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The Effects of Location-Based Mobile Personalization on Users' Behavior

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Abstract

Firms send short message services (SMS) to customers' mobile phones to promote their products. Many firms personalize this content to increase the relevance of the recommendations and to avoid overloading users with too many messages. This research examines the effects of location-based personalization on users' intentions to use personalized mobile SMS. We draw on motivational theories to develop six hypotheses to predict the effects of location-based personalized mobile services. Through a two-week study, we found that perceived enjoyment and perceived community involvement are major drivers motivating users to accept location-based personalized SMS. Interestingly, precision of personalization is not significant in influencing users' intention. Hedonic motivators are more influential than utilitarian motivators. These findings provide empirical evidence of the effects of location-based personalization and help firms understand and quantify new mobile commerce opportunities. Overall, this research sheds light on personalization studies by examining the role of location in personalization.

Keywords: Mobile Personalization, Location-Based Personalization, Mobile Commerce, Short Message Services

1 INTRODUCTION

1.1 Location-Based Mobile Services

In the decade since its creation, mobile commerce has become a ubiquitous channel for firms to promote their products and conduct business (Allen 2003; Hong & Tam 2006; Stafford & Gillenson 2003). Firms collaborate with mobile service providers to disseminate product information using short message services (SMS) (Constantiou et al. 2007). This phenomenon has expanded rapidly in Europe and Asia—75% of mobile phone users in Spain receive advertising SMS, 62% in France, and 54% in Japan. In Europe, hundreds of millions of advertising SMS are sent out every month ("Mobile advertising" 2010).

Mobile service providers personalize SMS content to avoid overloading users with irrelevant information (Chae & Kim 2003). The process of personalization tailors content to the needs of individual customers. The technology enabler is a personalization agent, which is a collection of software modules that deploys tools to collect and analyze customers' behavior and their purchase transactions. These modules include data mining, collaborative technology, click stream analysis components, and pattern recognition. The technology allows service providers to detect user behaviour in real time and manipulate web content (Ardissono et al. 2002). Personalization is widely adopted on the web and its effectiveness in this medium has been well-proven (e.g., Tam & Ho 2005, 2006). However, results from prior research cannot be directly applied to mobile personalization for one important reason: mobile users carry the devices on their person and use them almost anywhere; hence, mobile service providers can analyze more contextual data to generate location-sensitive personalized content and to achieve a higher personalization level (Chae & Kim 2003). Researchers use the term "location-based personalization" to differentiate mobile personalization from web personalization (Georgiadis et al. 2005). The current study examines the effects of location-based mobile personalization on users' intentions to use mobile SMS.

Location-based services can be classified into various categories (Rao & Minakakis 2003). The first category is "where am I?" services, which are based on information about users' locations and navigations. Service providers first detect where clients are located, then send them information such as maps, driving directions, and telephone directory listings. "Where am I?" services are often used by drivers. The second category is "point-of-need" services. Service providers identify a client's location and their preference profile, then send relevant product information and promotions. The third category is industrial and corporate applications, which are business-to-business oriented. For example, some firms use barcode scanning technology to track materials and product movements (e.g., courier deliveries). Location-based services can also be incorporated into supply chain and asset management, and to send task checklists and real-time reports to workers.

Table 1 summarizes the features of location-based services. This research focuses on the second category: "point-of-need" services.

Type of Location-Based Service	Business Model	Information Used by Service Provider	Examples
Where am I?	B2C	Client's location	Maps, navigation systems
Point-of-need	B2C	Client's location and preferences	Mobile coupons, shopping recommenders
Industrial and corporate applications	B2B	Material's location and operational resource networks	Supply chain management, asset management systems

Table1. Three Categories of Location-Based Services

1.2 Research Questions

Mobile SMS advertising is growing at a phenomenal rate. Mobile service providers adopt personalization technologies to better communicate with their customers and generate more business opportunities. Disappointingly, few empirical studies examine the effects of personalized location-based SMS on users' intentions to use personalized mobile SMS. Thus, little information is available to guide mobile service providers. To fill this gap, this paper examines the following research question: *How do personalized location-based SMS influence users' attitudes and their intentions to use personalized mobile SMS?*

We address this question with a two-week experiment. We developed a personalized mobile SMS system which was capable of detecting users' locations, analysing their preferences, and sending personalized SMS. In the experiment, users regularly received personalized location-based SMS, and they reported their perceptions of, and their experience with, personalized mobile services at the beginning of the study and at the end of week 1 and week 2.

