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An empirical examination of user adoption of location-based services

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Abstract Location-based services (LBS) can present the optimal information and services to users based on their locations. This will improve their experience. However, this may also arouse users' privacy concern and increase their perceived privacy risk. From both perspectives of flow experience and perceived risk, this research examined user adoption of LBS. We conducted data analysis with structural equation modeling. The results indicated that contextual offering affects trust and flow, whereas privacy concern affects trust and perceived risk. Trust, flow and perceived risk affect the usage intention. Among them, flow has a relatively larger effect.

Keywords Location-based services · Privacy risk · Trust · Flow

1 Introduction

Mobile Internet has been developing rapidly in the world. According to a report issued by China Internet Network Information Center (CNNIC) in July 2012, the number of mobile Internet users in China exceeded 388 million, accounting for 72 % of its Internet population (538 million) [10]. This indicates the great mobile Internet user base. Mobile Internet frees users from the temporal and spatial constraints, and enables them to acquire information and services at anytime from anywhere. This will bring value to users and facilitate their adoption and usage. Faced with the great opportunity, mobile service providers have released a variety of services, such as mobile instant messaging, mobile shopping and location-based services (LBS). Typical LBS include mobile navigation, location-based advertisements, emergency evacuation and mobile check-in services. A few mobile services have received wide adoption among

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users. For example, about 83 % of mobile Internet users have ever used mobile instant messaging [10]. However, compared to these popular services, the user adoption rate of LBS is relatively lower [27]. Mobile service providers need to understand the factors affecting user adoption in order to facilitate his or her usage behavior.

Compared to other mobile services, the unique advantage of LBS is locatability, which means that LBS can present the optimal information and services to users based on their location [45]. The constraints of mobile terminals such as small screens and inconvenient input make it relatively difficult for users to search for information on the mobile Internet. Thus, the contextual information and services presented by LBS will reduce users' effort spent on information retrieval and improve their experience. However, LBS need to collect and utilize users' location information. This may arouse their privacy concern and increase their perceived privacy risk. Users may worry whether mobile service providers properly collect, store and use their location information.

Extant research has focused on the negative effect of privacy risk on LBS user behavior [29, 55]. However, it has seldom examined the positive effect of user experience on LBS adoption. The contextual and personalized services offered by LBS can deliver a better experience to users, which may help facilitate their usage behavior. For example, when users are in traveling, mobile service providers can recommend the nearby tourism scenes to users based on their location. This contextual information may be valuable to users and enrich their experience. Thus, adopting a single perspective of perceived risk may be unable to fully reflect LBS user behavior. To fill this gap, we combined both perspectives of enablers such as user experience and inhibitors such as perceived risk to examine user adoption. We measured user experience with flow, which reflects an optimal experience and has significant effects on user adoption of various mobile services such as mobile TV [26] and mobile games [22]. In addition, privacy risk may decrease users' intention to adopt LBS. They need to engender trust in service providers in order to mitigate perceived risk and to ensure a compelling experience. Thus, we included trust into the model.

This research makes three contributions. First, we examined the effects of both enablers such as flow and inhibitors such as perceived risk on LBS user behavior. The results indicated that the effect of flow on usage intention outweighs that of perceived risk on usage intention. This extends extant research that focuses on the single effect of perceived risk on LBS user behavior. Second, contextual offering strongly affects trust, which in turn affects flow. This highlights the need to build users' trust in order to improve their experience. Third, extant research has identified the effect of flow on user adoption of mobile TV and mobile games. This research generalizes it to LBS and verified its effect on user behavior.

The rest of this paper proceeds as follows. We present a literature review in the next section. Then, we develop the research model and hypotheses in section three. Section four describes instrument development and the data collection process. Section five presents results and section six discusses these results. We present the theoretical and managerial implications in section seven. Section eight concludes the paper.

