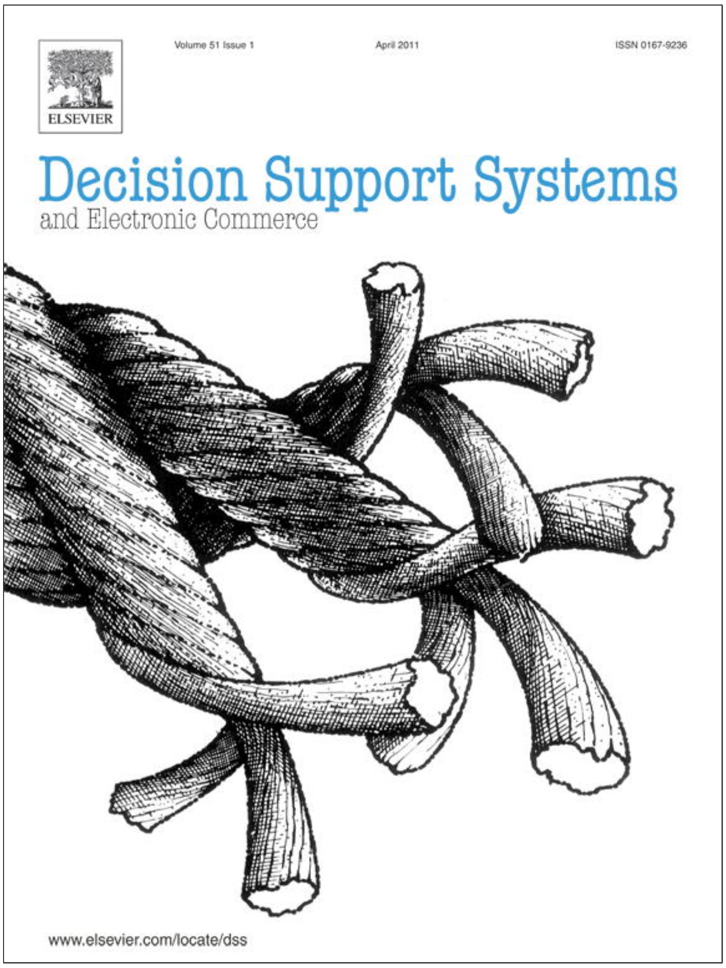
Volume 51 Issue 1
April 2011
ISSN 0167-9236
ELSEVIER
Decision Support Systems
and Electronic Commerce
www.elsevier.com/locate/dss

Decision Support Systems 51 (2011) 42–52

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing ☆

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ARTICLE INFO

Article history:
Received 24 October 2009
Received in revised form 13 August 2010
Accepted 17 November 2010
Available online 27 November 2010

Keywords:
Privacy decision making
Personalization privacy paradox
Location-aware marketing (LAM)
Covert personalization
Overt personalization

ABSTRACT

Despite the vast opportunities offered by location-aware marketing (LAM), mobile customers' privacy concerns appear to be a major inhibiting factor in their acceptance of LAM. This study extends the privacy calculus model to explore the personalization–privacy paradox in LAM, with considerations of personal characteristics and two personalization approaches (covert and overt). Through an experimental study, we empirically validated the proposed model. Results suggest that the influences of personalization on the privacy risk/benefit beliefs vary upon the type of personalization systems (covert and overt), and that personal characteristics moderate the parameters and path structure of the privacy calculus model.

1. Introduction

Recent advances in mobile communication technologies have presented decision-makers (e.g., marketing managers) with a new form of advertising channel: location-aware marketing (LAM). LAM has been defined as targeted advertising initiatives delivered to a mobile device from an identified sponsor that is specific to the location of the consumer [62]. With the increasing popularity of the new generation of GPS-enabled smartphones [1], marketers can utilize this emerging technological ground to deliver personalized marketing messages based on consumers' geographical locations and prediction of their needs, and to reach mobile consumers through their mobile devices on a geographically targeted basis.

Location-based services (LBS) revenues are expected to grow from $1.7 billion in 2008 to $14 billion by 2014 [1]. Many LBS providers see LAM as the cornerstone of their business models [1]. Despite the vast opportunities offered by LAM, many merchants and consumers are still skeptical about the idea. Besides the overarching concerns on limited indoor location technology and a fragmented location ecosystem, another important impeding factor is privacy-related user acceptance issues [1]. The potential intrusion of privacy becomes an important concern for mobile users who carry GPS-enabled smartphones [10]. Therefore, it is important to understand how consumers will respond to LAM in terms of their recognition and understanding of this double-edged sword: To consumers, on the one hand, they may identify great values in receiving customized messages galvanizing their intended purchases, while on the other hand privacy concerns about disclosing personal information in exchange for promotional messages may turn them away. This personalization-versus-privacy predicament mirrors a paradox where consumers give out their private information with subjective expectations that the associated service provider will personalize transactions based on their profiles and trust that the provider will not indiscriminately share their personal information [16]. In literature, it has been effusively noted that personalization is partly dependent on consumers' willingness to share their personal information and use personalized services whereas the consumers like to receive and/or obtain these services by giving out as little information as they could [16,57]. In this research, we attempt to examine such a central paradox for marketers investing in LAM: although the level of personalization increases the value of LAM, it also increases the level of privacy concerns.

The objective of this paper is to explore the relationships between personalization and privacy through the theoretical framework of

☆ The authors gratefully acknowledge the financial support of the National Science Foundation under grant CNS-0716646. Any opinions, findings, and conclusions or recommendations expressed herein are those of the researchers and do not necessarily reflect the views of the National Science Foundation.

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doi:10.1016/j.dss.2010.11.017

privacy calculus, with the considerations of interpersonal differences. Specifically, we seek to identify the antecedents to perceived benefits and risks of information disclosure as well as the consequences of those on purchase intention in the specific context of LAM. In addition, acknowledging that LAM in different personalization forms yields distinct psychological appeals of information disclosure to consumers [60], we seek to examine the differential effects of alternative protocols for locating client devices on the mobile consumer perceptions and behaviors. To offer personalized services that are tailored to mobile consumers' activity contexts, LAM providers deliver information content through mobile communication and positioning systems in two ways — *covert-based* and *overt-based* mechanisms. In the *covert-based* approach (i.e., push-based or proactive LBS), location-sensitive content is automatically sent by marketers to individuals based on covertly 'observing' their behaviors through tracking physical locations of their mobile devices [62,67]. In the *overt-based* approach (i.e., pull-based or reactive LBS), individuals request information and services based on their locations and marketers only locate users' mobile devices when they initiate requests, e.g., a user might request a list of nearby points of interest [62,67].

The contribution of this study lies in its focus on examining the personalization privacy paradox through a privacy calculus lens, for two different personalization approaches (i.e., covert versus overt), to different individuals (reflected by interpersonal differences such as previous privacy invasion experiences, personal innovativeness, and coupon proneness), and in an understudied technological phenomenon (i.e., LAM). In an effort to advance this line of research [62,67], this study furthers the theoretical contribution by incorporating the conditions and constraints (i.e., "under what personalization approaches", "to whom", and "about what technology"), which were previously neglected, into the understanding of personalization privacy paradox. Thus, this exploratory study opens new avenues of research and pragmatically calls for LAM practitioners' attentions to covert and overt personalization strategies and interpersonal differences.

The remainder of the paper is organized as follows. We first present the conceptual foundation for this research, describing the calculus perspective of information privacy. This is followed by a description of the research hypotheses, research methodology, and findings. The paper concludes with a discussion of the key results, directions for future research, and implications of the findings.

