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An empirical investigation of the utilitarian, social benefits in LBS information disclosure—The moderating effect of the gender based social role theory

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ABSTRACT

The prior studies on information disclosure in location-based services (LBS) suggested that the perceived benefits of information disclosure in LBS were manifested by three benefits, namely, locatability, personalization, and social benefits. The three benefits might affect information disclosure intention differently. As an extension, individual factors, such as gender, may affect the relationship. However, according to literature, little research has investigated on the combined influence of the three benefits on the information disclosure intention in LBS with the gender as a moderator. Based upon the self-determination and social role theories, this study intends to bridge the gap empirically. The hypotheses are largely supported by 215 respondents. Unexpectedly, the research findings show that for females, locatability and personalization are more important in predicting their information disclosure intention, whereas for males, the social benefit has more of an impact on information disclosure intention, which is opposite to the hypotheses and convention. Furthermore, the research findings indicate that the behaviors of males and females may conform to the roles distributed within a society of this information age rather than to the personalities of the individuals. Finally, the implications are presented.

1. Introduction

Nowadays smartphones are equipped with more and more advanced positioning technologies (Knoop, Bakker, Tiberius, & Arem, 2017; Liu, Cruz, Ruptash, Barnard, & Juzwishin, 2017; Mou, Westland, Phan, & Tan, 2020; Wen, Chang, & Wan, 2016). A user's location information could be used by application (APP) developers to provide tailored services (Ning, Guo, Cheng, & Meng, 2009). These types of technology applications are Location-Based Services (LBS). LBS could become an omnipresent part of the everyday lives of individuals. Consumers may rely on LBS to gain social benefits and receive real-time rewards, such as traffic information, finding friends, obtaining discount coupons, or playing location related games (Koohikamali, Gerhart, & Mousavizadeh, 2015; Xu, Teo, Tan, & Agarwal, 2009; Xu, Luo, Carroll, & Rosson, 2011). The unprecedented availability of personal data provides many opportunities for business innovations (Cichy, Salge, & Kohli, 2014). The research has also shown that companies are storing this captured location information and are using and selling it for purposes sometimes not approved by consumer (Cichy et al., 2014; Jung & Park, 2018). In a long term, utilizing such data effectively will rely heavily on the willingness of individual customers to disclose their data (Cichy et al., 2014). Therefore, understanding information disclosure by individuals in LBS is important but has been inadequately studied.

The LBS literature shows that a user's overall perceived benefits, as an important predictor of LBS information disclosure intention, are influenced by the user's utilitarian benefits (i.e., locatability and personalization) (Xu et al., 2009, 2011). Using the information on people's whereabouts to provide location-targeted services, such as directions or product recommendations, generates utilitarian benefits (Zickuhr & Smith, 2011). Further, the literature suggests that social benefits may also influence a user's overall perceived benefits (Koohikamali et al., 2015). Social benefits means sharing location-related videos and photos by "check in" at specific locations could benefit friends or the society (Zickuhr & Smith, 2011). Few studies have been investigated on the combined influence of utilitarian benefits (locatability and personalization) and social benefits on a LBS user's

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information disclosure intention, which is the research focus in this study.

While the three types of benefits represent a user's diverse needs, different people have different need structures (Weber, 2000). However, there is little research on how individual differences affect the three types of benefits related to information disclosure intention in LBS. While individual differences could come from many aspects, such as demographics and prior usage experiences (Bostrom & Sein, 1990), the gender difference is our focus due to two considerations. First, gender is one of the most basic individual characteristics, as Weber (2000) found that males and females had different decision-making processes. For example, the research literature indicates that males normally consider the perceived usefulness as more important in using a new technology than do females (Weber, 2000). Second, knowing gender differences could provide practical management insights. Practitioners could use different marketing strategies to effectively manage different gender groups as gender information is easy to distinguish and obtain (Ko, Yen, Chen, Chen, & Yen, 2005). In summary, the overall objective of this research is to investigate the combined effects of locatability, personalization and social benefits on information disclosure intention in LBS with gender as a moderator. The specific research questions are as follows.

RQ1 Do locatability, personalization, and social benefits impact a user's information disclosure intention in LBS?

RQ2 Does gender moderate the relationship between locatability (or personalization, or social benefits) and a user's information disclosure intention in LBS?

2. Theoretical foundation and research hypotheses

2.1. Self-determination theory and perceived benefits

There are two kinds of benefits related to information disclosure behavior in the literature, i.e., utilitarian benefits and social benefits. Utilitarian benefits mean practical material issues, such as location information and personalized purchasing recommendations. Unlike utilitarian benefits, social benefits mean to care for others or society (Koohikamali et al., 2015). People could consider both utilitarian benefits and social benefits when disclosing information, but these two kinds of benefits may have different importance in different contexts.

The self-determination theory (SDT) is an important motivation theory (Ryan & Deci, 2000). SDT argues that an individual's behavior may be motivated by her own hobbies and interests or by external reasons. Some motivations are completely voluntary because they involve their own interests, while others are completely external, as when one is pressured into doing something. Motivations could be classified into intrinsic motivations and extrinsic motivations. Intrinsic motivation means "doing something for satisfying own inherent satisfaction", whereas extrinsic motivation means "doing something to obtain separable awards" (Ryan & Deci, 2000). The SDT would help to better understand the context under which utilitarian or social benefits are more important. Intrinsically motivated behaviors are those that are performed out of interest and values. The primary "rewards" are the spontaneous feelings of enjoyment and satisfaction that accompany the behaviors. Extrinsic motivations are those that are performed for some separable consequences, such as an external reward or the attainment of a valued outcome (Ryan & Deci, 2017). Extrinsic motivations refer to potential future rewards. Intrinsic motivations refer to prosocial decisions (for example, the desire to help others) (Allison, Davis, Short, & Webb, 2015). Caring for others (social benefit) is associated with intrinsic motivation (Folbre, 2012), and utilitarian benefits are associated with extrinsic motivation. The prior research suggests that utilitarian benefits include locatability and personalization (Xu et al., 2009). Locatability and personalization are important practically and theoretically. In the post-hoc interview that we conducted, all the eleven interviewees mentioned locatability and personalization. For example, the first interviewee mentioned "I use LBS for knowing the location information whenever I need and find hotels tailored to my preferences", which is similar to the ninth interviewee's response, stating that "I use LBS for knowing just-in-time location information and delicious food around me that I like". In addition, the past research also investigated the importance of locatability and personalization in studying mobile based services (e.g., Xu et al., 2009, 2011; Zhao, Lu, & Gupta, 2012), but few studies have investigated locatability, personalization and social benefit simultaneously. From the self-determination theory's perspective, locatability, personalization and social benefits are essential parts of the motivations in LBS. Therefore, we considered locatability and personalization in our research model. Our proposed research model could also help understand whether utilitarian benefits or social benefits may be more important in LBS.

