Refining mobile location-based service adoption: the lens of pull effect- and push effect-related motivations

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Abstract

Purpose – Mobile location-based service (m-LBS) seems like a new class of personalized service due to location positioning technologies. This work aims to investigate consumer readiness (RED) toward m-LBS based on integrating pull effect- and push effect-related factors into the technology acceptance model (TAM).

Design/methodology/approach – An online survey collected data from 423 participants, and the research framework was analyzed using structural equation modeling (SEM).

Findings – The results divulge that consumer RED is determined by TAM antecedents, including usefulness (USE) and ease of use (EOU). EOU motivates USE in m-LBS. Regarding pull effect-related factors, absorptive capacity (ABC) is the strongest positive factor influencing consumer RED to use m-LBS, followed by technology willingness (TWI) and innovativeness (INN). Moreover, INN, trust (TRU) and perceived risk (RIS) significantly influence USE and EOU.

Originality/value – This work endeavors to explicate customer RED toward m-LBS by incorporating some meaningful pull effect-related dimensions (i.e. ABC, TWI and INN) and pushing effect-related dimensions (i.e. RIS) into crucial antecedents rooted in TAM. Thus, the findings assist practitioners in developing marketing strategies by boosting pull effects and controlling push effects on customer engagement in m-LBS.

Keywords Absorptive capacity, m-LBS, TAM, Technology willingness

Paper type Research paper

1. Introduction

The mobile era has already been established (Theodora *et al.*, 2012). Mobile technologies have facilitated the boom of mobile service applications. These applications offer customers better services and viable purchase options. M-LBS is generated from mobile services. It allows users to access value-added services via mobile telecommunication networks and integrated positioning technologies in mobile devices. M-LBS fulfills three main activities: identifying mobile devices' location, creating services owing to the relevant location and delivering location-enhanced services to customers. M-LBS is centered on users' location. Many m-LBS applications are created, including mapping, local search and information, navigation transport, tourism, social networking, entertainment, recreation and fitness, people locator services, resource management and advertisement (Ryschka *et al.*, 2016; Meng and Choi, 2019). The most expected benefit of m-LBS is personalization tailored to users' location in real time. Users receive relevant information and customized services due to location-inferring technologies. For instance, m-LBS provides a transformation from traditional search (e.g.

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paper maps or oral direction) to online search (e.g. mobile maps) (Ryschka *et al.*, 2016) or dispenses personalized advertisements to passers-by (Le and Wang, 2021). Therefore, m-LBS is purported as a killer application for the next-generation Internet.

In Vietnam, statistics indicated that 97% of Internet users owned mobile phones, with almost all phones being smartphones (Statista, 2021a), and 25% were frequent mobile Internet users and engaged in all online mobile-related activities (Appota, 2018). An increasing number of customers sought product/services information via mobile phones (Vietnam E-commerce Association, 2021). Moreover, reports showed that 79% of the respondents preferred using smartphone apps to patronize online during the period examined from 2016 to 2019 (Statista, 2021b). This hints that customers raise favorable perceptions and inclination to use mobile services, such as mobile application-based purchase, information search and location-based advertising (LBA) (Le and Wang, 2021; Vietnam E-commerce Association, 2021). Additionally, m-LBS enables users to convert into online services due to proper information and personalization. Thus, Vietnam has become a potentially emerging mobile service market.

Nevertheless, consumers still resist behavioral openness toward m-LBS, whereas service providers would like to get more details about the opportunity for deploying it (Ministry of science and technology, 2019). Several main challenges of developing m-LBS are the lack of information about m-LBS, technology infrastructure and immature experience of innovations (Ministry of science and technology, 2019). Also, researchers denoted major challenges in user activation due to the lack of innovation perceptions, privacy concerns and information disclosure. Hence, user RED in m-LBS remains low. Although extant studies have researched use intention toward m-LBS applications such as LBA (Le and Nguyen, 2021), retail (Verhagen *et al.*, 2021) and tourism (Meng and Choi, 2019), the topic has received less attention in the context of developing countries. To the best of our knowledge, little was conducted about consumer RED toward m-LBS in Vietnam.

This research aims to explore the formation of consumer RED to use m-LBS. Two questions are remedied as follows: (1) What are the important factors facilitating consumer RED? (2) What are the main resistances that need to be controlled to trigger consumer RED?