The rest of this paper is organized as follows: The next section outlines the theoretical frame of the current work and presents the hypotheses. Sections 3 and 4 describe the experiment. Section 5 discusses the implications of the work. Section 6 concludes the paper.

2 THEORETICAL FRAMEWORK

Psychology literature tells us that motivation is a key factor determining an individual's intentions and their engagement in a particular behavior (Deci & Ryan 1985). There are two forms of motivational forces: intrinsic and extrinsic.

2.1 Intrinsic Motivation

Ryan and Deci (2000, pp. 56) defined intrinsic motivation as "the doing of an activity for its inherent satisfactions rather than for some separable consequence. When intrinsically motivated, an individual is moved to act for the fun or challenge entailed rather than because of external prods, pressures and rewards." Intrinsic motivation arises from within, and occurs only for behaviors that are inherently interesting to an individual. Lindenberg (2001) identified two types of intrinsic motivation: enjoyment-based intrinsic motivation and community-based intrinsic motivation.

Enjoyment-based intrinsic motivation refers to the motivation that arises when an individual has fun participating in an activity. Prior literature considers enjoyment to be the central idea of intrinsic motivation (Deci & Ryan 1985). Csikszentmihalyi (1975) suggested that an individual pursues activities for the sake of the enjoyment derived from doing them. When enjoyment is intense and maximized, the individual reaches a state of "flow". In information systems literature, perceived enjoyment has been found to relate to one's attitude to use a technology (e.g., Venkatesh 2000) or system (e.g., Venkatesh & Speier 1999, 2000). Hence, we anticipate that if an individual enjoys personalized mobile SMS, s/he will have a positive attitude to use the services in the future.

H1: If individuals perceive using personalized mobile services to be enjoyable, they will have a positive attitude to use personalized mobile services.

The other type of intrinsic motivation is community-based intrinsic motivation (Lindenberg 2001). An individual likes to socialize into acting in a manner consistent with norms of his or her peers. Therefore, if an individual believes that personalized mobile services will help them make friends or be involved in a community, they will be intrinsically motivated, and have a positive attitude to use personalized mobile SMS.

H2: If individuals perceive that using personalized mobile services will help them be more involved in the community, they will have a positive attitude to use personalized mobile services.

2.2 Extrinsic Motivation

In contrast to intrinsic motivation, extrinsic motivation emphasizes variables that exist outside the person. The individual is extrinsically motivated to perform a behavior because the behavior is a means to an end for reaching valued outcomes, such as rewards and recognition (Lawler & Porter 1967; Vroom 1964).

Prior information systems research shows that extrinsic motivation is a strong predictor of users' attitudes to adopt a technology. In these studies, "perceived usefulness" is typically provided as an example of extrinsic motivation (Davis & Bagozzi 1992; Moon & Kim 2001). Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1989). For example, if a software application is perceived to improve work performance, then employees will be extrinsically motivated and more likely to adopt the system. Prior research has also shown that perceived usefulness directly influences computer usage (Davis & Bagozzi 1992). Hence, we anticipate the following:

H3: If individuals perceive personalized mobile services to be useful, they will have a positive attitude to use personalized mobile services.

One variable specific to the context of location-based mobile personalization is the precision of personalization. Mobile service providers use various technologies, such as global positioning systems, to detect an individual's location. Some technologies are less precise and can only locate an individual to a suburb (i.e., within a few kilometers); other technologies are more precise and can locate an individual to a street (i.e., within a few meters). Location-based content is more relevant when it is closer to the current location of the user. Hence, we anticipate the following.

H4: If individuals perceive personalization to be very precise, they will have a positive attitude to use personalized mobile services.

According to the Theory of Reasoned Action, an individual's behavioral intention depends on his/her attitude about the behavior (Ajzen and Fishbein 1980). Therefore, individuals who have a more positive attitude toward personalized mobile services will have a stronger intention to use the services in the future. We anticipate the following:

H5: If individuals have a more positive attitude towards personalized mobile services, they will have a more positive intention to use the services.

H6: If individuals have a more positive intention to use personalized mobile services, they are more likely to use the services.