The literature review (see Appendix A) shows that information disclosure intention is usually affected by perceived benefits and perceived risks. The perceived benefits have been largely investigated in the following two ways: the perceived benefits as an overall construct and a specific aspect of the perceived benefits. The specific aspects of perceived benefits include social benefits, financial benefits, utility benefits, utilitarian benefits, hedonic benefits, locatability, personalization, informational support, emotional support, and connectedness. Locatability and personalization would be classified as "extrinsic benefits" because they emphasize the utilitarian benefits. Social benefits would be conceptualized as "intrinsic benefits" because they indicate prosocial decisions (for example, the desire to help others). The extrinsic benefits and intrinsic benefits combined represent a more holistic landscape of motivations from the perspective of the self-determination theory. To better address the roles of locatability and personalization in studying LBS, we study the combined effects of the two benefits.

Regarding the dependent variable, i.e., information disclosure intention, the following reasons are considered. According to Fishbein and Ajzen (1975), intention means that an individual is willing to do something. Thus, an individual's actual information disclosure is highly determined by his/her intention to disclose information. The research has shown that the best way to predict whether an individual will do a specific behavior is to ask if he/she intends to do it (Fishbein & Ajzen, 1975).

It is important to note that information disclosure intention is different from other similar concepts, which are clarified as follows. Information disclosure refers to "a user intentionally and voluntarily reveals personal information to others" (Lowry, Cao, & Everard, 2011). Information disclosure usually involves privacy issues (Zhao et al., 2012). According to the privacy calculous theory, people usually weigh both the costs and benefits before making the decision to disclose information (Dinev & Hart, 2006).

Information sharing refers to adding new information to blogs regularly and maintaining the information on blogs regularly (Lu & Hsiao, 2007). Information sharing is important to an online community, because the values of online communities rely on rich content (i.e., shared information) (Chiu, Hsu, & Wang, 2006). Technology adoption/usage emphasizes the use of emerging new technology (Venkatesh, Morris, & Ackerman, 2000). People could use certain technology with no information disclosure. Continued technology usage refers to an individual continuing to use a new technology after they have adopted the technology (Hong, Thong, & Tam, 2006). Our research purpose is to investigate the impacts of the LBS benefits on possible information disclosure. Therefore, information disclosure intention is chosen as the dependent variable.

Locatability refers to a consumer who could obtain the required information or services exactly and timely (Xu et al., 2009), which means to provide information in the right place and at the right time. Locatability emphasizes the ability to determine the physical location. Locatability needs the latest Global Positioning System (GPS) technologies. Based on social exchange theory (Xu et al., 2009), people may exchange certain personal information to gain access to the information or services that they need (Mou, Shin, & Cohen, 2016). Hence, we propose as follows:

H1. Locatability is positively related to information disclosure intention.

Personalization means that the LBS could provide information, and services which are consistent with a user's preferences and interests (Xu et al., 2009). In the context of LBS, personalization refers to that LBS could provide a service or a product fitting with an individual consumer's current specific preference and need. From the perspective of social exchange theory (Xu et al., 2009), a consumer may disclose her personal information in exchange for the personalized service or information that she needs (Mou, Benyocef, & Kim, 2020). Hence, we propose as follows:

H2. Personalization is positively related to information disclosure intention.

According to the research literature, social benefits can be both egoistic and altruistic (Zhao et al., 2012). The research on the altruistic perspective of social benefits is relatively rare. In our research, the social benefits are studied mainly from an altruistic perspective, which means helping others or benefiting society (Koohikamali et al., 2015). In the interviews we conducted, all of the interviewees said that their peers/friends could gain benefits or feel joyfulness through the location-based information they shard, and because of that, they would disclose information in an LBS APP. Furthermore, Koohikamali et al. (2015) states that after experiencing a restaurant in a specific location, individuals could share the information about the restaurant's poor or high quality service or special discount and that sharing such information could help others to make a better decision. Therefore, according to the SDT theory, being able to help others would increase a user's intrinsic motivation. Hence, we propose as follows:

H3. Social benefit is positively related to information disclosure intention.

2.2. Social role theory (SRT) and gender differences

Past studies investigated gender as it is one of the most important individual difference variables (Lin & Wang, 2020; Liu, Li, Zhang, & Huang, 2017). The social role theory (Eagly, 1987) states that a gender-related difference in behavior is mostly the result of a social construction process (Venkatesh & Morris, 2000). In online services, gender could make a difference as males and females have different use styles (Weiser, 2000) and that they rate differently on various needs (Alderfer & Guzzo, 1980). For example, males use the Internet mainly for entertainment and leisure, whereas women use it mainly for interpersonal communication and educational help (Weiser, 2000). Hence, males and females could perceive various LBS benefits differently, thus likely leading to different information disclosure intentions.

For utilitarian benefits and social benefits, past studies show that tasks and goals are main drivers for males' behaviors, and males would think that work, accomplishment, and eminence are more important (Carlson, 1971). Taylor and Hall (1982) find that males' behaviors are more utilitarian and task-oriented than females' behaviors. Spence and Helmreich (2014) find that expressive and communal goals are the main drivers for females' behaviors. Females think that the activity process is more important than the outcomes of the activity. This finding suggests that males pay more attention on extrinsic motivators and females report higher levels of caring about intrinsic motivators (Spence & Helmreich, 2014). Regarding social network websites, Lin and Lu (2011) find that for continued use intention, usefulness is more important for males and enjoyment is more important for females. Therefore, we propose as follows:

H4(a). The relationship between the utilitarian value of locatability and information disclosure intention is stronger for males than for females.

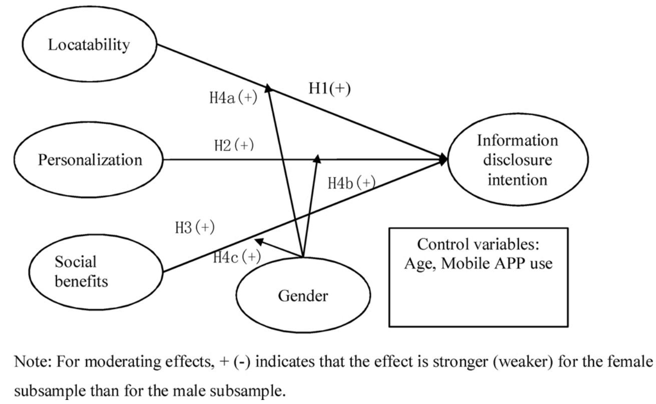

Fig. 1. Research model.
Note: For moderating effects, + (-) indicates that the effect is stronger (weaker) for the female subsample than for the male subsample.