A mechanism of consumer RED toward m-LBS is clarified in our proposed model based on the extended TAM. The basic variables of TAM, namely USE, EOU and consumer RED, are employed. Following this theory, the higher consumer perceptions of USE and easiness, the more possible they are to do a given action toward information technology (IT). As researchers have doubted that, as a general consumer behavior theory, TAM is enough to enlighten given behaviors, an extension of TAM by recruiting external variables was deemed in a given setting (Theodora *et al.*, 2012). In the light of this statement, this study extends TAM by considering additional factors that represent pull effects (i.e. INN, ABC, TWI and TRU) and push effect (i.e. RIS) into the m-LBS setting. These factors are identified as underlying determinants of consumer engagement in different ITs, such as mobile payment (Yusfiarto *et al.*, 2021) and mobile devices (Lee, 2019). Hence, we respond to the growing call for more scholarly research on the influence of pull effect- and push effect-related dimensions on consumer RED. There are three contributions. First, this research reaffirms the benchmark of TAM in explaining consumer RED to utilize m-LBS. Second, we complement the current literature on behavioral intentions by combining some pull effect- and push effect-related constructs with TAM and by understanding these constructs that drive consumer RED in m-LBS. Third, this study is expected to offer insights into consumer engagement in m-LBS in developing countries, including Vietnam. Based on the findings, pinpointing the factors that influence behavioral intention would enhance the ability of practitioners to develop marketing tactics for popularizing m-LBS by manipulating the independent constructs.

2. Conceptual background and research framework

2.1 Technology acceptance theory

Various prominent theories were developed to edify behavioral intentions toward ITs. Among those, major paradigms are conceded in m-LBS applications, including theory of reason action (TRA) (Aloudat *et al.*, 2014), theory of planned behavior (TPB) (Meng and Choi, 2019), uses and gratifications (Le and Wang, 2021) and choice value model (Le and Nguyen, 2021). With the deliberation of the literature on technology adoption, TAM seems to be a suitable model as it can explain consumer RED toward m-LBS.

TAM was designed to measure how consumers use ITs by examining the impacts of USE and EOU on RED. Since it was originally built to manage IT activities in the workplace (Davis, 1989), the emphasis of the TAM-related research perspectives is confined to interpreting the adoption process in the organizational setting (Yang *et al.*, 2012). Albeit TAM emphasizes technology RED in organizations, it is insightful to be general and global (Phan and Daim, 2011). Thus, TAM is deemed for consumer behavior studies toward ITs due to its fundamental background.

Customer behavioral intentions toward m-LBS have drawn attention from academia (see Table 1). Kim *et al.* (2017) illustrated a formation of use intention by integrating the privacy calculus model into TAM. Coupon proneness, familiarity, TRU and privacy concern were explored to explain use intention. Verhagen *et al.* (2021) showed that attitude toward location-based messages is influenced by benefit-related, sacrifice-related factors and perceived value. Zhou (2016) enlightened continuance intention due to flow experience theory. Flow, TRU and privacy concerns are the determinants of continued usage. Furthermore, Meng and Choi (2019) developed a behavioral intention model by converging the elaboration likelihood model with TPB and found that the central and peripheral routes are crucial predictors of attitude. TPB antecedents (i.e. attitude, social norm and behavioral control) motivate use intention. Notably, the common idea among these theories, demonstrated in different studies on m-LBS behavioral intentions, is the stress on the importance of pull effects (e.g. information value, perceived benefits, personalization and TRU) and push effects (privacy concern, RIS and intrusiveness) in behavioral intentions. The pull effect depicts a positive influence attracting people for a specific behavioral purpose, while the push effect delineates a negative influence impeding people's performance based on the disadvantageous conditions (Moon, 1995). Each theoretical framework has its strengths and weaknesses and explains how various pull and push effects drive perceptions and behavioral intentions. Hence, it is holistic for further studies to add each other to illuminate behavioral intentions. For instance, scholars provided insights into usage intention in LBS by integrating proper constructs into TRA and TAM, such as TRU and RIS (Aloudat *et al.*, 2014).

After reviewing the literature, we find some theoretical supports of TAM for elucidating consumer RED in m-LBS. Its antecedents still remain, including USE, EOU and RED. Besides, Hong *et al.* (2006) posited that when a deeper explanation of behavioral intentions is required, other variables should be associated with TAM. The reaffirmation was emphasized in mobile services (Theodora *et al.*, 2012). Though TAM variables were identified as necessary precursors of RED toward m-LBS (Aloudat *et al.*, 2014), an extended mechanism of facilitating and hampering consumer perceptions and behavioral intentions should be revealed. Therefore, this study incorporates some pull effect- and push effect-related constructs into TAM that drive perceptions and RED. Researchers found that pull effect (i.e. TRU) and push effect (i.e. RIS) significantly influence consumer perceptions and behavioral responses toward mobile services (Barua *et al.*, 2017), m-LBS (Zhou, 2016) and LBA (Heo and Chang, 2018). Also, past studies witnessed consumer engagement in m-LBS through different pull effect-related indicators such as personalization, perceived benefits and contextual offers (Choi *et al.*, 2017;