2. Conceptual foundation and research hypotheses

Information privacy has been generally defined as the ability of the individual to control the terms under which personal information is acquired and used [64]. The calculus perspective of information privacy is especially evident in works of analyzing privacy issues [23,25]. A general implication from these studies is that consumers can be expected to behave as if they are performing a calculus (risk–benefit analysis) in assessing the outcomes they will receive as a result of information disclosure [23]. In this research, we examine the privacy personalization paradox through the privacy calculus lens and argue that the influences of personalization on the privacy calculus and willingness to disclose personal information in LAM depend on the type of personalization approaches (covert versus overt) as well as personal characteristics. Fig. 1 presents the research model.

2.1. Understanding the personalization privacy paradox through the calculus lens

Drawing on the exchange theory [33], Culnan and Bies [23] introduced the concept of "second exchange" to explain the privacy calculus as a utilitarian exchange whereby personal information is given in return for the value such as higher quality of services [23]. Applying this second exchange framework to the LAM context, we may interpret the information disclosure in LAM as an exchange where consumers disclose their personal information and location data in return for added value such as personalized ads that will be delivered based on their context and location. LAM can provide a user with the contextualization value by sending the user with relevant promotional information based on the user's interests, activities, locations, and the time of the day [34]. One of the key factors of using LAM is the value of personalization that adds to the user experiences and smoothness of interactions [34]. Personalization has been generally defined as "the ability to provide content and services that are tailored to individuals based on knowledge about their preferences and behaviors" [2]. Consumers may be motivated to disclose their personal information in exchange for personalized services and/or information access. Personalization is gained when LAM are tailored to individual customers' interests, location, identity, activity and time [34]. Thus LAM is ideal for marketers to channel their marketing opportunities into customized wireless content delivery for mobile consumers. Therefore, we hypothesize:

Hypothesis 1. Personalization is positively related to perceived benefits of information disclosure.

It has been suggested by prior studies that personalized information and services have significant privacy implications because of large amounts of personal data collected for performing personalization [40]. In the LAM context, geographical location information often

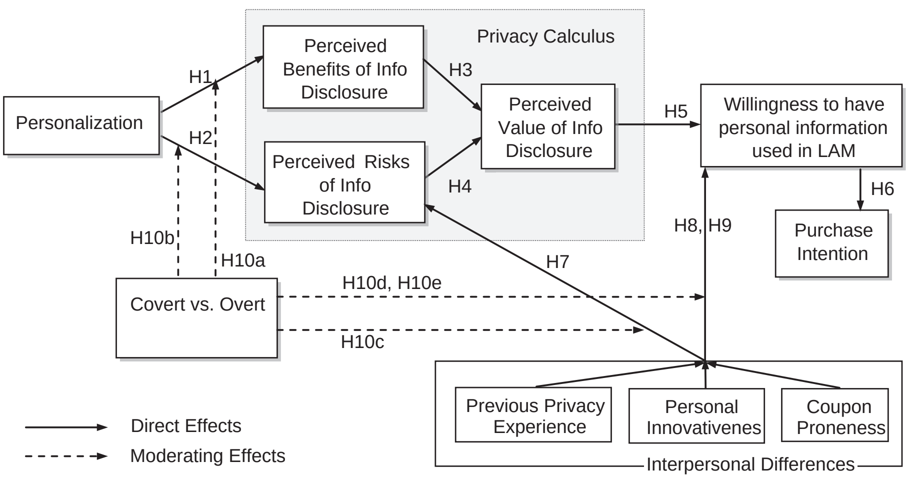

Fig. 1. The conceptual model.

reveals the position of a person in real time, rendering the potential intrusion of privacy a critical concern [11]. Improper handling of consumer location data and other personal information could result in the discovery and tracking of consumer identity and behavior, which may be used for unsolicited marketing, price discrimination or unauthorized access [40]. In the context of mobile commerce, it has been shown that consumers' privacy concerns were raised when they were presented with a personalized shopping list that was derived from their previous purchasing history [41,55]. Despite the added value provided by personalized information and services, consumers are concerned about their personal information collected and used to perform personalization [4,58]. Therefore, we hypothesize:

Hypothesis 2. Personalization is positively related to perceived risks of information disclosure.

2.2. Outcomes of the privacy calculus

The notion of the privacy calculus suggests that consumers, when requested to provide personal information to firms, would perform a risk–benefit analysis that accounts for inhibitors and drivers of information disclosure [4]. The outcome of such calculus is considered to be the cumulative effect of risks and benefits, which is analogous to the construct of *perceived value* [79]. Adapting Zeithaml's definition [69] into the context of current research, we define perceived value of information disclosure as the individual's overall assessment of the utility of information disclosure based on perceptions of privacy risks incurred and benefits received. As discussed earlier, individuals are likely to agree to give up a degree of privacy in return for potential benefits related to information disclosure. To the extent that the anticipation of benefits provides direction for choice behavior through enhancing the perceived value of various outcomes, a higher expectation of benefits should amplify the overall assessment of the utility of information disclosure. Therefore, we hypothesize:

Hypothesis 3. The perceived benefit of information disclosure is positively related to perceived value.

Privacy risk has been defined as the degree to which an individual believes that a high potential for loss is associated with the release of personal information to a firm [28,44]. Prior privacy literature [28,44] has identified sources of organizational opportunistic behaviors, including insider threat or unauthorized access, selling personal data to, or sharing information with business associates, or other third parties. It has been argued, particularly in management literature, that risk is positively related to value [46]. This contention dictates that higher rewards (monetary values in terms of compensation) are attributed to activities with higher risks (firm's uncertainties). Yet this notion departs from the arena of LAM where regular consumers, instead of an organization's top executives, differ from the CEO in terms of risk taking. In the context of LAM, improper handling of personal information could result in the mining of location data and identity [30,63], which may enhance the visibility of consumer behavior and increase the scope for situations that may be personally embarrassing to them [9,19]. Therefore, consumers' assessments of the utility of information disclosure will be low if they sense that there exist high risks of privacy invasion. Hence, we hypothesize:

Hypothesis 4. The perceived risk of information disclosure is negatively related to perceived value.

According to the economic theory of utility, individuals try to achieve maximum utility or satisfaction through the choice object, given their resource limitations. Perceived value, therefore, represents an overall estimation of the choice object for the decision making. Once a value has been internalized, it becomes a criterion for developing and maintaining the intention toward relevant objects and situations [48,66].Thus, the cognitive aspect of a person's attitudes may largely consist of expectations about how her values are served through the agency of the attitude object [38,66]. Hence, we expect a similar relationship between perceived value of information disclosure and positive attitudes toward information disclosure in the LAM context:

Hypothesis 5. Perceived value of information disclosure is positively related to willingness to have personal information used in LAM.

Previous advertising research has shown that the degree to which consumers accept the marketing messages is the best predictor of sales effects [32]. Recent empirical studies have highlighted the positive relationship between attitude toward advertising and purchase intention in many of the online shopping empirical researches [37,39]. Hence, we argue that mobile consumers who are willing to have their personal information used in LAM should be very interested in marketing promotions in their vicinity and thus they are more likely to make a purchase. Therefore, we hypothesize:

Hypothesis 6. Willingness to have personal information used in LAM is positively related to purchase intention.

2.3. Influences of individual characteristics

Scholars have argued that privacy relevant beliefs and technology acceptance should be better related to individuals' own experiences and characteristics rather than be regarded as a global consequence of technology use per se [65]. Thus another hypothesized source of influences in the research framework is related to individual characteristics. In this research, the individual characteristics we examine are previous privacy invasion experience, personal innovativeness and coupon proneness.

