Correlation Matrix

	EXCON	PU	CINT	HABIT	NEMOT	PEMOT
EXCON	**0.89**					
PU	0.69	**0.90**				
CINT	0.58	0.71	**0.90**			
HABIT	0.54	0.51	0.56	**0.82**		
NEMOT	-0.46	-0.40	-0.29	-0.20	**0.87**	
PEMOT	0.47	0.39	0.32	0.48	0.02	**0.85**

5.2 Structural model test and results

After confirming the reliability and validity of our measurement models, we turn our attention to the estimation of three competing structural models, (1) the baseline model, (2) the model including emotions, and (3) the full research model including emotions and habit. The significance of the path coefficients in each model was estimated using the bootstrapping algorithm of SmartPLS. On this basis, a t-test was carried out to determine the significance of the path coefficients between the latent endogenous and the latent exogenous variables.

Figure 2 presents the baseline model without emotions and habit. This model is similar to the IS continuance model by Bhattacherjee (2001), but also includes the actual use. Figure 2 illustrates the path coefficients and the R^2 values of the structural model. The results indicate that all the path coefficients are significant as hypothesized. Besides the model in Figure 2 accounts for 11.0% of the variance in LBS continuance, 51.2% of the variance in LBS continuance intentions, 54.9% of the variance in satisfaction and 48.1% in perceived usefulness.

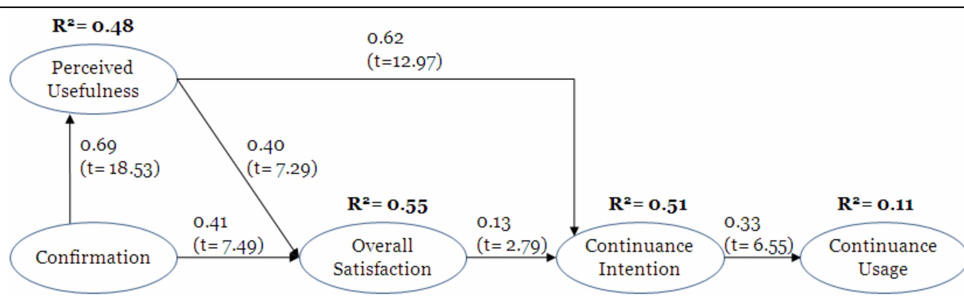

Figure 2. Baseline Model of LBS continuance

Figure 3 presents the model of LBS continuance including positive and negative emotions. The results show an increased variance explained in satisfaction of 61.9%. Besides, confirmation explains 22.1% of the variance in positive emotions and 21.2% of the negative emotions. The path coefficients are significant and show the hypothesized directionality (i.e., negative for negative emotions and positive for positive emotions). Similarly, the path coefficients of confirmation followed the hypothesized directionality. Interestingly, negative emotions seem to have a stronger influence on satisfaction (-0.31) than positive emotions (0.15).

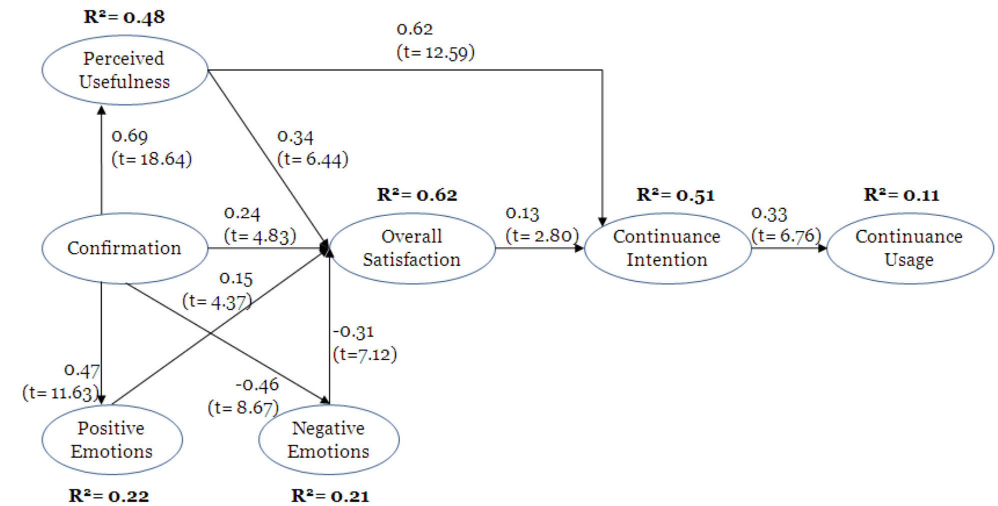

Figure 3. Model of LBS continuance including emotions

Figure 4 presents the proposed research model of LBS continuance including emotions and habit. This model accounts for 18.7% of the variance in LBS continuance. The explained variance for habit is 24.6% and the path coefficients are all significant. It is interesting to note that the coefficient of continuance intentions on LBS continuance decreased from 0.33 to 0.15. The habit coefficient on LBS continuance is 0.33.