Authors	Theory	Pull effects	Push effects	Main findings
Kim *et al.* (2017)	TAM and privacy calculus model	Coupon proneness, familiarity and trust	Privacy concern	Coupon proneness, familiarity, trust, privacy concern → Use intention
Aloudat *et al.* (2014)	TRA and TAM	Visibility, responsiveness, currency, accuracy, trust, usefulness and ease of use	Perceived risk	Visibility, responsiveness, currency, accuracy, trust, perceived risk → Usefulness Usefulness, ease of use → Attitude Usefulness, attitude → Behavioral intention
Le and Wang (2021)	U&G	Conditional value (i.e. contextual offer), advertising value (i.e. incentives, trustworthiness and Personalization) and social value (i.e. social facilitation)	Perceived risk	Conditional value, advertising value, societal value → Attitude Attitude, perceived control → Behavioral intentions
Verhagen *et al.* (2021)	Perceived value and store entry	Benefits (i.e. personalization and location congruency) and perceived value	Sacrifices (i.e. privacy concern and intrusiveness)	Benefits, sacrifices → Perceived value, attitude
Meng and Choi (2019)	ELM and TPB	Central route (i.e. information value), peripheral route (i.e. customer review), subjective norm and behavior control		Attitude, social norm, behavior control → Behavioral intention Central route, peripheral route → Attitude
Choi *et al.* (2017)	Sequential consumer search theory	Ease of use, personalization and perceived benefits		Ease of use, personalization, perceived benefits → Adoption Personalization → Information searching, decision-making
Zhou (2016)	IS success model	Flow, trust, information quality, service quality and system quality	Privacy concern	Information quality, service quality, system quality → Flow Trust → Privacy concern Flow, trust, privacy concern → Continuance intention

Table 1.
A summary of extant studies on pull effects and push effects in well-established theories toward m-LBS applications

Meng and Choi, 2019; Verhagen *et al.*, 2021). Although pull effect-related factors (i.e. INN, ABC and TWI) were adapted to explain consumer RED in different settings, such as near field communication (NFC)-based mobile payment (Pham and Ho, 2015), online purchase (Kaur and Thakur, 2019) and mobile devices (Lee, 2019), little is known about whether and what extent they influence USE, EOU and RED toward m-LBS. Additionally, scholars affirmed that external constructs such as user characteristics (e.g. cognitive and personality features), system characteristics and task characteristics directly influence TAM factors (Lee, 2019).

Thus, the gap is identified in our research by assessing the viability of m-LBS in an emerging trend of mobile services.

2.2 Research framework

INN indicates individuals' willingness to try out a new IT (Rogers, 2003). INN is an important personality trait and fosters behavioral responses (Pham and Ho, 2015). Extant literature reflected close associations of INN with USE and EOU in mobile services. Lee (2019) posited that INN positively influences USE and EOU in mobile device adoption. These findings imply that greater INN leverages more positive beliefs about the easiness and USE of ITs. Likewise, Theodora *et al.* (2012) denoted that INN motivates USE and EOU in mobile services. Customers who their peers respect for their first-hand knowledge and usage of IT are deemed technically competent. Generally, an open attitude toward the change in new ITs leads to positive perceptions of USE and easiness to utilize the ITs. From an m-LBS perspective, INN is expected to be closely related to USE and EOU. Therefore, the hypotheses are proposed as follows:

H1a. INN positively influences USE.

H1b. INN positively influences EOU.

Furthermore, a significant influence of INN on consumer RED was affirmed in the current literature. Pham and Ho (2015) concluded that INN is an important precursor of RED in NFC-based mobile payment. Scholars supported the close relationship between INN and behavioral responses, including attitude toward mobile payment (Wang and Dai, 2020) and the adoption of mobile services (Theodora *et al.*, 2012). It purports that innovative individuals readily accept new ITs by confronting the uncertainty of the ITs as they have self-confidence about their behaviors (Rogers, 2003). Though this relationship was empirically examined in earlier mobile service studies, its interpretation is inadequate in m-LBS. Thus, the hypothesis is proposed as follows:

H1c. INN positively influences RED.

ABC reflects firms' ability to identify the value of new information, assimilate it and use it for business purposes (Cohen and Levinthal., 1990). Scholars stressed its importance in firms' capacity from receiving externally acquired knowledge. Researchers documented a positive influence of ABC on innovation performance. From an individual perspective, ABC delineates users' capacity to value, assimilate and apply new knowledge about new ITs. Lee *et al.* (2012) asserted a strong effect of ABC on user acceptability toward mobile services. Likewise, individuals' ability to perceive the value of NFC-based mobile payment, absorb it and apply it to conduct transactions is essential to their willingness to utilize mobile payment (Pham and Ho, 2015). Generally, ABC plays an essential role in triggering RED toward mobile services. Stated formally, as it correlates closely to engage in m-LBS, the hypothesis is proposed as follows:

H2. ABC positively influences RED.

TWI reflects individuals' inclination to embrace new ITs for gaining goals (Parasuraman, 2000). TWI determines perceptions and behavioral responses toward an IT since it is considered as functional value. Technological innovation drives how information is formulated, disseminated and exchanged in a given system. Customers elicit a positive outlook (Kaur and Thakur, 2019) and usage RED toward ITs (Lin *et al.*, 2015), as TWI serves a practical function in general and knowledge function in particular. The more adept consumers perceive new ITs, the more positive they become about the usage (Kaur and Thakur, 2019). M-LBS fulfills personalized customer needs due to the utility of positioning technologies (Ryschka *et al.*, 2016), leading to their engagement in m-LBS. Hence, the following hypothesis is offered to apply the same logic from an m-LBS perspective:

H3. TWI positively influences RED.