H4(b). The relationship between the utilitarian value of personalization and information disclosure intention is stronger for males than for females.

H4(c). The relationship between the social benefits and information disclosure intention is stronger for females than for males.

Fig. 1 shows the research model of this study. Age and mobile use frequency are the control variables in the model (Yoon & Occea, 2015). Age has a significant effect on Internet use (Weiser, 2000). Younger people used the Internet more for interpersonal communication, such as online chatting and meeting new people, than older individuals did (Weiser, 2000). Younger people would like to disclose information for their social purpose more than older people would. People with more Internet experience provided higher ratings for the reasons for using the Internet, such as online chat, looking around, shopping, meeting new people, staying informed, and online games, than the respondents with less Internet experience did (Weiser, 2000). Thus, people who use mobile devices more frequently would be more likely to disclose their information for those purposes. Age and mobile use frequency can be studied in future research.

3. Research methodology

3.1. Measurements

We conducted an online questionnaire survey to validate the proposed research model. The questionnaire was sent to real users of LBS. The items of all the constructs were adapted from the past research using a seven-point Likert scale. Before the formal data collection, we first performed one pretest and one pilot test following the recommended procedures (Boudreau, Gefen, & Straub, 2001). Then, we refined all the constructs accordingly. We employed 30 students who used LBS to do the pilot test. The pilot test provided many feedback and suggestions, then we made further revisions to the questionnaire. As the questionnaire was sent to Chinese subjects, we conducted backward translation to ensure measurement consistency between the Chinese and English versions. This resulted in the final measurement version containing fifteen items in total. The final questionnaire is shown in Table B1.

3.2. Data collection

We use Sojump (http://www.sojump.com) to collect data, an established Chinese website providing online survey services (Lien, Cao, & Zhou, 2017; Tang & Chen, 2020; Yang, Gong, Zhang, Liu, & Lee, 2020; Zhang, Li, Wu, & Li, 2017). Based on the hyperlinks and IP addresses, Sojumep could prevent repetitive submissions. To ensure quality data collection, the payment service provided by sojump.com has been

Table 1
Demographic information of the survey respondents.

Characteristic		Frequency	Percentage
Gender	Female	118	54.88%
	Male	97	45.12%
Education level	High school	11	5.09%
	Bachelor's degree	180	83.8%
	Master's and PhD degrees	24	11.11%
Age	18−29 years old	72	33.49%
	30−37 years old	102	47.44%
	38−41 years old	14	6.51%
	More than 42 years old	27	12.56%
Income	2000 and below	10	4.65%
	2001−5000	112	52.09%
	5001 and above	93	43.26%
Usage frequency of mobile APP	Six times one week and below	23	10.70%
	Once a day	43	20.00%
	Twice a day and above	149	69.30%

adopted to obtain the sample. There are 2.6 million members in Sojump now (http://www.sojump.com). 72 percent of their members are full-time employees. The members have various job categories, such as white collar, IT people, and senior managers. We employed Sojump to randomly select 500 members with LBS experience from the database of registered members and then sent email invitations to them. In the first part of questionnaire, we explained our research context and purpose. We asked the respondents to fill the questionnaire based on their most frequently used LBS.

There were 269 members that responded to our survey. All of them had unique IP addresses and submitted time information. However, 54 of those answered our survey in less than 5-minutes, in more than 60-minutes, or provided contradictory answers. According to Deutskens, De Ruyter, Wetzels, and Oosterveld (2004), our final valid survey sample consisted of 215 responses. The subjects' demographic characteristics are shown in Table 1.

The non-response bias issue is addressed as follows. We use a time-trend extrapolation method to compare the early and late respondents to determine the possibility of a non-response bias issue (Armstrong & Overton, 1977). We use Chi-square tests to compare early (first-quartile) respondents and late (fourth-quartile) respondents on their characteristics (gender, age, education, etc.). No significant differences (p value is more than 0.5) were found; the non-response bias was not a significant factor.

4. Data analysis and model estimation results

A two-steps process was used to analyze the collected data. First, we measured the measurement model by reliability and convergent and discriminant validity. Second, we used SmartPLS 3.0 to examine the strength and direction of the relationships between constructs.

We chose SmartPLS 3.0 to analyze the data for the following reasons.

Table 3
Confirmatory factor analysis for the full sample (N = 215).

items	LOCA	PERS	SBENE	INTEN
LOCA1	**0.8820**	0.5249	0.5198	0.3650
LOCA2	**0.8411**	0.5416	0.5186	0.2842
LOCA3	**0.8515**	0.5923	0.5142	0.2408
PERS1	0.5467	**0.8097**	0.5424	0.2878
PERS2	0.5432	**0.8317**	0.5478	0.2751
PERS3	0.5853	**0.8331**	0.5428	0.2045
SBENE1	0.4978	0.5438	**0.8405**	0.4702
SBENE2	0.5106	0.5772	**0.8525**	0.4275
SBENE3	0.5258	0.5569	**0.8513**	0.3723
INTEN1	0.2860	0.3119	0.4814	**0.8556**
INTEN2	0.3085	0.2465	0.4055	**0.8620**
INTEN3	0.3076	0.2520	0.4247	**0.8944**

Note: LOCA is the abbreviation of locatability. PERS is the abbreviation of personalization. SBENE is the abbreviation of social benefits. INTEN is the abbreviation of information disclosure intention.

Partial least squares (PLS) has been adopted a lot in the past research (e.g., Fu, Yan, & Feng, 2018; Xiang, Zheng, Lee, & Zhao, 2016). The mechanism of PLS is component-based structural equation modeling. Compared to regression and covariance-based structural equation modeling (CBSEM), PLS has several advantages as follows. First, PLS is a second-generation technique, which could model relationships among multiple predictors and dependent variables (Chin, 1998). Particularly, PLS can measure the reliability and validity of the constructs (by estimating loadings) and the causal relationships among constructs (Fornell & Bookstein, 1982) at the same time. In addition, different from the CBSEM, PLS is still robust with fewer statistical identification issues. PLS is suitable for a relatively small sample size (Hair & Sarstedt, 2011), which is the case in this study. In this study, the subsample size was relatively small, with 118 female and 97 male participants. Finally, since this study combined SDT and SRT conceptual constructs for the first time, PLS was suitable for exploratory study. PLS is more suitable for predicting key target constructs or identifying key "driver" constructs (Sarker, Ahuja, & Sarker, 2018). The objective of the analysis is prediction. Thus, we chose the PLS method rather than other SEM models.