2 Literature review

2.1 LBS user adoption

As an emerging service, LBS user adoption has received attention from researchers. They used information technology adoption theories such as the technology acceptance model (TAM), task technology fit (TTF) and the unified theory of acceptance and use of technology (UTAUT) as the theoretical bases. TAM proposes that perceived usefulness and perceived ease of use represent two main factors affecting user adoption of an information technology [12]. TTF notes that user adoption is determined by the fit between task characteristics and technology characteristics [19]. UTAUT suggests that performance expectancy, effort expectancy, social influence and facilitating conditions are the main factors affecting user adoption [52]. Junglas and Watson [27] found that perceived usefulness and perceived ease of use have significant effects on LBS user behavior. Junglas et al. [28] noted that the fit between location sensitiveness as task characteristics and locatability and mobility as technological characteristics will determine user adoption of LBS. Xu and Gupta [53] reported that performance expectancy, effort expectancy and personal innovativeness significantly affect LBS usage. In addition to these information technology adoption theories, perceived value is also drawn to examine LBS user behavior. Pura [46] noted that conditional value, monetary value and convenience value affect user intention to adopt LBS. Xu et al. [54] noted that multimedia location-based advertisements have a significant effect on users' purchase intention.

Extant research has also noted the effect of privacy risk on LBS user behavior. Xu et al. [55] stated that three interventions, which include compensation, industry self-regulation and government regulation, affect privacy benefits and risks, both of which further determine the intention to use LBS. Junglas et al. [29] suggested that five personality traits, which include agreeableness, extraversion, emotional stability, openness to experience and conscientiousness, affect privacy concern, which further affects perceived risk and LBS user behavior. Kofod-Petersen et al. [32] reported that privacy affects user attitude towards location-aware social network services.

2.2 Flow

The concept of flow originates from psychology [11]. Flow represents a holistic sensation that people feel when they act with total involvement [11]. Hoffman and Novak [24] noted that flow is characterized by: (1) a seamless sequence of responses facilitated by machine interactivity, (2) intrinsic enjoyment, (3) a loss of self-consciousness, and (4) self-reinforcement. Flow reflects a balance between users' skills and challenges. When the skills exceed challenges, users feel bored. In contrast, when the challenges exceed skills, users feel anxious. If both skills and challenges are lower than the threshold values, users feel apathy. Only when both skills and challenges exceed the threshold values and have a good match will users experience flow.

As an elusive concept, flow consists of multiple components, including perceived enjoyment, concentration, perceived control [33], mergence of action and awareness [21], and curiosity [23]. Among them, perceived enjoyment, concentration and perceived control are the most often used dimensions [14, 33]. Perceived enjoyment reflects the pleasure and enjoyment associated with using an information technology. Concentration reflects user immersion in the activity. Perceived control reflects the feelings of control over the activity and surrounding environment.

Extant research has noted that flow as an optimal experience may facilitate user behavior [25]. In the information systems context, researchers have used flow to understand user adoption of various applications, such as Internet [1], online shopping [20, 21], instant messaging [38], and e-learning [23]. O'Cass and Carlson reported that flow affects users' satisfaction with and loyalty towards professional sporting team websites [43]. Animesh et al. [3] argued that flow influences users' intention to purchase virtual products in virtual worlds. Recently, researchers have also applied flow to examine user adoption of mobile services, such as mobile TV [26] and mobile games [22]. Possible determinants of flow include perceived complexity [21], content quality [26], and perceived ease of use [22]. In line with these studies, we used flow to reflect LBS user experience in this research.

2.3 Trust

Trust reflects a willingness to be in vulnerability based on the positive expectation towards another party's future behavior [42]. Trust includes three beliefs: ability, integrity and benevolence. Ability means that mobile service providers have the necessary ability and knowledge to fulfill their tasks. Integrity means that mobile service providers keep their promises and do not deceive users. Benevolence means that mobile service providers are concerned with users' interests, not just their own.

Trust has been extensively examined in the e-commerce context, which involves great uncertainty and risk [8, 18, 51]. Researchers have identified that trust can mitigate perceived risk and facilitate consumer behavior [30, 37]. As LBS may bring potential risk to users, they need to build trust in service providers in order to adopt and use the services. Junglas et al. also stated that trust and perceived risk affect user intention to use LBS [29]. Considering the significant role of trust in user behavior, we include it into the research model.