When customers provide their information to online companies, a "social contract" is initiated when there are expectations of social norms (i.e., generally understood obligations) that govern the behavior of those involved [14]. One generally understood social contract is that firms will undertake the responsibility to manage consumers' personal information properly [51]. Consumers may consider such an implied contract breached if they think their personal information has been misused [21,51]. In the context of online marketplaces, it has been found that an online consumer's perceived contract violation by a single online seller could lead to the perception of contract violation by the entire community of online sellers [49]. Thus, individuals who have been exposed to or have been the victim of personal information abuses could have stronger concerns regarding information privacy [59]. Therefore, we argue that previous experiences of privacy invasion should increase individuals' risk perceptions of information disclosure in LAM.

Hypothesis 7. Previous privacy invasion experience is positively associated with perceived risk of information disclosure.

Two individual-specific traits are examined in this research. First, personal innovativeness, defined as willingness of an individual to try out new technology [3], has long been examined in the research of innovation diffusion and technology adoption. As an individual-specific trait, Rogers [54] noted that individuals with higher innovativeness exhibit certain characteristics and behaviors such as active information seeking, greater exposure to mass-media, and less reliance on subjective evaluation of other members in their social circle about the innovation. This implies that those who are more innovative are likely to disclose personal information to try out LAM than others. Second, as another individual-specific trait, coupon proneness is defined as the propensity to respond to a purchase offer [43]. We argue that people who enjoy collecting conventional or electronic coupons might be more likely to accept LAM. Hence, we hypothesize that the coupon form of the promotional information positively affects users' willingness to have personal information used in LAM:

Hypothesis 8. Personal innovativeness is positively associated with willingness to have personal information used in LAM.

Hypothesis 9. Coupon proneness is positively associated with willingness to have personal information used in LAM.

2.4. Moderating impacts of personalization approaches

2.4.1. Covert versus overt personalization approaches

To offer personalized ads that are tailored to mobile users' activity contexts, marketers and advertisers gather personal location information through mobile communication and positioning systems in two ways — covert and overt approaches [60]. In the *covert* approach, marketers send relevant ads to users by covertly ‘observing’ their behavior through tracking physical locations of their mobile devices. With these data, personalization systems tailor the ads based on the user's known proximity to a store or merchant. Haag et al. [31] describes a covert-based application that pushes video rental information to customers: whenever appearing in the vicinity of a participating video store, the customer's mobile phone triggers a system within the video store that evaluates that customer's rental history against store inventory. If the system indicates an available video will be of interest, it sends a text message to the customer's mobile phone with the rental details on the film.

Different from the covert approach, the *overt* personalization systems only locate users' mobile devices when they initiate the requests. This type of LAM may be seen in some ‘on demand’ services where the user dials or signals a service provider for specific information/service such as the coupons for the nearest Starbucks store. In this approach, location information is ephemeral and useful only to complete the transaction requested (e.g., sending coupons of the nearest Starbucks to the user). One example was a service launched by ZagMe in the United Kingdom [12]. By calling a number or sending a text message to activate location tracking, customers could receive promotional information and coupons through text messages based on their geographical location in a designated mall.

2.4.2. Impacts on the association between personalization and privacy calculus

As discussed earlier, higher levels of personalization should lead to higher level of perceived benefits of information disclosure. However, this relationship is likely to be contingent on the type of personalization approaches. The covert approach enables a higher level of flexibility and mobility because it allows delivery of dynamic content directly to a pre-determined and intended group of users in real time without any explicit efforts by users [35]. Hence, comparing to the overt-based LAM, the covert-based LAM should increase the level of timeliness and locatability of information access as the covert personalization systems enable users to obtain their needed information as soon as it is available [35]. Moreover, for the covert-based LAM, a user may perceive higher level of personalization value when the service content adapts itself automatically based on the user's profile without the user's involvement. Thus service providers could deliver a greater quantity of personalized promotional information and coupons based on customers' interests, geographical locations, and time of day. Therefore, the covert-based LAM should have the advantages of improving the timeliness and locatability of personalized information delivery, which should amplify the impacts of personalization on perceived benefits of information disclosure. Thus, we hypothesize:

Hypothesis 10a. The predicted positive association between personalization and perceived benefits of information disclosure will be stronger when the personalization approach is covert than when it is overt.

As prior studies have confirmed that the ability of the consumer to control the disclosure of personal information could offset the risk of possible negative consequences [26], we contend that the level of control over the interaction may moderate the relationship between perceived privacy risk and intention to disclose personal information. We further presuppose that different levels of control over the disclosure of personal information accordingly vary in the context of LAM [30,42,63]. In essence, in the overt-based LAM where the consumer's decision to initiate contact with the marketer is volitional, the consumer exercises greater control over the interaction as location of the consumer is surrendered exclusively to complete the transaction requested [35,62]. The covert-based LAM departs from the overt-based LAM because the consumer's location is constantly traceable and relevant commercial information is automatically sent to the consumer's mobile device according to his/her location and previously stated preferences [35,62]. As such, the covert-based LAM entails less control and less effort than the overt-based LAM which warrants higher levels of consequent time and cognitive investment to manage personal information. Despite the fact that the covert-based LAM may reduce the consumer's information processing and retrieval efforts, users might have to encounter the increasing amount of potentially irrelevant information. Therefore, it is conjectured that the covert-based LAM would be more intrusive to individual privacy and tend to interrupt the consumer because the consumer has less control over his/her interactions with service providers. This leads to the following hypothesis in regard to the impact of privacy risk perceptions:

Hypothesis 10b. The predicted positive association between personalization and perceived risks of information disclosure will be stronger when the personalization approach is covert than when it is overt.

2.4.3. Impacts on the individual characteristics

The personalization approaches may also act as a moderator that influences the relationship between privacy risk perceptions and interpersonal differences. As discussed earlier, the individual characteristics we examine in this research are previous privacy invasion experience, personal innovativeness and coupon proneness. In terms of previous privacy invasion experience, since the covert-based LAM would potentially trigger higher risk perceptions of information disclosure, individuals who have encountered privacy invasions should be more aware of undesirable consequences in the covert-based LAM based on previous experience. Thus those who encountered privacy invasions before should have higher privacy risk perceptions in the covert-based LAM. Hence, we hypothesize:

Hypothesis 10c. The predicted positive association between previous privacy invasion experience and perceived risk of information disclosure will be stronger when the personalization approach is covert than when it is overt.

The positive relationships between individual-specific traits (personal innovativeness and coupon proneness) and willingness to have personal information used in LAM may be moderated by the personalization approaches. It has been suggested in the literature that any innovation is associated with greater risk, uncertainty, and imprecision [61]. Rogers [54] argued that innovators and early adopters are able to cope with higher level of uncertainty. As such, a more innovative individual should be more likely to cope with higher risks inherent in the covert-based LAM, and thus should develop more positive attitudes toward the information disclosure in the covert-based LAM as compared to a less innovative individual. In terms of coupon proneness, since the covert-based LAM could potentially deliver more numbers of coupons or promotional messages based on users' physical locations, individuals who have higher level of coupon proneness should be more willing to have personal information used in the covert-based LAM. Hence, we hypothesize:

Hypothesis 10d. The predicted positive association between personal innovativeness and willingness to have personal information used in LAM will be stronger when the personalization approach is covert than when it is overt.

Hypothesis 10e. The predicted positive association between coupon proneness and willingness to have personal information used in LAM will be stronger when the personalization approach is covert than when it is overt.