4.1. Measurement model evaluation

We used several criterion (such as reliability, convergent validity and discriminant validity) to evaluate the measurement model. We performed the evaluation three times, for the full sample (N = 215), as well as the female (N = 118) and the male (N = 97) sub-samples.

First, Table 2 shows that the Cronbach's α and composite reliabilities (CR) for the full sample were greater than 0.70. We could conclude that the measurement model has an adequate level of reliability (Fornell & Larcker, 1981). Table 3 shows that all the item loadings were greater than 0.70 with a significant t-value (>.96 when $p < 0.05$). It could be concluded that the measurement model has good convergent validity (Gefen & Straub, 2005). The square root of AVE for each construct was greater than the correlations between the constructs in all cases, so we could conclude that the measurement model has sufficient discriminant validity (Gefen & Straub, 2005). Specifically, the AVE of LOCA (locatability) is 0.79. The square root of 0.79 is 0.89. The correlations between

Table 2
Construct reliability and validity for the full sample (N = 215).

Construct	AVE	Mean	SD	Cronbach's α	Composite reliability	LOCA	PERS	SBENE	INTEN
LOCA	0.79	5.32	0.83	0.82	0.89	**0.89**			
PERS	0.67	5.37	0.78	0.77	0.86	0.80	**0.82**		
SBENE	0.72	5.18	0.84	0.80	0.88	0.60	0.66	**0.85**	
INTEN	0.76	4.82	1.04	0.84	0.90	0.35	0.31	0.50	**0.87**

Note: Bold diagonal numbers are the square roots of AVE.
LOCA is the abbreviation of locatability. PERS is the abbreviation of personalization. SBENE is the abbreviation of social benefits. INTEN is the abbreviation of information disclosure intention.

Table 4
The HTMT results.

	LOCA	PERS	SBENE	INTEN
LOCA				
PERS	0.846			
SBENE	0.742	0.840		
INTEN	0.614	0.489	0.410	

Note: LOCA is the abbreviation of locatability. PERS is the abbreviation of personalization. SBENE is the abbreviation of social benefit. INTEN is the abbreviation of information disclosure intention.

Table 5
Confirmation factor analysis.

Fit Index	Threshold	Model
RMR	(< = .10)	0.05
CFI	(> = .90)	0.93
NNFI	(> = .90)	0.92
GFI	(> = .90)	0.87
AGFI	(> = .80)	0.79

LOCA and PERS (personalization), SBENE (social benefit) and INTEN (information disclosure intention) are 0.80, 0.60, 0.35, respectively. 0.89 is greater than 0.80, 0.60, and 0.35. The AVE of PERS is 0.67. The square root of 0.67 is 0.82. The correlations between PERS and LOCA, SBENE and INTEN are 0.80, 0.66 and 0.31, respectively. 0.82 is greater than 0.80, 0.66 and 0.31. The AVE of SBEBE is 0.72. The square root of 0.72 is 0.85. The correlations between SBENE and LOCA, PERS and INTEN are 0.60, 0.66 and 0.50, respectively. 0.85 is greater than 0.60, 0.66 and 0.50. The AVE of INTEN is 0.76. The square root of 0.76 is 0.87. The correlations between INTEN and LOCA, PERS and SBENE are 0.35, 0.31 and 0.50, respectively. 0.87 is greater than 0.35, 0.31 and 0.50. Table 4 shows that the values from HTMT are lower than 0.85 for conceptually distinct constructs.

Further, the variance inflation factors in the collinearity diagnostics were far below 10, which indicated that there was no multicollinearity concern (Hassenzahl, 2001). We performed two methods to address the common method bias. First, based on Podsakoff, Mackenzie, Lee, and Podsakoff (2003), we used Harman's one-factor test to check for common method bias. We extracted two factors, and they explained 59.642 % of the variance. The first factor accounted for 36.57 %, which indicated that no single factor accounted for most of the variance. Thus, we could conclude that there was no common method bias in our study.

Second, based on Liang, Saraf, Hu, and Xue (2007) and Podsakoff et al. (2003), we used common method factor to check for common method bias. We added a common method factor to the original PLS model. Indicators of the factor included all the principal constructs' indicators. Then we calculated each indicator's variances, which were substantively explained by the principal construct and by the method. From Appendix B, we can see the small magnitude and insignificance of the method variance. We could conclude again that there was no common method bias concern in this study.

For measurement of the model invariance, we used LISREL 8.8 to measure the confirmatory factor analysis (CFA). The results showed that our model had acceptable model fit (RMR 0.05, CFI 0.93, NNFI 0.92, GFI 0.87). Table 5 shows the results.

The RMR is the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model (Hooper, Coughlan, & Mullen, 2007). If the values are less than 0.05, we could conclude that model is well-fitting (Diamantopoulos & Siguaw, 2000).

The Comparative Fit Index (CFI) (Bentler, 1990) is a revised form of the NFI that takes into account the sample size. CFI performs well even when the sample size is small (Tabachnick & Fidell, 2007). If CFI $\geq$ 0.90, the model is acceptable (Bentler, 1990).

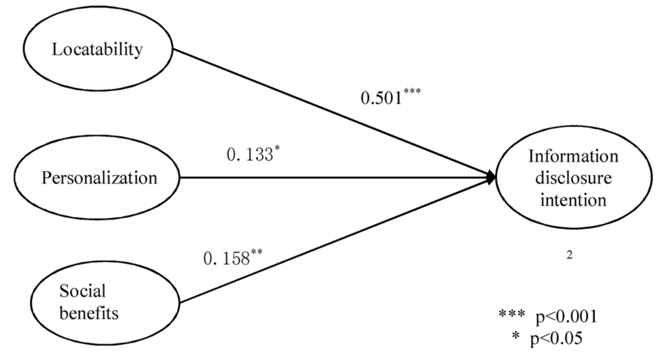

Fig. 2. Full sample (N = 215): results of the SmartPLS 3.0 analysis.

The Normed Fit Index assesses the model by comparing the $\chi 2$ value of the model to the $\chi 2$ of the null model (Bentler & Bonnet, 1980). The NFI was rectified by the Non-Normed Fit Index (NNFI), an index that prefers simpler models. Bentler (1990) recommended that a good fit model has a value greater than 0.90.

The Goodness-of-Fit statistic (GFI) calculates the proportion of variance that is accounted for by the estimated population covariance (Tabachnick & Fidell, 2007). The GFI value of this sample, which is 0.87, is below 0.9, but the GFI depends on the sample size (Mulaik et al., 1989). Thus, the GFI value is acceptable.

The evaluations of the research model for the sub-samples (the female group and male group) are similar to that for the full sample.