Figure 1 summarizes the research model. We conducted an experiment to test the hypotheses and our methodology and findings are outlined in the next two sections.

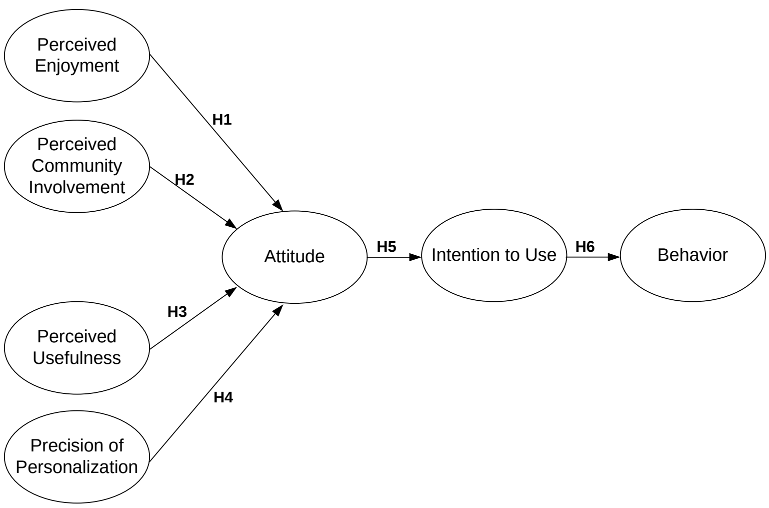

Figure 1. Research Model

3 METHODOLOGY

3.1 Development of Mobile Personalization Systems

The context of this study was restaurant recommendations. Participants received location-based personalized restaurant recommendations, in the form of SMS, on days when they planned to eat out. The recommendations were personalized to match participants' food preferences.

We developed a personalization system to send SMS content to participants. The system had two modules: a mobile module and a web module. The mobile module was built with programming interfaces provided by a mobile service provider. The module analyzed participants' profiles and generated personalized mobile content; in this case, a restaurant recommendation. It then sent the recommendations to participants' mobile phones in the form of an SMS. The web module was developed to collect quantitative data. The module sent an auto-email to invite participants to complete an online questionnaire at the beginning of the two-week study and after one week. In the second week, we observed the behavior of the participants to see whether their actual behavior matched what they reported in the questionnaires in the first week.

The process of "personalizing" recommendations is as follows: we recruited 15 students to provide lists of their favourite local restaurants. We compiled these lists into 212 different restaurants and supplemented the aggregate list with more restaurants, which we found by searching the Internet. The final restaurant database contained 250 restaurants. We used several attributes to describe each restaurant: name, location, cuisine (e.g., Chinese, Japanese), type of food (e.g., curry, fast food), average meal price, signature dish, and takeaway options. In the web questionnaire, participants reported their food preferences (cuisine and types of food), preferred price range, and intended days to eat out. The system detected the location of participants on the days they had planned to eat out and generated a recommendation based on location and food preferences.

3.2 Experimental Procedure

The experimental procedures were as follows. First, participants registered on a website. They filled in a short questionnaire on their demographics and food preferences (e.g., types of food, prices), and selected the days they would be likely to go out for lunch. They also reported their perceptions of personalized mobile services. The first part of the web process finished with a pre-task questionnaire.

On the mornings that participants were expecting to go out for lunch, the system sent a series of SMS to their mobile phones, offering restaurant recommendations. Participants replied to the system with an SMS that rated the restaurant recommendation (1 = very dislike; 9 = very like). This process was repeated on each day the participant had indicated they would be eating out. At the end of the first week, the system sent an email to invite participants to complete an online post-task questionnaire in the web module. In the second week, the same process repeated. We asked the participants to report whether they took our recommendations and ate out. The data in the second week helped us to confirm whether the participants' actual behavior was matched to their behavioral intention as reported in the end of week 1 questionnaire.

We conducted a pilot experiment with 11 participants to confirm that our mobile personalization system functioned properly; that is, that participants could receive our SMS recommendations and we could log their replies properly. We also used the pilot test to find out if anything could be added to enhance the experiment. Participants followed the same procedure in the pilot test as the main experiment. At the end, they completed an open-ended questionnaire to report system malfunctioning (if any) and offer suggestions for improving the experiment. Overall, the pilot participants suggested that the SMS recommendation process was smooth and it was easy to send their responses to the system with their mobile phones.