3. Research method

3.1. Scale development

To the extent possible, we adapted constructs from measurement scales used in prior studies to fit the LAM context (see Appendix A). *Purchase intention* (PINT) is a common effectiveness measure and often used to anticipate a response behavior. Respondents were often asked to evaluate an advertisement or product and then indicate their intention to purchase [8]. We used two items to measure the likelihood that subjects would purchase a product [53]. *Willingness to have personal information used in LAM* (WPI) was assessed based on two questions adapted from Culnan and Armstrong [22]. And *perceived benefits of information disclosure* (BEN) was measured with three items taken from Unni and Harmon [62]. *Perceived value of information disclosure* (VAL) was assessed based on three items taken from Kim et al. [38]. Consistent with prior privacy literature [25], we operationalized *perceived risks of information disclosure* (RISK) as a single-dimensional construct and defined it as the expectation of losses associated with the release of personal information. We measured *personalization* (PER) using three seven-point Likert scale items to reflect how much the LAM can be tailored to individuals' preferences, location and needs [68]. With regard to personal characteristics, *personal innovativeness* (INNV) was assessed with items taken from Agarwal and Prasad [3], *coupon proneness* (COUP) was measured with four questions taken from Lichtenstein et al. [43], and *previous privacy experience* (PPRE) was measured with questions adapted from Smith et al. [59].

3.2. Experiment design

We conducted an experiment to test the proposed model. LAM in our experiment was introduced as the personalized advertising services on mobile phones that have the ability to determine a user's geographical locations. This study was designed as a one-factorial experiment manipulating personalization approach (covert and overt) with participants randomly assigned to one of the two groups. One specific covert-based scenario and one overt-based scenario, i.e., location-aware Mobile Coupon (M-Coupon) services described in Haag et al. [31] and Buckley [12], were adapted in this study to have two balanced experiment scenarios. The covert-based M-Coupon service would involve recruiting consumers by service registration and interest subscription: consumers could register their mobile phone numbers and subscribe to a list of merchants that provided M-Coupon services, based on their interests and preferred period of time for receiving coupons. Profiling information would then be used to target the subscribers, and their mobile phones would be sent related promotional information when they came within the vicinity of their favorite stores. In the overt-based scenario, when consumers wanted to look for promotional information or coupons from merchants, they could dial a certain number and their location would be detected automatically via their mobile phones. The requested coupons from the nearest merchants would then be delivered to their mobile phones via text messages.

3.3. Participants

A total of 545 undergraduate and graduate students were recruited in a large university. The recruitment advertisement provided some background about the study without revealing the experimental details, and specified that participants must own a mobile phone to participate in the experiment. Specific demographic information of participants is given in Appendix B. Most of our participants had used mobile devices for at least two years (92%). While some might express concern about the use of student subjects, we do not think that this limits the generalizability of the results. In this study, university students are naturally a part of the population of interest, and they are active users of wireless applications. As mobile devices and mobile applications have become part of young people's daily routines [50], we believed that the use of university students as potential LAM users was appropriate.

3.4. Procedure and task

At the start of each experimental session, the subjects were told that all instructions were provided online and that they should read the instructions carefully and complete the experiment independently. After logging into our experiment system, all participants began the experiment by answering a pre-session questionnaire about their personal information and characteristics. As commonly used in marketing experiments that investigate consumer behavior, a cover story was provided to all the participants. They were told that location-aware M-Coupon service would soon be introduced in the local market, and their feedback would be very important for the evaluation of the service. Next, the subjects were randomly assigned to either the covert-based or the overt-based LAM scenarios. The subjects were asked to assume the role of an M-coupon service subscriber and were presented with the scenarios of using the covert-based or the overt-based M-Coupon service, which took the form of the interactive flash animation. Then the subjects were asked to complete a post-session questionnaire on the research constructs.

4. Data analysis and results

To address the threat of a common method bias [52], we performed Harman's single factor test by simultaneously loading all items from the combined dataset in the factor analysis using Varimax rotation. All indicators showed high factor loadings and low cross-loadings. Each principal component explained almost an equal amount of the 72% total variance, ranging from 7% to 13%. This indicates that our data do not suffer from common method bias.

4.1. Analysis strategy

A second-generation causal modeling statistical technique — partial least squares (PLS), was used for data analysis in this research. PLS is well suited for highly complex predictive models [17]. Prior research that applied PLS [36] has claimed that PLS is best suited for testing complex relationships by avoiding inadmissible solutions and factor indeterminacy. This makes PLS suitable for accommodating the relatively complex relationships among various constructs in current research. To test the influences of information delivery mechanisms, we split the datasets into two subsets and thus the measurement and the structural models were tested twice: once for the covert-based subset and the other for the overt-based subset.

Table 1

a. Overt

	Composite Reliability	Cronbach's Alpha	Variance Extracted	PER	BEN	RISK	VAL	WPI	PINT	PPRE	INNV	COUP
PER	.88	.80	.72	.85								
BEN	.93	.88	.81	.36	.90							
RISK	.93	.89	.82	.09	-.18	.91						
VAL	.89	.81	.74	.50	.28	-.15	.86					
WPI	.97	.93	.94	.29	.23	-.17	.51	.97				
PINT	.85	.90	.74	.36	.17	-.14	.40	.40	.86			
PPRE	.92	.82	.85	-.03	-.03	.07	.04	-.03	.01	.92		
INNV	.90	.84	.75	.12	.15	-.13	.21	.20	.19	.12	.87	
COUP	.93	.88	.81	.07	.05	-.03	.10	.08	.16	.15	.17	.90

b. Covert

	Composite Reliability	Cronbach's Alpha	Variance Extracted	PER	BEN	RISK	VAL	WPI	PINT	PPRE	INNV	COUP
PER	.89	.81	.72	.85								
BEN	.91	.86	.78	.62	.88							
RISK	.94	.90	.83	.23	-.15	.91						
VAL	.87	.80	.70	.57	.43	-.23	.84					
WPI	.97	.95	.95	.32	.28	-.22	.57	.97				
PINT	.81	.91	.68	.37	.15	-.19	.43	.46	.82			
PPRE	.93	.86	.88	-.03	-.05	.20	.05	-.07	.01	.94		
INNV	.91	.86	.76	.16	.17	-.18	.22	.23	.20	.12	.87	
COUP	.91	.85	.78	.08	.05	-.05	.21	.24	.18	.15	.17	.88

4.2. Evaluating the measurement model

We evaluated the measurement model by examining the convergent validity and discriminant validity of the research instrument. Convergent validity is the degree to which different attempts to measure the same construct agree [20]. In PLS, three tests are used to determine the convergent validity of measured reflective constructs in a single instrument: Cronbach alpha, composite reliability of constructs, and average variance extracted by constructs. Nunnally [47] proposed 0.7 as an indication of adequate Cronbach alpha. We assessed item reliability by examining the loading of each item on the construct, and found that the reliability score for all the items exceeded the criterion of 0.707 (see Appendix A). PLS computes composite reliability of constructs by taking into account relationships among constructs. As shown in Table 1a and b, composite reliabilities of constructs with multiple indicators exceeded Nunnally's [47] criterion of 0.7. The variance extracted by constructs was computed based on the extent to which all items measuring a construct actually tap into the same underlying construct. The average variances extracted for the constructs were all above Fornell and Larcker's [29] criterion of 50%. These tests support the convergent validity of the measurement model.