4.2. Path estimate for the whole sample

We use the bootstrapping technique to examine the structural models for their path significance and explanatory power (Sia et al., 2009). We use one tailed t-tests to measure significance. All statistical tests are assessed at the 5% significance level ($p < 0.05$). The SmartPLS 3.0 results for the whole sample are shown in Fig. 2. The relationships among locatability, personalization, social benefits and the willingness to disclose, are all significantly positive. Thus, H1, H2, and H3 are supported. 36.8 % of the variation in the willingness to disclose is explained by locatability, personalization, and social benefit. The result is shown in Table 6. The predictive sample reuse technique (Q^2) measures the predictive relevance, which is based on a blindfolding procedure (Chin, 2010; Geisser, 1975; Stone, 1974). We define $Q^2 > 0$ as predictive relevance, whereas $Q^2 < 0$ is defined as a lack of predictive relevance. The Q^2 values for H1, H2 and H3 are 0.121, 0.049, and 0.037, respectively, indicating good predictive validity.

The effect size f^2 measures the strength of the relationship between two variables on a numeric scale. It is calculated using $[R^2(T|C) /\{1 - R^2(C) - R^2(T|C)\}]$. $R^2(C)$ is the R^2 value of only the control variables. $R^2(T|C)$ is the amount added to the overall R^2 value by the treatment variables after the control variables. Cohen (1988) defines small effects as values near 0.02, medium effects as values near 0.15, and large effects as values above 0.35. Thus, H1 has a medium effect, H2 has a small effect and H3 has a medium effect.

4.3. Multi-group PLS analysis

We should also compare the research model for females and males. Multi-group PLS analysis can serve this analysis goal. Its key principle is to compare the differences in the path coefficients for the female samples and male samples (Keil et al., 2000). Fig. 3a and b show the results of the SmartPLS 3.0 analyses for the female subsample and the male subsample, respectively.

The SmartPLS 3.0 results for the female sample are shown in Fig. 3a. The relationships among locatability, personalization, social benefits and the willingness to disclose are all significantly positive. A significant

Table 6
The result of the SmartPLS 3.0 analysis.

Hypothesis	Relationship	Path coefficients	t-value	Q2	f2	bootstrap sample	Decision
H1	Locatability→ Information disclosure intention	0.501	4869	0.121	0.189	5000	Supported
H2	Personalization→Information disclosure intention	0.133	1.977	0.049	0.08	5000	Supported
H3	Social benefit →Information disclosure intention	0.158	2.271	0.037	0.12	5000	Supported

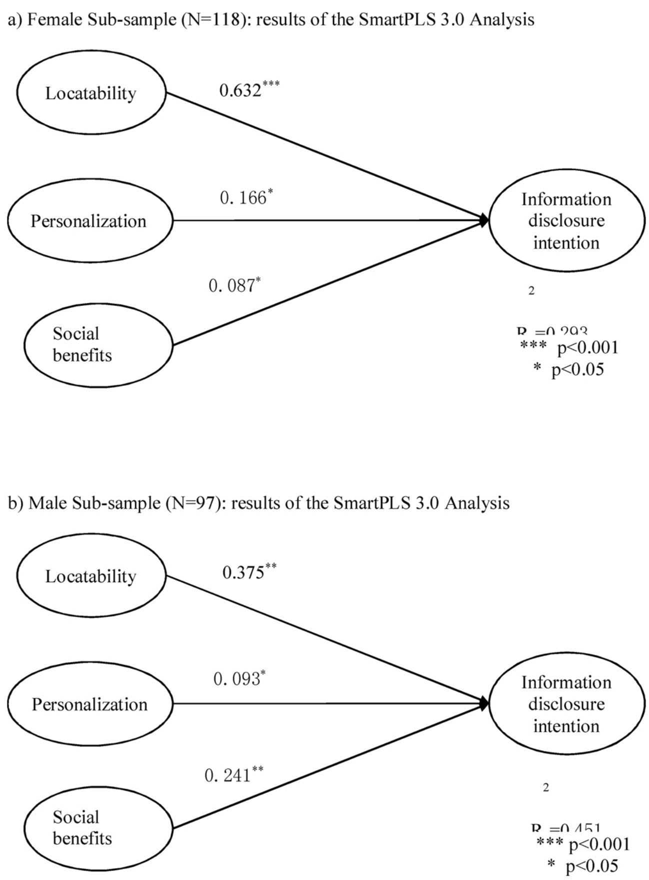

Fig. 3. a. Female sub-sample (N = 118): results of the SmartPLS 3.0 analysis. b. Male sub-sample (N = 97): results of the SmartPLS 3.0 analysis.

Table 7
Path coefficients comparison statistics between females (N = 118) and males (N = 97).

Path	Path coefficients		$T_{spooled}$	Hypothesis support
	Female (N_1 = 118)	Male (n_2 = 97)		
H4a: Locatability→ Information disclosure intention	0.632***	0.375**	1.649*	Not Supported
H4b: Personalization→ Information disclosure intention	0.166*	0.093*	1.845*	Not Supported
H4c: Social benefit → Information disclosure intention	0.087*	0.241**	1.943*	Not Supported

Notations: *** P < 0.001, ** P < 0.01, * P < 0.05.

amount of the variation (29.3 %) in the willingness to disclose is explained by locatability, personalization, and social benefit. The SmartPLS 3.0 results for the male sample are shown in Fig. 3b. The relationships among locatability, personalization, social benefits and the willingness to disclose, are all significantly positive. A significant amount of variation (45.1 %) in the willingness to disclose is explained by locatability, personalization, and social benefits.

Table 7 shows the PLS-MGA results. The T tests of the path coefficients show that there are significant differences for locatability→information disclosure intention, personalization→information disclosure intention, social benefits→information disclosure intention between females and males. However, the directions are opposite to our hypotheses. The relationship between the utilitarian value of locatability or personalization and information disclosure intention is stronger for females than for males. The relationship between social benefit and information disclosure intention is stronger for males than for females. Thus, H4a, H4b and H4c are not supported.

Table 8
Characteristics of the respondents in the qualitative study (note: F: female, M: male).

Participant	Age	Gender	Education	Occupation	Frequency
1	51	F	Colleague	Free job	Every day but randomly
2	39	M	Master	No job	Every day
3	28	M	Bachelor	Web security Engineer	4–6 h/per day
4	38	F	PHD	Professor	4–5 h/per day
5	50	F	Master	Education	1 h/per day
6	42	F	MBA	International Communication	4 h/per day
7	25	M	Master degree student	Student	Every day
8	31	F	PHD student	Student	Every day
9	28	M	PHD student	Student	Every day
10	22	M	Undergraduate	Student	Every day
11	24	F	Master degree student	Student	Every day

4.4. Post-hoc qualitative study/test

We conducted a post-hoc qualitative study/test to explain the importance of some specific social benefits.