3.3 Design and Manipulation

We generated location-based mobile content as follows. First, we decided that the recommended restaurant must be within reasonable walking distance of the participant's location. Our participants would be students, so we assumed that they have neither the time nor the means to travel long distances for lunch. Specifically, the city in which the study was conducted is about 1,000 kilometers square and made up of eight districts. The average distance between the centers of two districts is 12.61 kilometer[1]. The district in which the university is located is divided into 14 suburbs. The recommended restaurant was always in the suburb where the participant was located. We sent the recommendations to participants at 11:30am, giving them a reasonable amount of time to walk to the restaurant for a lunch break starting at 12 noon.

All participants received an SMS recommendation on the day they had planned to eat out. They rated the SMS recommendations via their mobile phones. After a one-week experience, they completed a post-task questionnaire, reporting whether they actually ate lunch at the recommended restaurants.

3.4 Dependent and Control Variables

We captured the dependent variables in an online survey. The dependent variables included users' attitudes towards personalized mobile services and their intentions to use the services. The constructs, perceived usefulness, attitude, and intention to use, were adapted from Venkatesh et al. (2003). The construct, perceived enjoyment, was adapted from Davis et al. (1992). No information systems literature, of which we are aware, provides references for the constructs, perceived community involvement and precision of personalization. We self-developed these two constructs—The researchers initially suggested eight items for each construct, asked 13 undergraduate students to complete the draft questionnaires, and tested the item reliability and validity. Finally we came up with the lists of items for these constructs. The final questionnaire items are reported in Appendix I.

We included two control variables in our data analysis, in addition to the dependent and independent variables. The control variables were the participant's mobile phone experience and his/her mobile phone usage. The participant's mobile phone experience was operationalized as the number of years he/she had used a mobile phone. The participant's mobile phone usage was operationalized as the average amount of airtime that he/she had used in the previous 12 months.

3.5 Manipulation Check

We performed manipulation checks to confirm that the location-based recommendations had been correctly implemented. In the post-task online questionnaire, we asked participants to rate three statements: "The recommended restaurants were always near to where I was", "It was a short walking distance to the recommended restaurants", and "The recommended restaurants were always next to where I was." (1 = Strongly Disagree; 9 = Strongly Agree). The average score of these items was 6.4 (out of 9). This score was significantly larger than 5 (i.e., the mid-point of a 9-point Likert scale) ($p < 0.05$). Thus, we considered that the location-based recommendations have been correctly implemented.

[1] The city was 1,000 kilometers square. The average size of each of the eight regions was 125 kilometers square. Assuming that the districts were circular, the distance between the centers of two districts was 12.61 (= sqrt(125 / π) $\times$ 2) kilometre.

4 FINDINGS

4.1 Sampling

Our target participants were students in a public university in Australia. We believed that university students were legitimate participants because they tend to be heavy mobile phone users (Kim 2002). We distributed flyers on the university campus to recruit participants. The main study had 130 participants, 83 males and 47 females, and their average age was 20 years. All of them were active mobile phone users. All went out for lunch at least one day per week. During the experiment period, we sent 445 SMS recommendations to the 130 participants. On average, each participant received three SMS recommendations within a week.

4.2 Measurement Model Results

Throughout the paper, individual items have been standardized unless noted otherwise. The statistical analysis technique applied is partial least squares (PLS), as implemented in SmartPLS version 2.3. PLS and LISREL are two ways of modeling latent variables and their relations to each other within a set of manifest variables. Both are used for causal modeling. They simultaneously assess the reliability and validity of theoretical construct measures and estimate the relationships among these constructs (Chin 1998; Goodhue et al. 2007). LISREL requires stronger theory than PLS and is preferred for confirmatory testing of the fit of a theoretical model to observed data (Barclay et al. 1995). PLS is better suited for theory development; thus, we used PLS to analyze our data.

PLS judges the adequacy of a measurement model by three criteria: (1) individual item reliabilities, (2) the convergent validities of measures associated with individual constructs, and (3) discriminant validity between constructs (Hulland 1999).