TRU reflects individuals' reasonable expectation that providers possess the characteristics of trustworthiness, which, in turn, guides decision-making (Ajzen, 1991). It offers confidence and guarantees for consumers who will acquire their desired outcomes (Zhou, 2013). Extant studies demonstrated that TRU leverages USE and EOU of new ITs. Ha and Stoel (2009) postulated a strong relationship between TRU and USE in e-shopping. Hansen *et al.* (2018) examined a TAM-based framework and found a significant correlation between TRU and EOU in social media-based transactions. Theodora *et al.* (2012) revealed that TRU is a facilitator of USE and EOU in mobile services. From these supporting backgrounds, the following hypotheses are drawn:

H4a. TRU positively influences USE.

H4b. TRU positively influences EOU.

Besides, TRU plays a pivotal role in behavioral intentions, leading to the building, maintaining and developing of a long-term relationship between customers and firms (Le and Wang, 2021). Scholars indicated that TRU is a predictor of RED toward ITs (Zhou, 2016). Zhou (2013) opined that TRU boosts RED among young adults in m-LBS. RED will be displayed based on customers' and providers' beliefs, reliability and honesty. TRU is generally considered a critical motivation for RED in mobile services. Consistent with these arguments, we surmise that consumers who perceive m-LBS as greater TRU are more likely to embrace it. Therefore, the hypothesis is proposed as follows:

H4c. TRU positively influences RED.

RIS depicts a combination of uncertainty with the seriousness of the outcome involved (Cunningham, 1967). RIS describes consumers' feelings of unpleasantness because its importance is made in the decision-making process. RIS in mobile services has paid researchers' attention (Hansen *et al.*, 2018). As m-LBS is a new type of mobile service, consumers raise their awareness of uncertainty and its potential risks, including information disclosure and personal data usage for commercial purposes. Therefore, bearing in mind the great level of potential uncertainty in m-LBS, it is assumed that RIS can reduce USE toward m-LBS. Extant studies revealed that RIS negatively influences USE in m-LBS (Aloudat *et al.*, 2014). In contrast, others investigated the insignificant relationship in contactless credit card usage (Wang and Lin, 2019). The greatest advantage of using this innovation pertains to efficiency rather than effectiveness. Otherwise, earlier research argued that RIS is significantly associated with EOU in social media for purchase (Hansen *et al.*, 2018). A probable interpretation is that RIS reduces due to security mechanisms or protective functions that of themselves make it easier to use. Thus, the hypotheses are proposed as follows:

H5a. RIS negatively influences USE.

H5b. RIS negatively influences EOU.

Furthermore, RIS was identified as an impeder of behavioral responses toward mobile payment (Pham and Ho, 2015), self-service technology (Barua *et al.*, 2017) and purchase intention of counterfeit outdoor products (Tseng *et al.*, 2021). Zhou (2013) recorded that RIS adversely influences RED toward LBS. A possible explanation is that individuals' worry about the loss of personal information is an important reason behind the resistance toward mobile services. Moreover, when consumers perceive that m-LBS poses possible information leakage based on location-tracking technologies, they erode their embracement toward m-LBS. Similarly, Heo and Chang (2018) supported this argument in m-LBA. Following these clues of past studies, the hypothesis is proposed as follows:

H5c. RIS negatively influences RED.

EOU and USE are two key constructs in TAM. EOU delineates the degree of one's belief that interacting with an IT would be free of perceptive exertion, while USE mirrors the degree of individuals who believe that IT would improve their performance (Davis, 1989). TAM detected the significant relationships from EOU and USE to RED. Indeed, the influence of EOU on USE was opined by earlier studies in contactless credit cards (Wang and Lin, 2019), mobile payment (Wang and Dai, 2020) and mobile devices (Lee, 2019). Consistent with these findings, Aloudat *et al.* (2014) advocated the significant relationship in mobile location-based government services. Hence, the hypothesis is proposed as follows:

H6. EOU positively influences USE.

Otherwise, USE and EOU are the important conditions for the success of behavioral intentions toward ITs (Davis, 1989). Prior studies substantiated that RED is driven by USE and EOU in m-LBS (Aloudat *et al.*, 2014), social media-based transactions (Hansen *et al.*, 2018) and mobile services (Theodora *et al.*, 2012). Generally, USE and EOU are facilitators of RED toward innovative services. Aligned with TAM and earlier evidence, the following hypotheses are appeared in m-LBS:

H7. USE positively influences RED.

H8. EOU positively influences RED.

A summary of the research model is exhibited in Figure 1.