In recruiting interviewees, we employed a random sampling strategy and invited participants who had LBS experience. According to the study of French, Luo, and Bose (2017), we invited 11 interviewees to participate in the study. Due to the COVID-19 pandemic, online interviews were carried out. Each interview took approximately 8–15 min. In the qualitative study, we did not offer incentives to the participants except that the research finding would be shared with them.

To gain more insights regarding the specific social benefit and its effects on the user's LBS sharing behavior, we asked a series of questions, such as the frequently of using the LBS APP, what types of social benefits they can gained from using LBS, as well as "Do you think your peers/ friends can gain benefits from the location information you shard?"

Based on the recommendations of Corbin and Strauss (2008), we recorded and transcribed the interviews. Further, we used an open, axial and selective coding process. Two researchers coded the data followed by a discussion to identify the concepts that were mentioned in the textual data and grouped the concepts into broad categories. Then, axial

Table 9
Specific construct for social benefits. The number in the parentheses means the number of times mentioned.

Specific construct	Category	Example responses
Helping	For others (11)	Help to obtain more appropriate information Help seller to promote the store Help peers to know whether a specific store is good or not Help peers to make a better decision
	For society (1)	Help to control the shopping mall's flow
Convenience	Easy to find somewhere/ someone (3)	My friend can reach a location easily My friends can find me easily An online car-hailing driver can find me easily

coding and selective coding were performed, which allow us to find the cause-effect relationships between the specific social benefits and information disclosure intention, as well as to integrate the social benefit into the self-determination theory.

The characteristics of the samples are shown in Table 8. Among the 11 participants, there are 6 females, and 5 males. Their ages range from 24 to 51. Further, the respondents have different education background levels ranging from college to PhD degrees. Finally, the occupations among the participants differ, varying from no job, freelance job, web engineer, educator, or student.

All the participants use LBS frequently for location-identification, online car-hailing services, ordering food online, searching for famous restaurants around a specific area, as well as helping friends or peers to find information. Furthermore, all the participants mention that LBS has become a part of their daily life, with some of them expressing concerns regarding privacy issues, such as the possibly of misusing their disclosed location-based information.

In analyzing the interview data, helping others or society was grouped into the social benefit category. Accordingly, we grouped the similar categories into a specific construct, such as helping and convenience. Through the post-hoc qualitative test, we were able to identify some specific aspects of social benefits. The detailed coding results are shown in Table 9.

Finally, we asked an open question ("what else do you like to comment?") to obtain more insights from the participants. Most of the participants indicated their concerns about disclosing their location information. However, to use some functions or services, they must disclose their information. As a result, mandatory disclosure may not be a good practice for LBS service providers. The participants think that voluntary usage is more appropriate and also enhances an APP's public image.

5. Discussion and implications

5.1. Discussion on research findings

This paper studied the comprehensive effects of utilitarian benefits (i.e., locatability and personalization) and social benefits on information disclosure intention, moderated by gender, in LBS.

First, we find that a LBS user's perceived benefit is an important predictor of the LBS user's information disclosure intention, which is consistent with the previous literature (Koohikamali et al., 2015; Sun, Wang, Shen, & Zhang, 2015; Zhao et al., 2012). The three types of perceived benefits provided by LBS represent the different needs of users, but these three types of perceived benefits have not been studied in one research model previously. These benefits are positively related to the information disclosure intention. More specifically, locatability has the largest impact on the information disclosure intention for all samples, followed by personalization and social benefit, sequentially. All the hypotheses are supported statistically. The relative importance of the three drivers were locatability ($\beta = 0.501$), social benefits ($\beta = 0.158$), and personalization ($\beta = 0.133$) for the whole sample.

Locatability means the technical capability to provide users with the current physical location exactly and in a timely manner (Xu et al., 2009). LBS are applications of technologies that obtain a user's location information to provide the needed services. Hence, the ability to accurately locate is the basis of LBS. It is reasonable that locatability is the most important driver. Social benefits mean that the users could provide benefits to other people by sharing information through the LBS (Koohikamali et al., 2015). Currently, increasing numbers of people like to share information and communicate with others online. They benefit from the information others share and also share useful information to help others. The social benefits are, thus, also an important driver of LBS use. Personalization means the ability to provide users with services that are in accord with the users' preferences (Xu et al., 2009). Usually, the tailored content is based on past behavior. Sometimes people want to try something new, which is different from their past behavior. The changing of user preferences is one of the main challenges faced by online recommendation services (Patel, Desai, & Panchal, 2017). Thus, personalization may be perceived as the least important driver thus far.

The above analysis is also in consistent with the findings of the interviews we conducted. For example, the eighth interviewee said that "during the usage of LBS, I could know my latest location information, receive the store information tailored to my preferences. Sharing my comments on those stores could help others to make better decisions, which I felt good about." The seventh interviewee mentioned that "when using LBS, I could immediately know the location when I reached a new place and can help others by sharing my comments about the place. Personalization is not that important, as I always want to try different things."

Second, an unexpected gender effect of the benefits on the information disclosure intention is found in LBS. H4a, H4b and H4c hypothesize that females would place more emphasis on social benefits (and less on utilitarian benefits) than males. However, this study reports the opposite results, i.e., that females are more enticed by utilitarian benefits and males are motivated more by social benefits. Specifically, in terms of perceived benefits, locatability, as well as personalization, are more important to female users than to male users. Regarding the perceived benefits, social benefits are more important to male users than they are to female users. These findings are interesting (and unexpected), because they are different from the conventional wisdom and the past studies' findings. Further analysis is shown below.

For H4a, locatability is a type of utilitarian benefit that is related to the intrinsic quality of the information or service. The prior research shows that females tend to expect higher information quality than males in an online context (Liu, Cruz et al., 2017; Liu, Li et al., 2017). We found that females put more emphasis on locatability than males in the context of LBS. To better interpret the research findings, we applied the social role theory. The theory posits that gender differences and similarities are caused by the fact that a society distributes different social roles to males and females. The behaviors from males and females generally conform to the historical labor divisions (Eagly & Wood, 2016). Through the development process of human society, females are responsible for fulfilling daily life duties (Lauderdale, Piipari, Irwin, & Layne, 2015), which would be time-consuming. Obtaining services information in a timely manner could help females save time. Therefore, locatability with the right services information is more important to females than to males in LBS.

For H4b, a high level of personalization means that LBS could provide services information that meets a user's preferences. According to the social role theory, from ancient times to the present, males are responsible for working outside while females are responsible for fulfilling household duties, such as buying daily necessities (Lauderdale et al., 2015). The research also suggests that females report higher levels of caring about the aspects of daily life than males, in terms of shopping and watching movies (Eagly & Koenig, 2006). Compared to males, females usually shop more because they are responsible for buying items to meet the daily needs of family members. A high level of personalization could provide females with suitable items, which could help them save time and energy. Therefore, compared to males, females put more emphasis on personalization in the context of LBS.