To assess the reliabilities of individual items, we checked the composite reliabilities in Table 2. The individual item reliabilities were above 0.9; thus, the first criterion was met. To assess convergent validity, we checked all loadings and confirmed that all were greater than the recommended threshold of 0.70 (Nunnally 1978). Hence, the second criterion was fulfilled. To assess discriminant validity among the constructs, Fornell and Larcker (1981) suggested that researchers use average variance extracted (AVE) to measure the variance between a construct and its measures. A rule for assessing discriminant validity requires that the square root of AVE be larger than the correlations between constructs (Barclay et al. 1995). According to Table 3, the square root of the AVE values are consistently greater than the off-diagonal correlations, suggesting at least adequate discriminant validity at the construct level.

Construct	Reliability
Attitude	0.95
Behavior	1.00
Community	0.93
Enjoyment	0.97
Intention	0.94
Precision	0.92
Usefulness	0.95

Table 2. Composite Reliability of the Constructs

	Attitude	Behavior	Community	Enjoyment	Intention	Precision	Usefulness
Attitude	**0.97**						
Behavior	0.50**	**1.00**					
Community	0.43**	0.18**	**0.94**				
Enjoyment	0.58**	0.60**	0.34**	**0.97**			
Intention	0.74**	0.59**	0.38**	0.64**	**0.97**		
Precision	0.42**	0.35**	0.52**	0.45**	0.53**	**0.93**	
Usefulness	0.30**	0.37**	0.03	0.26**	0.32**	-0.03	**0.93**

* denotes significant correlations at the p < 0.05 level; ** denotes significant correlations at the p < 0.01 level. The diagonal elements (in bold) represent the square root of AVE.

Table 3. Latent Variable Correlations

4.3 Structural Model Results

The predictors used in this study did a good job of explaining the variance in users' attitudes to using personalized mobile services (R^2 = 47.5%), their intentions to use the services (R^2 = 54.5%), and their behavior (R^2 = 27.7%). Figure 2 summarizes the findings.