3. Methodology

3.1 Measurements

The measurement scales were adapted from the current literature. The items were measured based on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). INN was modified from Yang *et al.* (2012) and Rogers (2003); ABC was adapted from Lee *et al.* (2012) and Cohen and Levinthal (1990); TWI was given from Demirci and Ersoy (2008); RIS was drawn from Xu *et al.* (2011); TRU was borrowed from Johnson (2007); USE and EOU was

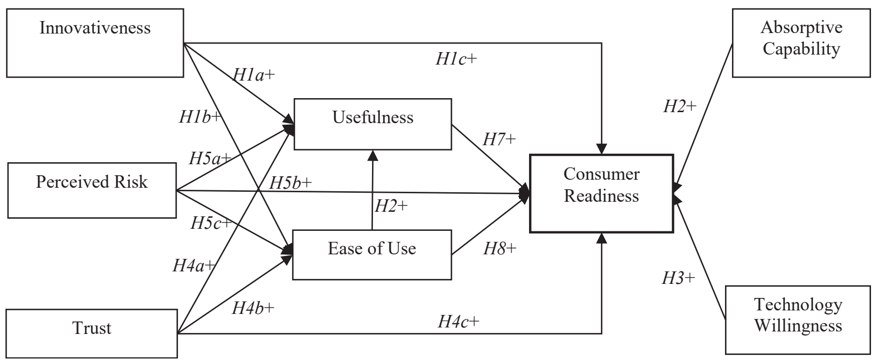

Figure 1.
Conceptual model

developed from Davis (1989) and RED was amended from Yiu *et al.* (2007). Scale items were shown in Table A1.

3.2 Data collection

The target population was Vietnamese mobile users. Reports showed that 97% of Internet users in Vietnam owned mobile phones, with almost all of these phones being smartphones (Statista, 2021a). A convenience sampling method was applied due to the absence of a valuable list of m-LBS users and the easy accessibility to researchers. Moreover, this method provides cost-saving and is widely applied in IT studies. Participants were those who were inclined to use m-LBS. An online survey was conducted between January 2021 and March 2021. Data were accumulated through a structured quantitative questionnaire. The questionnaire first was translated into Vietnamese; then, we translated it back into English to ensure the consistency between the two versions. The electronic form was uploaded via Google Docs and distributed via Facebook. We deliberately scrutinized the answers to each question. The study excluded 32 responses because of some issues, including the same answers to all questions and incomplete responses. Consequently, 423 responses remained valid and were used for further analysis.

The collection process was divided into two main stages: pre-test and pilot test. First, a pre-test was performed to refine the survey instrument with two marketing experts. Second, pilot tests (with 40 responses) were conducted to warn about the issues of clarity and accuracy that were not anticipated or needed to address before generating the formal survey. Respondents answered all questions by following the instructions. Items of three constructs were amended based on the misunderstanding and similarity, including TRU, TWI and ABC. Initial results reported that coefficient alpha values of constructs exceeded 0.7, and they were not presented in the main survey.

Of the respondents, 61.9% were female, 58.9% were in their twenties, 26% were in their thirties and 11.8 and 3.3% were under 20 and above 40, respectively. Regarding education, 55.8% were graduate, followed by 22.9%, 17.3 and 4% were postgraduate, master and above, and high school, respectively; 57% used the Internet on smartphones for over five years, 39% used the Internet for three to five years and 4% used the Internet for under three years; 85.4% used smartphones for over five years, followed by 11.8% for one to five years and 2.8% for under one year. Table 2 illustrates demographic information.

Measure	Item	Frequency	Percentage (%)
Gender	Male	262	61.9
	Female	161	38.1
Age	Under 20	50	11.8
	20–29	249	58.9
	30–39	110	26.0
	Above 40	14	3.3
Education	High school	17	4.0
	Graduate	236	55.8
	Postgraduate	97	22.9
	Master and above	73	17.3
Internet usage period (via smartphones) (years)	Under 3	17	4.0
	3–5	165	39.0
	Over 5	241	57.0
Smartphone usage period (years)	Under 1	12	2.8
	1–5	50	11.8
	Over 5	361	85.4

Table 2.
Survey respondent profile

4. Data analysis and results

4.1 Measurement model

Common method bias (CMB) can occur as the data in our study were gathered via a web-based survey. Harman one-factor (HOF) was employed to assess CMB (Podsakoff *et al.*, 2003). The result indicated that HOF value (42.574%) was less than 50%. Hence, CMB was unlikely to be a concern in this research.

A two-phase analysis was performed for the measurement model. The first phase was the usage of exploratory factor analysis (EFA) with principal axis factoring and Promax rotation to purify the scales. The Kaiser-Meyer-Olkin's (KMO = 0.903) and Barlett's sphericity test (sig = 0.000) verified the appropriateness of conducting the EFA. Factors explaining 75.768% of the total variance were extracted.