As far as H4c (social benefit), the information systems of LBS APPs may provide anonymity and, thus, psychological safety than the normal physical information exchange settings, such as face-to-face meetings (Huang & Wei, 2000). The research shows that males could feel more comfortable sharing emotional information online, and thus, they may be more inclined to share social information online than females, given that traditional offline mechanisms in the physical world have social norms that normally discourage males from expressing their social feelings publicly (Lu, Lin, Hsiao, & Cheng, 2010). Such social norms would be dampened in the online mobile LBS world. In addition, according to the social role theory, males would undertake more social responsibility compared to females (Lauderdale et al., 2015). Responsibility also means taking care of others. In summary, males place more emphasis on the social benefits in LBS than do females, which is different from the normal convention of the physical world. This is also confirmed in the qualitative test. For example, the third interviewee talked about his experience of using LBS, saying that "I tended to be more free to express or share my likes or dislikes in using LBS, which seems to be different from my public image of being a quiet person normally."

In summary, this study found out that females are more concerned about extrinsic utilitarian benefits when using LBS and are less concerned about intrinsic social benefit than males, which is opposite to the hypotheses. This finding may suggest that the gender effect may differ between our normal physical work and the new virtual LBS world. This may be an interesting research finding that is worth deeper study in the future.

In addition, the post-hoc qualitative test can actually help us to identify some specific social benefits and their relationship with location information disclosure behavior. The post-hoc qualitative test found that helping and convenience are the specific constructs of a social benefit. Helping means both being helpful for others and for society. Convenience means that it is easy to find a place or a person.

5.2. Implications for research

First, the prior research on LBS suggests that information disclosure intention would be separately influenced by utilitarian benefits (including locatability and personalization) (Xu et al., 2009) and by social benefits (Koohikamali et al., 2015). Based on the SDT, this study combines utilitarian benefits and social benefit into a research model, thus leading to a more comprehensive understanding that has not been found in the literature. The research findings show that locatability shows the largest impact on information disclosure intention for all the samples, followed by personalization and social benefits, sequentially. For the full model, locatability is the most important driver, social benefit is the second most important driver and personalization is the least important driver. The SDT normally claims that intrinsic motivation is more important than extrinsic motivation in driving behavior. However, we find that it is not always true in LBS, as locatability (one type of extrinsic motivation) is more important than the social benefits (one type of intrinsic motivation), as shown in Fig. 2. A possible explanation is as follows. LBS APPs are becoming increasingly popular and are becoming a part of some people's daily lives, such as Google Maps for routine navigation or positioning. As a result, locatability is perceived to be more important than social benefits.

Second, interestingly, although the prior technology usage research studies gender difference widely, this study shows that, in the LBS context, females and males conform to the social roles differently from the roles distributed within a traditional society. Females care more about extrinsic utilitarian benefits than males, whereas males are more concerned with intrinsic social benefits than females. We could conclude that the behaviors resulting from characters may not always be consistent with the behaviors resulting from social roles. It may be that the responsibility undertaken is one key factor. Knowing this would help better understand people's behaviors. Knowing that gender differences may have unconventional effects on the usage behavior in LBD would help service providers to develop applications that both females and males may enjoy, which would increase customer satisfaction. Higher satisfaction may lead to higher LBS usage and higher related product adoption. This is important to the IS research literature.

5.3. Implications for practice

First, the findings suggest that companies may need to provide adequate benefits to users. The perceived benefits are considered critical elements that impede the LBS users' information disclosure intentions (e.g., Xu et al., 2009, 2011; Zhao et al., 2012). Currently, information could bring wealth. The more information users are disclosed, the more information companies could capture and analyze. In this paper, we investigated three benefits, including locatability, personalization, and social benefits. These three benefits are all very important but have different weights.

Locatability means the technical capability to provide users the current physical location exactly and in a timely manner (Xu et al., 2009), which is the most important driver of information disclosure intention. In the post-hoc interview we conducted, the first, second, third, fourth, seventh and ninth interviewees all mentioned that the most important purpose for using LBS is to obtain a current physical location. To increase locatability, LBS providers should enhance their location-determination technology when developing LBS, such as the latest GPS technology. LBS companies should emphasize locatability in their slogans.

Personalization means the ability to provide users with products, content, and services that are in accord with their preferences (Xu et al., 2009). In the post-hoc interview we conducted, the first, second, seventh, eighth, ninth and eleventh interviewees all mentioned that they use LBS to obtain nearby shopping and restaurant information. Thus, accurate recommendations from LBS providers are needed. Therefore, LBS providers should use the latest recommendation systems. In addition, service providers should use more technique to integrate more location-related information to offer better personalized advice, such as promotion information from nearby stores or interesting activities nearby. LBS providers could cooperate with companies or stores to provide more rewards, coupons, and discounts that the users may be interested in.

Social benefits mean that people could benefit socially from the shared information in LBS. In the post-hoc interview we conducted, the seventh, eighth, tenth and eleventh interviewees mentioned that other people could benefit from the information they shared, so they are willing to disclose information in LBS. Using and sharing comments in LBS should be easy. Comments with text and photos and videos are preferred, as they provide rich information to others. It is also a useful way to provide reward points to users who share information frequently. The reward points could be redeemed for money or beautiful physical stuff.

More importantly, this research finds that there should not be a "one-size-fits-all" approach for all LBS users. LBS developers should work out different approaches to target male and female users. Specifically, for female users of LBS who tend to place more emphasis on personalization and locatability, LBS developers and/or vendors should provide more specific technological functions for location-based utilitarian services to fit their needs. For example, when females go to a new place, LBS should push the latest location information and relevant shopping mall and supermarket coupon information based on their past behaviors. On the other hand, for male LBS users, who put more emphasis on sharing social information with others, LBS developers and/or vendors would design more interaction functions. For example, it should be easy to use and share social messages with the LBS.

5.4. Research limitations and suggestions for future research

Research limitations exist in the study. First, we only collected cross-sectional data for analysis. Cross-sectional data allow us to examine interrelationships rather than causal relationships. We worked to control this factor by formulating all the hypotheses, which are based on past literature and the existing theories, while developing causal relationships between the constructs (Cheung & Lee, 2009). Longitudinal investigations are encouraged for future research for this purpose.

Second, future research could consider further investigating the gender effect of switching the socially expected roles in LBS, such as going beyond only gender differences or in contexts other than LBS. For instance, the future research may study other individual differences, such as age and personal LBS use experience (Weiser, 2000), and their impacts on information disclosure in LBS.