Discriminant validity is the degree to which measures of different constructs are distinct [13]. To test discriminant validity, the square root of the variance shared between a construct and its measures should be greater than the correlations between the construct and any other construct in the model. Table 1a and b reports the results of discriminant validity which may be seen by comparing the diagonal to the non-diagonal elements. All items in our experiment fulfilled the requirement of discriminant validity.

4.3. Testing the structural model

After establishing the validity of the measures, we tested the structural paths in the research model using PLS. We conducted hypothesis tests by examining the sign and significance of the path coefficients. Each hypothesis should be tested based on the sign and statistical significance for its corresponding path in the structural model. Table 2 presents the results of hypothesis testing. The

Table 2
Results of the structural model.

Hypotheses	Coefficient		Supported
	Covert m = 267	Overt n = 278	
H1: Personalization → perceived benefits of info disclosure	0.62**	0.25**	Yes
H2: Personalization → perceived risks of info disclosure	0.29**	0.06	Partially supported for covert
H3: Perceived benefits of info disclosure → perceived value of info disclosure	0.56**	0.48**	Yes
H4: Perceived risks of info disclosure → perceived value of info disclosure	−0.32**	−0.20**	Yes
H5: Perceived value → willingness to disclose info	0.60**	0.56**	Yes
H6: Willingness to disclose info → purchase intention	0.47**	0.41**	Yes
H7: Previous privacy experience → perceived risks of info disclosure	0.20**	0.07	Partially supported for covert
H8: Personal innovativeness → willingness to disclose info	0.19**	0.11*	Yes
H9: Coupon proneness → willingness to disclose info	0.15**	0.04	Partially supported for covert

* Significant at 5% level of significance.
** Significant at 1% level of significance.

explanatory power of the structural model is assessed based on the amount of variance explained in the endogenous construct (i.e., purchase intention). Our structural models for covert and overt approaches could explain 39.7% and 35.8%, respectively, of the variance for purchase intention. This greatly exceeded 10%, which was suggested by Falk and Miller [27] as an indication of substantive explanatory power.

Our results indicate that personalization was positively related to perceived benefits of information disclosure for both covert and overt approaches (H1 was supported). In support of H3 and H4, the positive relationship between perceived benefits of information disclosure and perceived value, and the negative relationship between privacy risk and perceived value were found significant in both covert and overt approaches. Perceived value of information disclosure was positively related to willingness to have personal information used in LAM (WPI) (H5 was supported); WPI was found to positively relate to purchase intention (H6 was supported). The proposed impact of personalization on privacy risk was significant in the covert approach but insignificant in the overt approach (H2 was partially supported).

H7, H8 and H9 postulate the influence of personal characteristics on privacy risk and WPI. In support of H8, the positive relationship between personal innovativeness and WPI was found significant in both covert and overt approaches. However, the proposed impact of precious privacy experience on privacy risk was significant in the covert approach but insignificant in the overt approach (H7 was partially supported). Also, the proposed impact of coupon proneness on WPI was significant in the covert approach but insignificant in the overt approach (H9 was partially supported).

Hypotheses related to the moderating effects of covert versus overt personalization approaches (H10a–H10e) were tested with the multi-group analysis suggested by Chin [17,18]. The multi-group analysis was conducted by testing the effects of the personalization approaches with the PLS-generated path coefficients and their standard errors. The results of these tests are shown in Table 3. In support of H10a and H10b, the positive relationship between personalization and perceived benefits of information disclosures was stronger for the covert approach (t (543) = 14.94, $p<0.01$); and the positive relationship between personalization and privacy risks was also stronger for the covert approach (t (543) = 4.57, $p<0.05$). H10c on the positive relationship between previous privacy experience and privacy risks (t (543) = 2.01, $p<0.05$), H10d on the positive relationship between personal innovativeness and intention to use (t (543) = 2.08, $p<0.05$), and H10e on the positive relationship between coupon proneness and intention to use (t (543) = 2.60, $p<0.01$) were all shown stronger for the covert approach.

4.4. Further analyses on purchase intention: spontaneous versus deliberate purchases

Drawing on Baumgartner's [6] typology of purchase intentions, we further analyzed the purchase intention for those subjects who

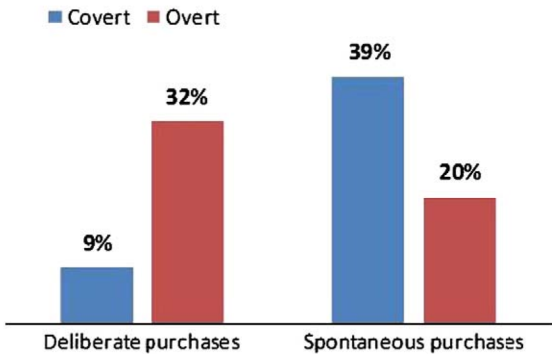

Fig. 2. Spontaneous versus deliberate purchase behaviors.

indicated their purchase intentions in this study (i.e., their ratings on purchase intentions were higher than the neutral value of 4). In his typology of purchase intentions, Baumgartner [6] categorizes two distinct forms of purchase intentions:

1) Deliberate purchases: these purchases are typically classified as being predictable, repeatable, and routine and usually include:
   a) extended purchase (e.g., making a purchase based on objective, logical criteria and for utilitarian reasons);
   b) symbolic purchase (e.g., making a purchase to project a certain image or because it meets with social approval);
   c) repetitive purchase (e.g., making a routine purchase or buying something because you are loyal to it);
   d) hedonic purchase intention (e.g., buying something because you like it).
2) Spontaneous purchases: these purchases are typically classified as being unpredictable, non-repeatable, and non-routine and usually include:
   a) promotional purchase (e.g., buying something because it is on sale);
   b) exploratory purchase intention (e.g., buying something out of curiosity or because of a desire for variety);
   c) casual purchase intention (e.g., buying something without thinking much);
   d) impulsive purchase intention (e.g., buying something on impulse).

We used a multiple-answer question "you decide to buy the movie ticket because…" to gain more insights based on the types of purchase intention classified by Baumgartner [6]. Among those subjects whose ratings on purchase intentions were higher than the neutral value of 4 (see Fig. 2): 39% of the subjects in the covert scenario and 20% of them in the overt scenario were spontaneous purchases; 9% of the subjects in the covert scenario and 32% of them in the overt scenario were deliberate purchases. It appears that the covert-based LAM is more

Table 3
Results on moderating impact of covert versus overt personalization approach.

Hypotheses	Coefficient (standard error)		t	Supported
	Covert m = 267	Overt n = 278		
H10a: Personalization → perceived benefits of info disclosure (covert > overt)	0.62 (0.047)	0.25 (0.048)	14.94**	Yes
H10b: Personalization → perceived risks of info disclosure (covert > overt)	0.29 (0.067)	0.06 (0.068)	4.57**	Yes
H10c: Previous privacy experience → perceived risks of info disclosure (covert > overt)	0.20 (0.066)	0.07 (0.059)	2.01*	Yes
H10d: Personal innovativeness → intention to use (covert > overt)	0.19 (0.039)	0.11 (0.052)	2.08*	Yes
H10e: Coupon proneness → intention to use (covert > overt)	0.15 (0.043)	0.04 (0.063)	2.60**	Yes

* Significant at 5% level of significance.
** Significant at 1% level of significance.

likely to trigger consumer spontaneous purchases. Limited by the simulated LAM experience, the influences of the covert-based LAM on spontaneous purchase in our study could be largely under-estimated. Despite this, the results have indicated that the covert-based LAM has the potential to trigger spontaneous purchases.