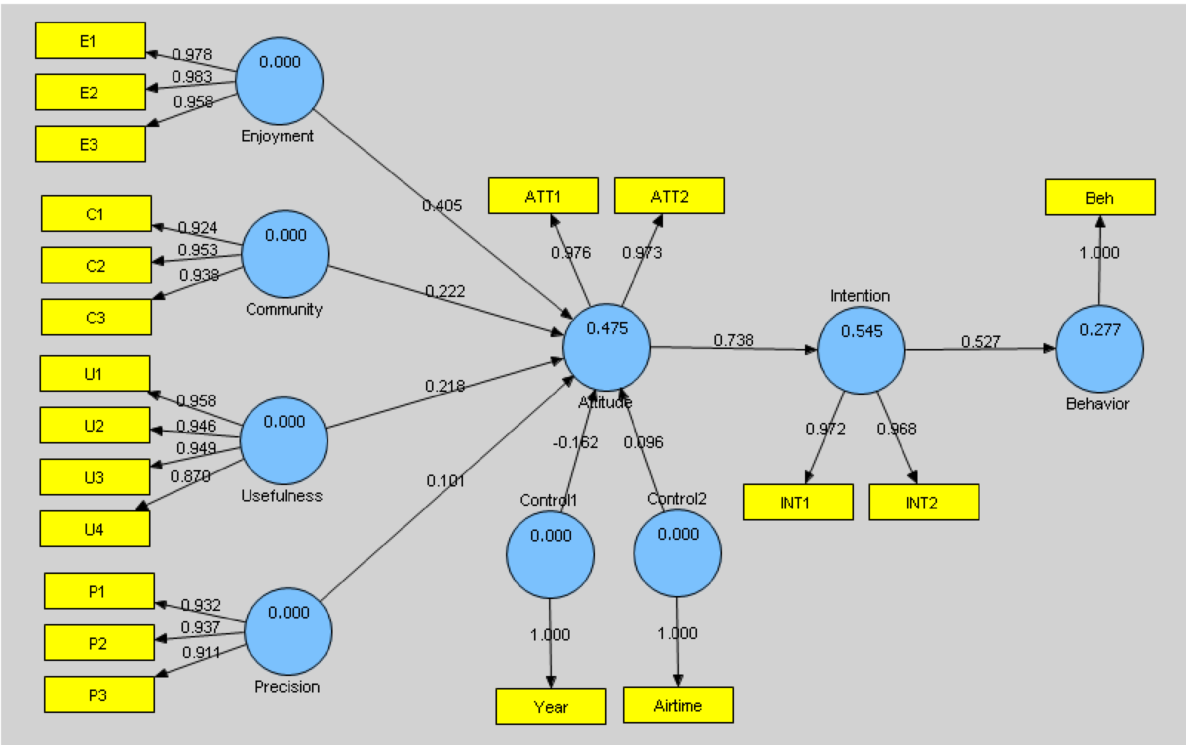

Figure 2. Research Findings

H1 was supported (p < 0.01, coefficient = 0.41). Perceived enjoyment was a significant factor affecting users' attitudes towards personalized mobile services. If users perceived personalized mobile services to be enjoyable, they were more likely to form a positive attitude toward the services. Perceived enjoyment exerted the strongest effect on users' attitudes. This suggests that users look for fun when using personalized mobile services. Users perceived the hedonic features of the services to be more important than the utilitarian features, in influencing their attitudes.

H2 was supported (p < 0.05, coefficient = 0.22). Perceived community involvement exerted a significant main effect on attitudes towards personalized mobile services. Participants who believed that personalized mobile content would give them information about external worlds and about their friends were more likely to have a positive attitude towards personalized mobile services. Also, they were more intrinsically motivated to use the services.

The two factors related to extrinsic motivation had different results in our model. Participants who perceived personalized mobile services to be useful were willing to use personalized mobile services, supporting H3 ($p < 0.01$, coefficient = 0.22). However, precision of personalization exerted no main effect on users' attitudes towards personalized mobile services, rejecting H4 ($p > 0.1$, coefficient = 0.10).

As predicted, users who have a more positive attitude towards personalized mobile services will have a more positive intention to use the services, supporting H5 ($p < 0.01$, coefficient = 0.74). Also, a more positive intention to use the services will lead to a higher usage, supporting H6 ($p < 0.01$, coefficient = 0.53).

Regarding control variables, the number of years that an individual had used a mobile phone had a significant effect on users' attitude towards personalized mobile services ($p < 0.01$), but the average amount of airtime that an individual had used in the previous 12 months had no significant effect on users' attitudes ($p > 0.1$).

5 DISCUSSION

Prior research has confirmed that personalization influences users' information processing on the Internet; however, our understanding of its effectiveness in mobile personalization is far from conclusive. This research aims to bridge the gap between the potential growth of mobile personalization and the lack of understanding of mobile users' intentions to use personalized mobile services. No prior information systems research, of which we are aware, examines this issue. This study conducts an experiment with mobile phone users, and our results offer some practical guidelines for firms who want to leverage personalized mobile services to improve service quality and generate business. Table 4 summarizes the findings.

Hypotheses	p-value
H1: If individuals perceive using personalized mobile services to be enjoyable, they will have a positive attitude to use personalized mobile services.	$p < 0.01$
H2: If individuals perceive that using personalized mobile services will help them be more involved in the community, they will have a positive attitude to use personalized mobile services.	$p < 0.05$
H3: If individuals perceive personalized mobile services to be useful, they will have a positive attitude to use personalized mobile services.	$p < 0.01$
H4: If individuals perceive personalization to be very precise, they will have a positive attitude to use personalized mobile services.	$p > 0.1$
H5: If individuals have a more positive attitude towards personalized mobile services, they will have a more positive intention to use the services.	$p < 0.01$
H6: If individuals have a more positive intention to use personalized mobile services, they are more likely to use the services.	$p < 0.01$

Table 4. Summary of Findings

5.1 Implications

This study has three primary implications.

First, it is a pioneering effort to examine the location dimension in personalization research. Personalization of IT services intends to provide the right content in the right format to the right person at the right time in the right location. Recent research on personalization has focused on content personalization (e.g., Tam & Ho 2005; 2006) and adaptive interfaces (e.g., Billsus et al. 2002).

Little work has been done on the location dimension. However, it is imperative to understand whether individuals are willing to share location-related information with mobile service providers and what potential location-based personalized services can be offered, because the success of personalization in mobile commerce hinges on understanding the context of location-sensitive interaction. Together, these dimensions (user preferences, content, layout, and location) capture many of the functionalities of personalization and user characteristics at a particular instant. This represents a formal characterization of the notion of personalization.