Third, this research measured social benefits from an overall perspective. Future research could address more individual social benefits, such as personal relationships and accessibility to family.

Fourth, there is no specific type of LBS being studied in this research. Future research could study different types of LBS to see the relative importance of the three benefits (locatability, personalization and social benefits). The type of LBS could be a moderator variable for further study.

Fifth, we found in the qualitative test that helping and convenience are important to motivate users to share their location information. This can be verified further using a quantitative study.

6. Conclusion

As LBS providers rely on the information provided by users to recommend customized services, understanding which factors could influence the user's willingness to provide their personal information is very important. The user's perceived benefit is an important predictor of their LBS information disclosure intention. The perceived benefits include utilitarian benefits (i.e., locatability and personalization) and social benefits. As far as we know, this paper is the first to integrate two types of benefits into a comprehensive research model. Further, in the LBS context, females and males conform to the social roles differently from the roles distributed within a traditional society. The findings of this research could provide helpful suggestions for future research and LBS developers.

CRediT authorship contribution statement

Yahui Li: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Jian Mou:** Methodology, Writing - review & editing. **Liying Ye:** Writing - review & editing, Software, Validation. **Jing Long:** Writing - review & editing, Supervision. **Wei (Wayne) Huang:** Methodology, Project administration, Funding acquisition, Writing - review & editing.

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Appendix A. Review of the literature

Appendix B. Questionnaire

Table B1
Measurements of constructs.

Constructs	Items	Source
Personalization	The LBS can provide me with personalized services tailored to my activity context. The LBS can provide me with more relevant information tailored to my preferences or personal interests. The LBS can provide me with the type of information or service that I might like.	Xu et al. (2009)
Locatability	With the LBS, I am able to obtain the up-to-date information/services whenever I need. With the LBS, I am able to access the relevant information/services at the right place. With the LBS, I can get the just-in-time information/services.	Xu et al. (2009)
Social benefit	I benefit others when I use LBS. Using LBS has many advantages for society. When I use LBS, others benefit from the information that I share.	Koohikamali et al. (2015)
Information disclosure intention	I am very interested in having my personal information (including your location) used in LBS. It is likely that I will provide my personal information (including your location) to use LBS. I am very willing to have my personal information (including your location) used in LBS.	Xu et al. (2011), 2009

Authors	Context	Ivs	Dvs	Findings
Koohikamali et al. (2015)	LB-SNAs	Social norm, perceived risk, perceived benefit, opinion leadership	Location Disclosure on LB-SNA	Attitudes toward LB-SNA and incentives have influence on location disclosure. Social norm, perceived risk, perceived benefits and opinion leadership are key drivers for attitudes toward LB-SNA.
Ryu & Prak (2020)	Location-based advertising (LBA)	Financial and utility benefits, privacy concerns	Intention to disclose personal information	Users' attitudes towards LBS affect their personal information disclosure, which would affect the ultimate LBS acceptance. Attitudes toward LBS is calculated by perceived benefits and perceived harms. Perceived benefits include financial benefit and utility benefit. Perceived benefits and perceived harms are based on subjective persuasion knowledge which is determined by objective persuasion knowledge.

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(*continued*)

Authors	Context	Ivs	Dvs	Findings
Sun et al. (2015)	Location-based social network	Utilitarian benefit, hedonic benefit, privacy risks	Intention to disclose location information	Perceived benefits are determined by utilitarian benefits and hedonic benefits simultaneously. Hedonic benefits are more important than utilitarian benefits. Intension to disclose information is based the calculus of perceived benefits and privacy risks. As to gender difference, females think hedonic benefits are more important and males think utilitarian benefits are more important. Males think perceived benefits are more important and females think privacy risks are more important.
Xu et al. (2009)	Location based services	Locatability, personalization, privacy risks	Intension to disclose personal information in LBS	Disclosure privacy benefits include locatability and personalization. Users' privacy decision making process is determined by compensation, industry self-regulation, and government regulatio, but the effects of the three privacy intervention approaches are different for different types of information delivery mechanism (pull and push).
Xu et al. (2011)	Location-aware marketing	Personalization	Willingness to have personal information used in LAM	Personalization is significantly related to perceived benefit of information disclosure for both overt-based and covert-based LAM. The relationship between personalization and privacy risks is significant in covert-based LAM and insignificant in overt-based LAM. Previous privacy experience would increase users' privacy risk in covert-based LAM but not in over-based LAM.
Zhang et al. (2018)	Online health communities	Perceived benefits (informational support and emotional support), health information privacy concerns	Personal health information (PHI) disclosure intension	PHI disclosure intention is motivated by the privacy calculus of perceived benefits and perceived risks. Perceived benefits include information support and emotional support. Privacy concern is positively affected by threat appraisals and negatively affected by coping appraisals. Threat appraisals include perceived severity and perceived vulnerability. Coping appraisals include response efficacy and self-efficacy.
Zhao et al. (2012)	Location-based social network services	Extrinsic benefits-personalization, intrinsic benefits-connectedness, privacy concerns	Intension to disclose location-based information	Perceived benefits and privacy concerns are antecedents of intention to disclose location-related information. Perceived benefits include personalization and connectedness. Incentives provision could increase personalization and interaction promotion could increase connectedness. Privacy control and privacy policies could reduce privacy concerns. Previous privacy invasions do not have influence on privacy concerns.

Appendix C. Common Method Bias Analysis

*$P < 0.05$, **$p < 0.01$.

Note: LOCA is the abbreviation of locatability. PERS is the abbreviation of personalization. SBENE is the abbreviation of social benefit. INTEN is the abbreviation of information disclosure intention.

Construct	Indicator	Substantive Factor Loading(R1)	$R1^2$	Method Factor (R2)	$R2^2$
Locatabilty	LOCA1	0.839**	0.703921	0.051	0.002601
	LOCA2	0.847**	0.717409	−0.010	0.0001
	LOCA3	0.890**	0.7921	0.042	0.001764
Personalization	PERS1	0.752**	0.565504	0.064	0.004096
	PERS2	0.952**	0.906304	−0.118	0.013924
	PERS3	0.770**	0.5929	0.055	0.003025*
Social benefit	SBENE1	0.835**	0.697225	0.009	0.000081
	SBENE2	0.825**	0.680625	0.028	0.000784
	SBENE3	0.884**	0.781456	−0.037	0.001369
INTEN	INTEN1	0.865**	0.748225	0.016	0.000256
	INTEN2	0.828**	0.685584	0.018	0.000324
	INTEN3	0.920**	0.8464	−0.030	0.0009
Average		0.845933333	0.720347667	0.005933333	0.004371267

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