The measurement model was evaluated using confirmatory factor analysis in the second phase. Goodness-of-fit, convergent validity and discriminant validity illustrate the adequacy of the measurement model (Hair *et al.*, 2018). The goodness-of-fit indices comprise chi-square/degree of freedom (CMIN/df), comparative fit index (CFI), the goodness-of-fit index (GFI), Tucker–Lewis fit index (TLI) and root mean square error of approximation (RMSEA). CMIN/df value should be less than 3; CFI, GFI and TLI values should exceed 0.9, whereas RMSEA value should be lower than 0.08 (Hair *et al.*, 2018). The results demonstrated adequate evidence of goodness-of-fit (see Table 3).

Convergent validity was evaluated using three criteria: reliability of measurement items, composite reliability (CR) and average variance extracted (AVE). Standardized loadings (SLs) should exceed 0.5; CR and AVE values should be greater than 0.7 and 0.5, respectively (Fornell and Larcker, 1981). SLs, CRs and AVEs surpassed convergent validity for all constructs. Cronbach's alpha exceeded 0.7 (Hair *et al.*, 2018), thus presenting good reliability (see Table 4).

Diagonal constructs depict the square root of AVEs, and off-diagonal constructs depict the correlations among the constructs. The requirements of discriminant validity were fulfilled since the correlations among the constructs were less than the square root of AVE (see Table 5).

4.2 Structure model

To evaluate the structural model, SEM was conducted using AMOS (analysis of moment structures) 23.0. Results of hypotheses testing are reflected in Table 6. In total, 12 out of the 14 hypotheses are significant. The explained variances of USE, EOU and RED are 46.9%, 29.5% and 76.7%, respectively.

Regarding pull effect-related factors, INN positively influences USE ($\beta = 0.219, p = 0.000$), EOU ($\beta = 0.317, p = 0.000$) and RED ($\beta = 0.106, p = 0.009$), thus supporting H1a, H1b and H1c. Similarly, ABC ($\beta = 0.458, p = 0.000$) and TWI ($\beta = 0.195, p = 0.000$) significantly influence RED, thus supporting H2 and H3. Moreover, TRU significantly affects USE ($\beta = 0.174, p = 0.000$) and EOU ($\beta = 0.110, p = 0.015$), thus supporting H4a and H4b. However, the impact of TRU ($\beta = 0.035, p > 0.05$) on RED is insignificant; therefore, H4c is not supported.

Fit index	Recommended value	Results
CMIN/df	≤3.0	1.241
CFI	≥0.9	0.993
GFI	≥0.9	0.946
TLI	≥0.9	0.991
RMSEA	≤0.08	0.024

Table 3. Goodness-of-fit

Table 4.
Standardized loading, CA, AVE and CR

Constructs		SLs	CA	AVE	CR
Innovativeness (INN)	INN1	0.852	0.928	0.765	0.929
	INN2	0.906			
	INN3	0.893			
	INN4	0.847			
Absorptive capacity (ABC)	ABC1	0.830	0.845	0.737	0.894
	ABC2	0.877			
	ABC3	0.868			
Technology willingness (TWI)	TWI1	0.791	0.872	0.696	0.873
	TWI2	0.838			
	TWI3	0.871			
Perceived risk (RIS)	RIS1	0.916	0.937	0.832	0.937
	RIS2	0.907			
	RIS3	0.913			
Trust (TRU)	TRU1	0.860	0.897	0.745	0.897
	TRU2	0.843			
	TRU3	0.885			
Usefulness (USE)	USE1	0.834	0.851	0.745	0.898
	USE2	0.881			
	USE3	0.874			
Ease of use (EOU)	EOU1	0.847	0.895	0.749	0.900
	EOU2	0.914			
	EOU3	0.834			
Consumer readiness (RED)	RED1	0.878	0.917	0.787	0.917
	RED2	0.901			
	RED3	0.882			

Table 5.
Discriminant validity

	INN	ABC	TWI	RIS	TRU	USE	EOU	RED
INN	*0.875*							
ABC	0.505	*0.858*						
TWI	0.451	0.494	*0.834*					
RIS	−0.332	−0.417	−0.409	*0.912*				
TRU	0.284	0.341	0.449	−0.272	*0.863*			
USE	0.452	0.549	0.509	−0.583	0.390	*0.863*		
EOU	0.438	0.517	0.401	−0.412	0.281	0.432	*0.865*	
RED	0.591	0.794	0.637	−0.507	0.426	0.629	0.632	*0.887*

Regarding push effect-related factors, RIS negatively affects USE ($\beta = -0.349, p = 0.000$) and EOU ($\beta = -0.231$, $p = 0.000$), thus supporting H5a and H5b. However, RIS ($\beta = -0.031$, $p > 0.05$) insignificantly influences RED; hence, H5c is not supported.

Regarding TAM antecedents, EOU ($\beta = 0.105, p = 0.042$) positively affects USE, whereas USE ($\beta = 0.118$, $p = 0.006$) and EOU ($\beta = 0.210$, $p = 0.000$) significantly impact RED. Therefore, H6, H7 and H8 are supported.