Secondly, our findings show that precision of personalization was not a significant factor affecting users' attitudes. Individuals probably did not expect the personalization to be very precise (mean = 2.31), and therefore did not factor it into their considerations. In addition, perceived enjoyment dominated all other factors. From a research point of view, the difference between the findings of prior studies (i.e., perceived usefulness was highly significant in influencing users' attitudes and intentions) and this study (i.e., perceived enjoyment dominated other factors) may be due to the nature of the technology. Compared with technologies at work, personalized mobile services are pleasure-oriented, rather than productivity-oriented (van der Heijden, 2004). From a practical point of view, it may imply that individuals use personalized mobile services mainly because they enjoy doing so. Therefore, mobile service providers should allocate their investments to developing or enhancing hedonic features.

Third, given that personalization is known to influence user behaviour, the use of personalization techniques should be balanced by a proactive approach to protecting data privacy. Prior information systems work (e.g., Awad & Krishnan 2006; Chellappa & Sin 2005) has confirmed that users are concerned about their privacy being compromised by the web personalization process. Our findings provide a better picture of users' expectations of personalized mobile services, but we have little information on users' privacy concerns regarding mobile personalization. Future work is required to explore users' privacy concerns when their location is detected by mobile service providers.

5.2 Limitations and Future Research

This study has a number of limitations. The first limitation is that our sample was university students. Although university students are active mobile phone users, the findings of the study would be more representative if our sample includes people with different backgrounds. Future research can be conducted to examine how users of different characteristics (e.g., job types, household income, personalities etc) react with location-based personalized services. Second, the experimental setting involved low-involvement products (i.e., a meal of $20). Future research can explore the effectiveness of personalized mobile services for promoting different types of products via mobile SMS. An additional direction for future research regards how users react with location-based personalized services on high-involvement products.

6 CONCLUSION

In summary, the current work has investigated the effects of location-based mobile personalization. We used motivational theories to establish our theoretical framework and examined how variables influence users' attitudes and behaviors towards personalized mobile SMS. In general, it is easier to intrinsically motivate individuals to use personalized mobile services than to extrinsically motivate them. Therefore, mobile service providers should invest more in enhancing the hedonic features of personalized mobile services rather than utilitarian features. Overall, this study represents a first step toward understanding how location-based personalization affects users' attitudes towards personalized mobile content, and ultimately their behavior. It sheds light on the personalization literature by examining the importance of location in personalization.

References

Ajzen, I., and Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Englewood Cliffs, NJ: Prentice-Hall.

Allen, J.P. (2003). The evolution of new mobile applications: a sociotechnical perspective. International Journal of Electronic Commerce, 8 (1), 23-36.

Mobile advertising. (2010, May 5). In Wikipedia, the free encyclopedia. Retrieved May 21, 2010, from http://en.wikipedia.org/wiki/Mobile_advertising

Ardissono, L., Goy, A., Petrone, G., and Segnan, M. (2002). Personalization in business-to-customer interaction. Communications of the ACM, 45 (5), 52-53.

Awad, N.F., and Krishnan, M.D. (2006). The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS Quarterly, 39 (1), 13-28.

Barclay, D., Higgins, C. and Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal adoption and use as an illustration. Technology Studies, 2 (2), 285-309.

Billsus, D., Brunk, C.A., Evans, C., Gladish, B. and Pazzani, M. (2002). Adaptive interfaces for ubiquitous web access. Communications of the ACM, 45 (5), 34-38.

Chae, M. and Kim, J. (December 2003). What's so different about the mobile internet? Communications of the ACM, 46 (12), 240-247.

Constantiou, I.D., Damsgaard, J. and Knutsen, L. (2007). The four incremental steps toward advanced mobile service adoption. Communications of the ACM, 50 (6), 51-55.

Chellappa, R.K. and Sin, R.G. (2005). Personalization versus privacy: an empirical examination of the online consumer’s dilemma. Information Technology and Management, 6, 181-202.

Chin, W.W. (1998). Issues and opinions on structural equation modeling. MIS Quarterly, 22 (1), 7-16.

Csikszentmihalyi, M. (1975). Beyond boredom and anxiety. Jossey-Bass, San Francisco.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13 (3), 319-340.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22 (14), 1111-1132.

Deci, E. L. and Ryan, R.M. (1985). Intrinsic motivation and self-determination in human behavior. New York: Plenum Press.