5. Discussions and implications

5.1. Discussion of findings

The goal of this study was to investigate the dynamics of privacy–personalization paradox when dealing with the disclosure of personal information in the LAM context. Toward this end, we constructed a conceptual model that features the roles of the covert and the overt personalization approaches as well as personal characteristics in individuals' privacy decision making process. Through a privacy calculus lens, we argued that personalization approaches and personal characteristics should influence the way individuals balance between the utility gained by disclosing personal information in LAM and the disutility of the adverse effects of such an action. In addition, our results provided some preliminary evidence to indicate that the covert-based LAM was more likely to entice spontaneous purchases.

The results also suggested that personalization can somehow override privacy concerns for both covert-based and overt-based LAM. Among the hypotheses on the relationships between personalization and perceived benefits/risks of information disclosure, the consumers' value for personalization (path coefficient for $PER \rightarrow BEN$ is 0.62) was almost two times more influential than their concerns for privacy (path coefficient for $PER \rightarrow RISK$ is 0.29) in the covert-based LAM; and the proposed relationship between personalization and privacy risks was insignificant in the overt-based LAM. These results suggested that consumers could more likely regard LAM as valuable if advertising messages are perceived to be relevant and customized to their context.

Although the empirical results provided overall support for the research model, they also revealed a few unexpected relationships that were not consistent with what we had hypothesized. While the proposed positive association between personalization and privacy risks was significant in the covert model, such relationship was not significant in the overt model. Drawing on prior research, we argued that the influences of personal characteristics in affecting privacy risks and willingness to disclose information would be different for the covert and the overt personalization approaches. Our results confirmed that the impact of personal innovativeness on willingness to disclose information was significant for both covert and overt models. However, the influences of previous privacy experience on users' privacy risk perceptions varied under different personalization models: previous privacy experience had an impact on increasing users' privacy risk perceptions in the covert model but this was not the case with the overt model. Likewise, coupon proneness had an impact on enhancing users' willingness to disclose personal information in the covert model but its effect was not significant in the overt model.

As to the insignificance of personalization and previous privacy experience in increasing users' privacy risk perceptions for the overt-based LAM, a possible explanation is because of the higher level of control inherent in the overt-based LAM. As discussed earlier, users exercise greater control over the interaction in the overt-based LAM: the decision to initiate contact with a merchant is volitional, and location information is disclosed only to complete the transaction requested. Thus, even for individuals who have been exposed to or have been the victim of personal information abuses, they may not worry too much about their privacy because of higher levels of control over releasing personal information. A plausible explanation for the insignificance of coupon proneness is that the use of the overt-based LAM is initiated by a well-defined need or desire, and to the extent that users seek fulfillment of their needs, the importance of the coupon proneness as an additional impetus diminishes.

5.2. Limitations and future research

It has been generally acknowledged that research on information systems can be carried out in a wide range of settings and by a variety of strategies [7]. Moreover, Dennis and Valacich [24] indicate that there is no perfect research because different strategies carry comparative strengths and weaknesses. As research on LAM is in the early stages, our exploratory efforts represent one of the first attempts to examine LAM personalization approaches and its influences on the personalization privacy paradox. So this study inevitably suffers from several limitations.

McGrath [45] argues that all empirical designs are subject to in here limitations because of the trade-offs between various research designs. According to his contention in respect to the research dilemma in three dimensions, we are aware that, as our object is to gain precision and control in the contrived settings, there is a corresponding loss of generalizability and realism. Researchers are encouraged to build upon our work and overcome its limitations in their future studies. First, the scenarios used in the study represent a simplification of all the covert-based and the overt-based LAM, which may limit the generalizability of our findings. Future work could examine the applicability of our findings to different LAM applications. Second, the value of LAM (especially for the covert-based LAM) could depend on how well a marketer or service provider anticipates the needs of consumers. For the purposes of this study, we assume that LAM matches consumer needs with high accuracy of location detection. Future research may examine how these factors may affect consumers' attitudes toward LAM.

Third, although we restricted our examination of risk-related factors only to privacy, a more comprehensive examination of risks that affect value perceptions is needed. Fourth, since earlier studies have shown that mobile advertising could be more effective for frequently purchased, low-cost products than for more expensive products [5], it is important to investigate the effectiveness of LAM for different types of products in future research. Related to this area is the potential for LAM to trigger spontaneous purchases. Although the subjects in this study may fall in the target market for LAM, the generalizability of this research to the general population is likely to be affected. Future research should be conducted with a more diverse sample for improved generalizability. Finally, future research may look into the possibility of further strengthening the extant instrument items such as Perceived Value of Information Disclosure (VAL) employed for this study in a different context.

5.3. Contributions and implications

Through the causal modeling of antecedents affecting personal information disclosure in LAM and purchase intention, our findings provide preliminary theoretical insights and empirical evidence into the dynamic structural relationships of these factors under two different types of personalization approaches. As pointed out by Chan et al. [15], there is a lack of research examining the role of technological attributes in influencing the theoretical development of privacy. This study attempts to fill in this gap by looking into the impacts of the covert and the overt personalization approaches (as one technological attribute) on users' privacy reactions to LAM. Findings from this research can help technology promoters and website operators better understand the personalization privacy paradox in other contexts such as social advertising [56]. The theoretical framework developed in this study can be applied in other personalization technologies or systems to assess its applicability across different contexts.

The current study strives to further extend prior research on privacy calculus in several ways. First, the findings of this study suggest that the conventional understanding of privacy as a calculus can be applied to explain to the personalization privacy paradox in the new LAM context. Serving as a starting point for future research in personal privacy, this research is an initial examination of issues relating to the roles of the covert and the overt personalization approaches as well as personal characteristics in the individuals' privacy decision making process. Second, the findings in this study highlight the contextual nature of privacy decision-making. The finding that the association between personalization and privacy risks was significant only in the covert-based LAM indicates that the conceptual structure of personalization privacy paradox is context-dependent. This has important implications for theoretical development since it opens a new avenue for the exploration of contextual nature of personalization privacy paradox. Even when certain factors influencing the personalization privacy paradox are potentially significant in all contexts, their relative importance may change depending on different technological attributes and personal characteristics.

From a practical perspective, this study has implications for various players in the LAM industry: application designers, merchants, marketers, LAM service providers, and privacy advocates. This research sends contradictory signals to LAM application designers and marketers. On the one hand, it suggests that the covert-based LAM may impose a higher level of privacy risks to users. But, on the other hand, it is evident that the covert-based LAM does trigger higher level of personalization value. Hence, with the covert-based design as a double-edged sword, the LAM application designers and marketers need to be aware of the tradeoff between *privacy* and *personalization* when selecting personalization approaches in LAM. The main advantage in pursuing a covert design is the opportunity to deliver more personalized marketing messages as well as the opportunity to trigger impulse buying. However, such covert-based approach would also increase mobile users' privacy concerns due to the location tracking. Thus LAM designers and marketers need to focus on allaying privacy concerns for the covert-based LAM through implementing privacy intervention strategies. For example, LAM application developers could build privacy enhancing features into the applications (whereby users may turn-off the LAM application anytime or may mask their locations); or LAM service providers may consider developing organizational privacy policies or participating in some privacy certification programs such as TRUSTe.

6. Conclusion

As an exploratory study, the findings of this research have provided preliminary empirical evidence about how users strike a balance between value and risk. The current research contributes to existing literature by theoretically investigating the personalization privacy paradox through a privacy calculus lens, for different personalization approaches (covert versus overt), to different individuals, in an understudied LAM environment. Our initial findings that the influence of personalization on the privacy calculus model depends on the type of personalization approaches as well as personal characteristics suggest the need for future studies to understand these effects more thoroughly. Using the groundwork laid in this study, future research along various possible directions could contribute to extending our theoretical understanding and practical ability to foster the acceptance of LAM.