Moreover, we tested our assumption that habit has a direct effect on LBS continuance rather than a moderating effect on the relationship between continuance intention and LBS continuance. To create an interaction term, the standardized indicator values of habit and continuance intention were multiplied using the integrated routine in SmartPLS. The analysis showed that the path coefficient from the interaction term on LBS continuance had a value of 0.03 and was not significant (t-value= 0.5). Furthermore, we controlled for demographic differences, i.e. in age and gender. We found that there were no significant influences on the reported results. Thus, our results on the influence of habit on continuance usage were stable across age groups and gender.

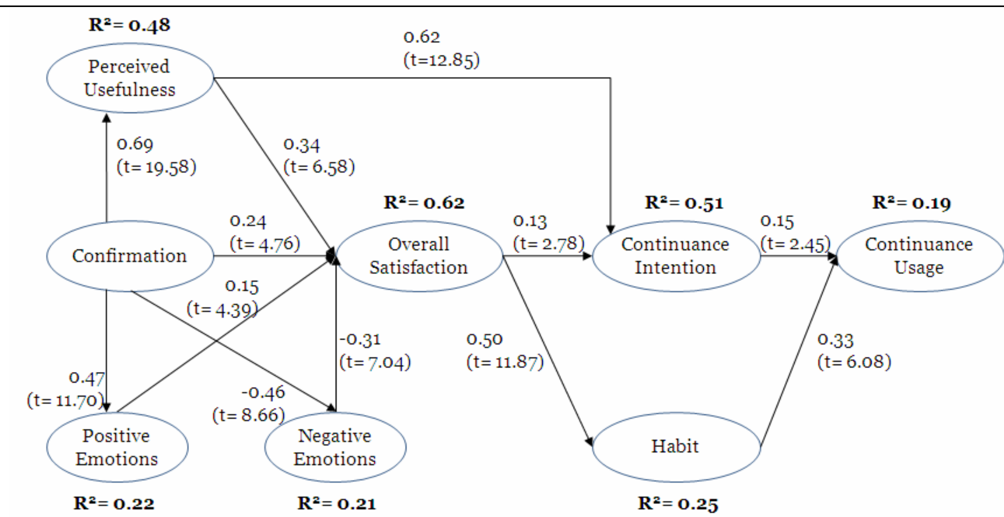

Figure 4. Model of LBS continuance including emotions and habit

6 Discussion

6.1 Theoretical Implications

The present study investigates LBS continuance and extends the model of Limayem et al. (2007). We highlight two interesting findings for the theory of IS continuance. First, we found evidence that emotions generated in specific use instances contribute significantly to user satisfaction beyond confirmation and perceived usefulness. Second, we found that habitual behavior is a powerful determinant of IS continuance.

Previous research efforts in IS continuance underline the importance of utilitarian determinants in user satisfaction and adopt a perceptual perspective. These findings imply that the user follows a comparative process by evaluating expectations and actual performance of a system, as well as assessing the perceived usefulness of the system. Satisfaction is measured as an aggregate emotional response to the perceptual evaluations of the different attributes and elements of the system. In the present study we separated the notion of satisfaction from emotions and measured the frequency of emotion occurrence during service use. We were inspired by the marketing literature (e.g., Oliver 1993) since LBS have similarities with consumer products. We found that confirmation influences both positive and negative emotions. It seems that when expectations are not met, negative emotions arise and vice versa. Additionally, our approach allowed us to investigate the influence of positive and negative emotions on satisfaction separately. Thus, we have provided an approach that enables deeper understanding of the role of emotions in the ECT. We believe that this approach better reflects satisfaction in the case of consumer products and services. Our study demonstrated that emotions affect users' satisfaction with LBS and that negative emotions have a more powerful influence on satisfaction than positive emotions. This indicates that satisfaction with consumer services is not purely the result of a cognitive process of performance assessment but also of an affective process based on emotional experiences during service use.

Previous research in IS continuance assumes that it is mainly driven by a user intentions. In the light of this research tradition, Limayem et al. (2007) found that habit moderates the relationship between intentions and continuance. Such research is influenced by a hypothesized perceptual approach in depicting a user's cognitive processes in service continuance. We assume that continuance can be equally influenced by a perceptual approach or an automated approach. Thus, we investigated the influence of continuance intentions and habit directly on LBS continuance. We found that habit has a higher predictive power over the LBS continuance behavior than continuance intentions. This indicates that the role of continuance intentions should be reconsidered. We measured habit by including a set of dimensions deriving from psychology research that allowed us to better understand the role of habit in LBS continuance. These dimensions included history of repetition, automaticity and expressing identity, which we believe capture a fuller picture of the habitual behavior of an LBS user.