Fornell, C. and Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18 (1), 39-50.

Georgiadis, C.K., Mavridis, I. and Manitsaris, A. (2005). Context-based humanized and authorized personalization in mobile commerce applications. International Journal of Computing and Information Sciences, 3 (2), 1-9.

Goodhue, D., Lewis. W. and Thompson, R. (2007). Statistical power in analyzing interaction effects: Questioning the advantage of PLS with product indicators. Information Systems Research, 18 (2), 211-227.

Hong, S.J. and Tam, K.Y. (2006). Understanding the adoption of multipurpose information appliances: the case of mobile data services. Information Systems Research, 17 (2), 162-179.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: a review of four recent studies. Strategic Management Journal, 20 (2), 195-204.

Kim, S. D. (2002). Korea: personal meanings. In Perpetual Contact: Mobile Communication, Private Talk, Public Performance (Katz, J.E. and Aakhus, M. Eds.), p. 63. 1st edition, Cambridge University Press, United Kingdom.

Lawler, E. E., and Porter, L. W. (1966). Predicting managers’ pay and their satisfaction with their pay. Personnel Psychology, 19, 363-373.

Lindenberg, S. (2001). Intrinsic motivation in a new light. KYKLOS, 54 (2/3), 317-342.

Moon, J.W. and Kim, Y.G. (2001). Extending the TAM for a World-Wide-Web context. Information & Management, 38, 217-230.

Nunnally, J.C. (1978). Psychometric theory. 2nd edition. McGraw-Hill, New York.

Rao, B. and Minakakis, L. (2003). Evolution of mobile location-based services. Communications of the ACM, 46 (12), 61-65.

Ryan, R. M., and Deci, E. L. (2000a). Intrinsic and extrinsic motivations: classic definitions and new directions. Contemporary Educational Psychology, 25, 54–67.
Stafford, T. F. and Gillenson, M.L. (2003). Mobile commerce: what it is and what it could be. Communications of the ACM, 46 (12), 33–34.
Tam, K.Y., and Ho, S.Y. (2005). Persuasiveness of web personalization: an elaboration likelihood model perspective. Information Systems Research, 16 (3), 271-291.
Tam, K.Y. and Ho, S.Y. (2006). Understanding the impact of web personalization on user information processing, behavior and judgment. MIS Quarterly, 30 (4), 865-890.
van der Heijden, H. (2004). User acceptance of hedonic information systems. MIS Quarterly, 28 (4), 695-704.
Venkatesh, V. (2000). Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model. Information Systems Research, 11 (4), 342–365.
Venkatesh, V., & Speier, C. (1999). Computer technology training in the workplace: A longitudinal investigation of the effect of mood. Organizational Behavior and Human Decision Processes, 79, 1-28.
Venkatesh V., & Speier, C. (2000). Creating an effective training environment for enhancing telework. International Journal of Human-Computer Studies, 55, 991-1005.
Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. (2003). User acceptance of information technology: toward a unified view. MIS Quarterly. 27 (3), 425-478.
Vroom, V. (1964). *Work and motivatio*n. New York: Wiley.

Appendix 1

Perceived Enjoyment

1. I find using personalized mobile services to be enjoyable.
2. I have fun using personalized mobile services.
3. I enjoy using personalized mobile services.

Perceived Community Involvement

1. I find that personalized mobile services involve me in the community.
2. I have a feeling of involvement in the community when using personalized mobile services.
3. Using personalized mobile services make me feel involved in the community.

Perceived Usefulness

1. Using personalized mobile services for restaurant-seeking would make the process easier.
2. I would find personalized mobile services useful for restaurant-seeking.
3. Using personalized mobile services would enhance the effectiveness of restaurant-seeking.
4. It is useful to use personalized mobile services for restaurant-seeking.

Precision of Personalization

1. Personalized mobile services provided recommendations close to where I was.
2. Personalized mobile services gave recommendations near to where I was.
3. Recommendations generated by personalized mobile services were close to where I am.

Attitude towards Personalized Mobile Services

1. I like using personalized mobile services.
2. I feel comfortable using personalized mobile services.

Intention to Use

1. Assuming I had access to personalized mobile services, I intend to use it.
2. Given that I had access to personalized mobile services, I predict that I would use it.