Appendix A. Survey instrument

Construct	Question wording	Loading	
		Covert	Overt
Perceived value of information disclosure (VAL)	I think my benefits gained from the use of M-Coupon service can offset the risks of my information disclosure.	0.89	0.90
	The value I gain from use of M-Coupon service is worth the information I give away.	0.87	0.87
	I think the risks of my information disclosure will be greater than the benefits gained from the use of M-Coupon service. (*reverse scale*)	0.73	0.80
Perceived benefit of information disclosure (BEN)	M-Coupon service reduces my searching time to find the promotional information that I need.	0.88	0.85
	M-Coupon service can provide me with the convenience to instantly access the promotional information that I need.	0.86	0.93
	Overall, I feel that using M-Coupon service is beneficial.	0.91	0.92
Perceived risk of information disclosure (RISK)	Providing the service provider with my personal information would involve many unexpected problems.	0.86	0.87
	It would be risky to disclose my personal information to the service provider.	0.94	0.94
	There would be high potential for loss in disclosing my personal information to the service provider.	0.93	0.91
Personalization (PER)	M-Coupon service can provide me with personalized deals/ads tailored to my activity context.	0.88	0.80
	M-Coupon service can provide me with more relevant promotional information tailored to my preferences or personal interests.	0.84	0.86
	M-Coupon service can provide me with the kind of deals/ads that I might like.	0.82	0.87
Previous privacy experience (PPRE)	How often have you personally been victim of what you felt was an invasion of privacy?	0.92	0.93
	How much have you heard or read during the last year about the use and potential misuse of personal information about consumers?	0.95	0.91
Personal innovativeness (INNV)	If I heard about a new information technology, I would look for ways to experiment with it.	0.90	0.79
	Among my peers, I am usually the first to try out new information technologies.	0.88	0.89
	I like to experiment with new information technologies.	0.84	0.91
Coupon proneness (COUP)	I enjoy collecting coupons.	0.89	0.86
	Beyond the money I save, redeeming coupons gives me a sense of joy.	0.87	0.92
	I enjoy using coupons, regardless of the amount I save by doing so.	0.89	0.91
Purchase intention (PINT)	How interested would you be in buying the movie ticket?	0.81	0.89
	How likely would you buy the movie ticket?	0.84	0.72
Willingness to have personal information used in LAM (WPI)	How interested would you be in having your personal information (including your location) used in the M-Coupon service?	0.98	0.97
	How likely would you provide your personal information (including your location) to use the M-Coupon service?	0.97	0.96

Appendix B. Respondent demographics

Demographic variables	Category	Frequency (percent)
Gender	Female	241 (44.3%)
	Male	304 (55.7%)
Age	18–24	284 (52.2%)
	25–29	140 (25.6%)
	30–39	60 (11.0%)
	40–49	49 (9.0%)
	50 and over	12 (2.2%)
Mobile phone ownership	Less than 12 months	44 (8.1%)
	12 months to 24 months	75 (13.8%)
	25 months to 36 months	99 (18.1%)
	More than three years	327 (60.0%)
Mobile application usage for the past six months	Never	138 (25.4%)
	Below 10 times	244 (44.8%)
	10 to 29 times	135 (24.8%)
	30 to 49 times	19 (3.5%)
	50 times and above	9 (1.5%)
Internet usage	Several times each week	28 (5.2%)
	Once per day	83 (15.2%)
	Several times each day	434 (79.6%)