Lastly, this study tested the influences of independent variables on the dependent variable through the mediation analysis procedure. The results show that the indirect effects among the variables are significant (see Table 6).

Hypotheses	Path	β-value	Results
Direct effects			
H1a	INN → USE	0.219***	Supported
H1b	INN → EOU	0.317***	Supported
H1c	INN → RED	0.106**	Supported
H2	ABC → RED	0.458***	Supported
H3	TWI → RED	0.195***	Supported
H4a	TRU → USE	0.174***	Supported
H4b	TRU → EOU	0.110*	Supported
H4c	TRU → RED	$0.035^{n/s}$	Not supported
H5a	RIS → USE	−0.349***	Supported
H5b	RIS → EOU	−0.231***	Supported
H5c	RIS → RED	$-0.031^{n/s}$	Not supported
H6	EOU → USE	0.105*	Supported
H7	USE → RED	0.118**	Supported
H8	EOU → RED	0.210***	Supported
Indirect effects			
INN → USE → RED		0.101***	Supported
INN → EOU → RED		0.033*	Supported
RIS → USE → RED		−0.117***	Supported
RIS → EOU → RED		−0.029*	Supported
TRU → USE → RED		0.052**	Supported
TRU → EOU → RED		0.013*	Supported
EOU → USE → RED		0.013*	Supported

Note(s): ***p < 0.001; **p < 0.01; *p < 0.05 and n/s: not significant

Table 6. Outcomes of direct and indirect effects

5. Theoretical and practical implications

5.1 Theoretical implications

Some theoretical implications are given. First, this work examined how to pull effect- and push effect-related dimensions to drive TAM antecedents in m-LBS. Pull effect-related factors (i.e. INN and TRU) significantly influenced USE and EOU. INN was posited to leverage USE and EOU, which aligns with earlier studies (Lee, 2019). These findings state that when consumers are interested in trying out innovative ITs and seeking useful mobile services, they would heighten USE perceptions of m-LBS, arouse curiosity about the services and feel easy to use them. Additionally, TRU was identified as a motivator of USE and EOU. These investigations conform to past research (Hansen *et al.*, 2018). This hints that m-LBS is perceived to be useful and easy to use as long as consumers arouse trustworthiness in its services. Our study revealed a strong relationship between push effect-related factors (i.e. RIS) and TAM constructs based on the above results. RIS destructively affected USE, which concurs with prior studies (Aloudat *et al.*, 2014). RIS reflects customers' perceptions of the potential loss of information disclosure, including information leakage and commercial purposes without customer consent. Thus, customer worries would reduce the USE of m-LBS. Moreover, EOU was adversely affected by RIS, hinting that lower perceptions of risk in m-LBS due to safety mechanisms and security measures would increase greater EOU of the services.

Second, this work revealed a mechanism of consumer RED toward m-LBS through the impacts of pull effect- and pushed effect-related dimensions. Pull effect-related factors were deemed as the important predictors of consumer RED. INN, ABC and technology will significantly influence consumer RED. The investigations hint that higher pull effects, including curiosity, assimilation and receptiveness, are likely to leverage customer acceptability. ABC had the strongest influence, which is consistent with past arguments (Lee *et al.*, 2012). It means that having more information and knowledge about m-LBS enables users to absorb new technologies and express engagement. Furthermore, TWI was opined as a motivation underlying consumer RED, supporting earlier studies (Kaur and Thakur, 2019). This shows that users exhibit openness and are inclined to evaluate m-LBS as helpful, such as searching information about nearby vendors or mapping services via smartphones integrated with global positioning systems (GPSs). Moreover, INN was an important idiosyncrasy influencing consumer RED. The result reinforces prior research (Pham and Ho, 2015). It is probably explained that individuals are primarily intrigued by their willingness and interest in utilizing new ITs. Unfortunately, the relationship between TRU and consumer RED was not supported, similar to extant findings (Theodora *et al.*, 2012). It implies that behavioral intention in m-LBS is not significantly influenced by reliability and safety measures. Likewise, the linkage between RIS and consumer RED was non-significant, fortifying the existing literature (Lin *et al.*, 2017). The association between uncertain feeling and seriousness of outcome possibly leads to insignificant impacts on consumer intention. Appota (2018) probably recorded that 82% of Vietnamese users tend to give away personal information for promotions of firms.

Lastly, this work acknowledged the worth of TAM to elucidate whether its antecedents navigate behavioral RED toward m-LBS. USE and EOU positively influenced consumer RED. These findings advocate extant affirmation (Lee, 2019). Generally, greater levels of being useful and "ready to use" are likely to enhance consumer adoption. Unsurprisingly, EOU was a facilitator of USE, which falls in consistence with earlier outcomes (Wang and Dai, 2020). The higher the degree of one's belief about easy exertion, the greater the belief about the enhancement in the actions.