6.2 Practical Implications

Mobile services providers compete for customer attention and retention. In the light of the high competition between market players and the increasing power of mobile users who are able to choose from an increasing variety of services and have low switching costs, the importance of investigating and understanding mobile user continuance behavior is prominent. Our study, motivated by these market trends, attempts to investigate the determinants LBS continuance. The study highlights important determinants of LBS continuance and offers mobile service providers interesting insights usable in marketing strategies to support customer retention.

Mobile service providers should particularly monitor how well users' expectations are met. It seems that there is a strong relationship between a user's expectation confirmation and their emotional response towards the service. A negative emotional response significantly decreases the user satisfaction and consequently may negatively influence continuance intentions. Mobile service providers should therefore investigate users' expectations and develop customer services to alleviate negative service experiences.

Finally, mobile service providers should try to benefit from habitual user behavior in the case of LBS. As the findings suggest, habit is an important determinant of LBS continuance. Service providers should develop strategies that motivate habit formation. For example, offering trials of a service for a period of time can motivate frequent use of the service and create an endowment effect which in turn may lead to a habit formation.

7 Conclusions

We have proposed a model, based on existing IS continuance research, to investigate the case of LBS. The findings particularly highlight the role of emotions and the importance of habit, suggesting important implications for both researchers and practitioners.

The present study was subject to some limitations. We utilized self-reported behavioral measures, which are generally accepted in IS literature (e.g., Limayem et al. 2007), but it would be useful for further research to apply more objective measures of service use, such those based on log files. Moreover, even after extending the Limayem et al. (2007) model, we only explain 19% of LBS continuance behavior. Although, similar research models in the IS field explain variance around 26%, further development of the model and refinements are warranted.

The present study focused on one target service, i.e., location-based services. Future research should explore to what extent the findings of this study are generalizable to other technologies.

Table 1. Measurement scales			
Constructs	**Indicators**		**Source**
Confirmation	Perception of the congruency between expectation and performance of system use.		Bhattacherjee (2001)
	EXCON1	My experience with using the service was better than what I expected.	
	EXCON2	The benefit provided by the service was better than what I expected.	
	EXCON3	Overall, most of my expectations from using the service were confirmed.	
Perceived Usefulness	Users' perception of the expected benefits of service use.		Limayem et al. (2007) adapted from Davis (1989)
	PU1	The service is of benefit to me.	
	PU2	The advantages of the service outweigh the disadvantages.	
	PU3	Overall, using the service is advantageous.	
Overall Satisfaction	Overall post-adoption evaluative judgment about previous LBS use.		Bhattacherjee (2001)
		How do you feel about your overall experience the service use (semantic differential scale):	
	OS	Very dissatisfied/Very satisfied	
Continuance Intention	User's intention to continue using the service.		Bhattacherjee (2001)
	CINT1	I intend to continue using the service rather than discontinue its use.	
	CINT2	My intentions are to continue using the service rather than use any alternative means.	
	CINT3	My intentions are to continue using the service in the future, at least as active as today.	
Habit	Perception of habitual service use.		Verplanken and Orbell (2003)
		Using __ (name of selected LBS) is something…	
	HABIT1	I do frequently.	
	HABIT2	I do automatically.	
	HABIT3	I do without having to consciously remember.	
	HABIT4	I have been doing for a long time.	
	HABIT5	I do without thinking.	
	HABIT6	that's typically 'me'.	
	HABIT7	that belongs to my (daily, weekly, monthly) routine.	
	HABIT8	I start doing before I realize I'm doing it.	
	HABIT9	I have no need to think about doing.	
Negative Emotions	Extent to which a user has experienced negative emotions during service use.		Beaudry and Pinsonneault (2010)
	Please indicate the extent to which you experienced each of the following emotion while using the service:		
	NEMOT1	Angry	
	NEMOT2	Anxious	
	NEMOT3	Disappointed	
	NEMOT4	Irritated	
Positive Emotions	Extent to which a user has experienced positive emotions during service use.		Beaudry and Pinsonneault (2010)
	PEMOT1	Eager	
	PEMOT2	Happy	
	PEMOT3	Joy	
	PEMOT4	Surprised	
Continuance	CONTUSE	In the last three weeks, how often did you use__ (selected LBS)?	Limayem et al. (2007)

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