References

[1] ABI, Mobile Location based services: applications, platforms, positioning technology, handset evolution, and business model migration in: ABI Research, (Allied Business Intelligence Inc, 2009).
[2] G. Adomavicius, A. Tuzhilin, Personalization technologies: a process-oriented perspective, Communications of the ACM 48 (10) (2005) 83–90.
[3] R. Agarwal, J. Prasad, A conceptual and operational definition of personal innovativeness in the domain of information technology, Information Systems Research 9 (2) (1998) 204–215.
[4] N.F. Awad, M.S. Krishnan, The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization, MIS Quarterly 30 (1) (2006) 13–28.
[5] P. Barwise, C. Strong, Permission-based mobile advertising, Journal of Interactive Marketing 16 (1) (2002) 14–24.
[6] H. Baumgartner, Toward a personology of the consumer, Journal of Consumer Research 29 (September 2002) 286–292.
[7] I. Bebbasat, An analysis of research methodologies, in: M. FW (Ed.), The Information Systems Research Challenge, HBS Press, Boston, MA, 1984, pp. 47–85.
[8] A. Beerli, M.D.J. Santana, Design and validation of an instrument for measuring advertising effectiveness in the printed media, Journal of Current Issues and Research in Advertising 21 (2) (1999) 11–30.
[9] E. Beinat, Privacy and location-based services: stating the policies clearly, GeoInformatics 4 (2001) 14–17.
[10] P. Bellavista, A. Kupper, S. Helal, Location-based services: back to the future, IEEE Pervasive Computing 7 (2) (2008) 85–89.
[11] R.A. Beresford, F. Stajano, Location privacy in pervasive computing, IEEE Pervasive Computing 1 (2003) 46–55.
[12] R. Buckley, Location based advertising — theory and practice, in, (White Paper, 2007).
[13] D.T. Campbell, D.W. Fiske, Convergent and discriminant validation by the multitrait-multimethod matrix, Psychological Bulletin 56 (1) (1959) 81–105.
[14] M.E. Caudill, E.P. Murphy, Consumer online privacy: legal and ethical issues, Journal of Public Policy & Marketing 19 (1) (2000) 7–19.
[15] Y.E. Chan, M.J. Culnan, K. Greenaway, G. Laden, T. Levin, H.J. Smith, Information privacy: management, Marketplace, and Legal Challenges, Communications of AIS 16 (2005) 593–634.
[16] R.K. Chellappa, R. Sin, Personalization versus privacy: an empirical examination of the online consumer's dilemma, Information Technology and Management 6 (2) (2005) 181–202.
[17] W.W. Chin, The partial least squares approach to structural equation modeling, in: G.A. Marcoulides (Ed.), Modern Methods for Business Research, Lawrence Erlbaum Associates, Mahwah, NJ, 1998, pp. 295–336.
[18] W.W. Chin, Multi-Group analysis with PLS: frequently asked questions — partial least squares & PLS-Graph, in, (2004).
[19] R. Clarke, Person location and person tracking: technologies, risks and policy implications, Information Technology & People 14 (2) (2001) 206.
[20] M. Cook, D.T. Campbell, Quasi-Experimentation: Design and Analysis Issues for Field Settings, Houghton Mifflin, Boston, 1979.
[21] M.J. Culnan, Consumer awareness of name removal procedures: implication for direct marketing, Journal of Interactive Marketing 9 (1995) 10–19.
[22] M.J. Culnan, P.K. Armstrong, Armstrong, information privacy concerns, procedural fairness and impersonal trust: an empirical investigation, Organization Science 10 (1) (1999) 104–115.
[23] M.J. Culnan, J.R. Bies, Consumer privacy: balancing economic and justice considerations, Journal of Social Issues 59 (2) (2003) 323–342.
[24] A.R. Dennis, J.S. Valacich, Conducting research in information systems, Communications of AIS 7 (5) (2001) 1–41.
[25] T. Dinev, P. Hart, An extended privacy calculus model for e-commerce transactions, Information Systems Research 17 (1) (2006) 61–80.
[26] R.E. Eddy, L.D. Stone, F.E. Stone-Romero, The effects of information management policies on reactions to human resource information systems: an integration of privacy and procedural justice perspectives, Personnel Psychology 52 (1999) 335–358.
[27] R.F. Falk, N.B. Miller, A Primer for Soft Modeling, University of Akron Press, Akron, Ohio, 1992.
[28] M.S. Featherman, P.A. Pavlou, Predicting e-services adoption: a perceived risk facets perspective, International Journal of Human-Computer Studies 59 (4) (2003) 451–474.
[29] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research 18 (2) (1981) 39–50.
[30] A. Gidari, No 'L-commerce' without 'L-privacy': fair location information practices for mobile commerce, L-Commerce 2000 — the Location Services & GPS Technology Summit, 2000, Washington, D.C.
[31] S. Haag, M. Cummings, A. Phillips, Management Information Systems for the Information Age, 6th ed., McGraw-Hill Higher Education, Irwin, 2005.
[32] R.I. Haley, L.A. Baldinger, The ARF copy research validity project, Journal of Advertising Research 31 (2) (1991) 11–32.
[33] S.F. Houston, B.J. Gassenheimer, Marketing and exchange, Journal of Marketing 51 (4) (1987) 3–18.
[34] I. Junglas, R.T. Watson, The U-constructs: four information drives, Communications of AIS 17 (2006) 569–592.
[35] E.J. Kendall, E.K. Kendall, Information delivery systems: an exploration of Web pull and push technologies, Communications of the AIS 1 (1) (1999) 2–42.
[36] D. Kim, I. Benbasat, The effects of trust-assuring arguments on consumer trust in internet stores: application of Toulmin's model of argumentation, Information Systems Research 17 (3) (2006) 286–300.
[37] D.J. Kim, D.L. Ferrin, H.R. Rao, A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents, Decision Support Systems 44 (2) (2008) 544–564.
[38] H.W. Kim, H.C. Chan, S. Gupta, Value-based adoption of mobile internet: an empirical investigation, Decision Support Systems 43 (1) (2007) 111–126.
[39] H. Ko, C.-H. Cho, S.M. Roberts, Internet uses and gratifications: a structural equation model of interactive advertising, Journal of Advertising 34 (2) (2005) 57–70.
[40] A. Kobsa, Privacy-enhanced personalization, Communications of the ACM 50 (8) (2007) 24–33.
[41] P. Kourouthanassis, G. Roussos, Developing consumer-friendly pervasive retail systems, IEEE Pervasive Computing 2 (2) (2003) 32–39.
[42] S. Levijoki, Privacy vs location awareness, in, (Helsinki University of Technology, 2001).
[43] D.R. Lichtenstein, G.R. Netemeyer, S. Burton, Distinguishing coupon proneness from value consciousness: an acquisition-transaction utility theory perspective, Journal of Marketing 54 (1990) 54–67.
[44] N.K. Malhotra, S.S. Kim, J. Agarwal, Internet users' information privacy concerns (IUIPC): the construct, the scale, and a causal model, Information Systems Research 15 (4) (2004) 336–355.
[45] J.E. McGrath, Dilemmatics: the study of research choices and dilemmas, in: J.E. McGrath, R.J. Kulka (Eds.), Judgment Calls in Research, Sage Publications, Beverly Hills, CA, 1982, pp. 69–103.
[46] J.S. Miller, R.M. Wiseman, L.R. Gomez-Mejia, The fit between CEO compensation design and firm risk, Academy of Management Journal 45 (4) (2002) 745–756.
[47] J.C. Nunnally, Psychometric theory, 2nd ed., McGraw-Hill, New York, 1978.
[48] S. Oskamp, Attitudes and opinions, 2nd ed., Prentice-Hall, Edition, NJ, 1991.
[49] P.A. Pavlou, D. Gefen, Psychological contract violation in online marketplaces: antecedents, consequences, and moderating role, Information Systems Research 16 (2005) 372–399.
[50] E.P. Pedersen, Adoption of mobile internet services: an exploratory study of mobile commerce early adopters, Journal of Organizational Computing and Electronic Commerce 15 (2) (2005).
[51] J. Phelps, G. Nowak, E. Ferrell, Privacy concerns and consumer willingness to provide personal information, Journal of Public Policy and Marketing 19 (1) (2000) 27–41.
[52] M.P. Podsakoff, B.S. MacKenzie, J.Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, Journal of Applied Psychology 88 (5) (2003) 879–890.
[53] S. Putrevu, R.K. Lord, Comparative and noncomparative advertising: attitude effects under cognitive and affective involvement conditions, Journal of Advertising Research 23 (1994) 77–90.
[54] E.M. Rogers, Diffusion of Innovations, 4th ed., Free Press, New York, NY, 1995.
[55] G. Roussos, J. Tuominen, L. Koukara, O. Seppala, P. Kourouthanasis, G. Giaglis, J. Frissaer, A case study in pervasive retail, Proceedings of the 2nd International Workshop on Mobile Commerce, ACM, Atlanta, Georgia, 2002, pp. 90–94.
[56] S.T. Schmidt, Inside the Backlash against Facebook, TIME, 2006.
[57] H. Sheng, F. Nah, K. Siau, An experimental study on U-commerce adoption: the impact of personalization and privacy concerns, Journal of Associations for Information Systems (JAIS) 9 (16) (2008), Article 15.
[58] H. Sheng, F. Nah, K. Siau, An experimental study on ubiquitous commerce adoption: impact of personalization and privacy concerns, Journal of the Association for Information Systems 9 (6) (2008) 344–376.
[59] H.J. Smith, J.S. Milberg, S.J. Burke, Information privacy: measuring individuals' concerns about organizational practices, MIS Quarterly 20 (2) (1996) 167–196.

[60] S.S. Sundar, S. Marathe, Is it tailoring or is it agency? Unpacking the psychological appeal of customized news, the 89th Annual Convention of the Association for Education in Journalism and Mass Communication, 2006, San Francisco, CA.
[61] F. Thiesse, RFID, privacy and the perception of risk: a strategic framework, Journal of Strategic Information Systems 16 (2) (2007) 214–232.
[62] R. Unni, R. Harmon, Perceived effectiveness of push vs. pull mobile location-based advertising, Journal of Interactive Advertising 7 (2) (2007), http://www.jiad.org/article91.
[63] P. Wallace, A. Hoffmann, D. Scuka, Z. Blut, K. Barrow, i-Mode Developer's Guide, Addison-Wesley, Boston, Mass., 2002
[64] A.F. Westin, Privacy and Freedom, Atheneum, New York, 1967.
[65] H. Xu, The Effects of Self-Construal and Perceived Control on Privacy Concerns, in: Proceedings of the 28th Annual International Conference on Information Systems (ICIS 2007), 2007, Montréal, Canada.
[66] H. Xu, L.B. Oh, H.H. Teo, Perceived effectiveness of text versus multimedia location-based advertising messaging, International Journal of Mobile Communications 7 (2) (2009) 154–177.
[67] H. Xu, C. Zhang, P. Shi, P. Song, Exploring the role of overt vs. covert personalization strategy in privacy calculus, Best Paper Proceedings of 69th Annual Meeting of the Academy of Management (AOM 2009), 2009, Chicago, Illinois.
[68] A.V. Zeithaml, A. Parasuraman, A. Malhotra, A conceptual framework for understanding e-service quality: implications for future research and managerial practice, MSI Monograph, Marketing Science Institute, 2000.
[69] V.A. Zeithaml, Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence, Journal of Marketing 52 (July 1988) 2–22.

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