Overall, although extant studies researched TAM and its association with other well-established theories such as TPB (Hansen *et al.*, 2018) and diffusion of innovation (Pham and Ho, 2015) and with external variables of system features, task features and personality (Lee, 2019) but not delved TAM with pull effect- and push effect-related factors in m-LBS. In addition to the importance of TAM in triggering consumer RED, pull effect- and push effect-related factors were alluded to as motivators and inhibitors of consumer engagement. Therefore, we endeavored to extend the current consumer RED literature in m-LBS and in an emerging country.

5.2 Practical implications

This study has several important implications. First, the relationships between pull effects and customer RED suggest that managers must tailor marketing trajectories that are the stimuli to these effects influencing behavioral responses. Marketing tactics should be adopted to entice earlier adopters and innovators. The demographic statistics indicated that young customers, a major proportion of smartphone users, evoke INN, promoting USE perceptions, easy exertion and openness. Besides the focus on young consumers in the m-LBS market, providers allow potential customers (e.g. under 20 and above 40) to apply new knowledge to the m-LBS performance. They have opportunities to acquire useful information, assimilate and learn about innovative services. Consequently, they would absorb up-to-date information about technological innovation and know how to operate m-LBS. Furthermore, given that TWI is asserted as an impetus for consumer RED, firms reinforce an association between m-LBS and consumers by developing a user-friendly interface that facilitates an initial inroad and increases the familiarity with m-LBS (Kaur and Thakur, 2019).

Second, the findings reveal that RIS and TRU negatively and positively affect USE and EOU. Managers must address issues of RIS and enhance TRU. Firms strive to establish safe mechanisms, security policies and alert programs that help users understand the purposes of using personal information, minimize frauds and cyber victimization and preclude potential loss of individual data. Providers should obtain user permission before delivering location-based information and services to mitigate the uncertainty. Besides, firms attempt to sustain TRU by using structural assurances (privacy seals) and reputation (early adopters and innovators) and developing online circles (experience and knowledge sharing).

Third, the significant relationship between EOU and consumer RED proposes that firms should improve the functional value of m-LBS. For example, accurate location positioning, relevant and personalized services in real time, faster loading time, navigation design, images and frequent questions and answers reinforce EOU and engagement. Consequently, EOU puts consumers at USE and elicits consumer RED. Furthermore, the result reveals that consumer RED is accelerated by USE. Firms strive to generate communication activities and permit users to test m-LBS by conveying instructions in different media formats (e.g. mobile apps, video advertisements and mobile webs).

6. Limitations and future research directions

This work reveals several notes on caveats for further studies. First, although this research explains consumer RED, it can be replicated in a specific m-LBS context (e.g. GPS-based mobile purchase applications). Appota (2018) reported that 52% of Vietnamese shoppers used mobile applications for online purchases and 72% of total e-commerce site visits were through positioning technology-based smartphones. Second, TRU and RIS are not influential to consumer RED. In the stream of the study, we continue examining the relationships in further longitudinal studies and systematically sampling from a more dispersed sample to make comparisons and enhance the generalizability. Lastly, besides the indispensability of the above factors, the current model can be extended by employing external factors for the success of behavioral intentions in m-LBS.

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Appendix

Constructs	Items	Measures
Innovativeness	INN1	If I hear information about new technologies, I will look for ways to experiment them
	INN2	Among my peers, I am the first to try new technologies
	INN3	I am eager to learn about new technologies
	INN4	I am eager to try new technologies
Absorptive capacity	ABC1	I have necessary knowledge to understand m-LBS
	ABC2	I have technical competence to absorb m-LBS
	ABC3	I have an understanding of goals, tasks and responsibilities of m-LBS
	ABC4	I can apply knowledge about mobile services to perform tasks using m-LBS*
Technology willingness	TWI1	I usually figure out new hi-tech services without others' help
	TWI2	I feel optimistic about new technologies and a belief that they offer me an increased control, flexibility and efficiency
	TWI3	New technologies are often complicated or discomfort to be useful
Perceived risk	RIS1	Providing service providers with my personal information would involve many unexpected problems
	RIS2	It would be risky to disclose my personal information to service providers
	RIS3	Information about my activities via m-LBS can be known to others
Trust	TRU1	I rely on m-LBS to finish services reliably
	TRU2	Given the state of existing m-LBS, I believe that technology-related errors are quite rare
	TRU3	In my opinion, m-LBS is reliable
Usefulness	USE1	My activities are more quickly using m-LBS
	USE2	My activities are more easily using m-LBS
	USE3	The effectiveness of activities would improve using m-LBS
	USE4	Decision-making would be better using m-LBS*
Ease of Use	EOU1	m-LBS is easy to learn
	EOU2	m-LBS is easy to understand
	EOU3	Getting information from m-LBS is easy
	EOU4	It is easy to become skillful at using m-LBS*
Consumer readiness	RED1	I intent to conduct activities via m-LBS
	RED2	I intent to boost m-LBS usage to conduct activities
	RED3	I will suggest others to use m-LBS

Note(s): *Items are dropped

Table A1.
Scale items

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