3 Research model and hypotheses

3.1 Contextual offering

Contextual offering means that mobile service providers present the optimal information and services to users based on their locations and preferences. With the help of mobile networks, service providers can acquire a user's real-time location. Then, they can match marketing information with user location and preferences, and push the relevant information to the user. The contextual information offered by LBS will reduce user effort spent on information search and help him or her obtain an enjoyable experience. Otherwise, due to the constraints of mobile terminals such as inconvenient input, users may need to spend much time on information retrieval and this will undermine their experience. Contextual offering may also affect user trust in mobile service providers. Presenting relevant information and services to users entails mobile service providers' effort and resource investment. Thus, contextual offering as a trust signal will affect user beliefs in service providers' ability, integrity and benevolence. Extant research has reported the effect of contextual offering on user trust and intention to conduct mobile transactions [34]. Contextual offering as a benefit of LBS may also reduce perceived risk. When users expect to receive relevant and personalized information and services from LBS, they may lower their risk perception as contextual offering provides a compensation for their personal information disclosure.

H1.1: Contextual offering positively affects flow.
H1.2: Contextual offering positively affects trust.
H1.3: Contextual offering negatively affects perceived risk.

3.2 Privacy concern

Privacy concern reflects a user's concern on his or her personal information, such as concern on improper access, unauthorized secondary use, errors and collection [47]. LBS need to collect and utilize users' location information. This will arouse their concern about this personal information. They may feel be tracked and worry whether mobile service providers can appropriately collect, store and use their location information. Privacy concern may increase users' effort spent on monitoring mobile service providers and decrease their perceived control and enjoyment. This will affect their experience. Privacy concern may also affect users' trust as they may doubt mobile service providers' ability, integrity and benevolence to protect their privacy. For example, users may doubt whether mobile service providers are concerned with their interests and do not share location information with the third parties. Privacy concern will directly affect perceived risk [50]. Users with privacy concern may worry about the potential losses and uncertainty associated with disclosing personal information. Extant research has reported the effect of privacy concern on trust and perceived risk [5, 29, 40].

H2.1: Privacy concern negatively affects flow.
H2.2: Privacy concern negatively affects trust.
H2.3: Privacy concern positively affects perceived risk.

3.3 Trust, flow and perceived risk

Trust may affect flow experience. Trust provides a guarantee that users will acquire their expected outcomes in future. In other words, trust enables users to believe that mobile service providers have enough ability, integrity and benevolence to deliver a good experience to them. Lee et al. [36] found that trust affects online banking users' flow experience. Trust may also affect perceived risk as it will reduce users' perceived uncertainty and ensure that they acquire the expected services. Much research has found the effect of trust on perceived risk [6, 31, 39].

H3: Trust positively affects flow.
H4: Trust negatively affects perceived risk.

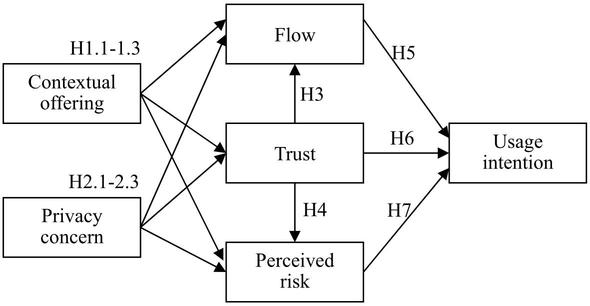

Fig. 1 Research model

3.4 Usage intention

Flow as an optimal experience may facilitate user intention. When users expect LBS to deliver a good experience to them, they will increase usage intention. Extant research has noted the effect of flow on user behavior [35, 43]. Trust may also promote the behavioral intention [7]. In addition, according to the theory of reasoned action, trust as a belief will affect usage intention, which in turn affects actual usage behavior [15]. Compared to the positive effects of flow and trust on usage intention, perceived risk will negatively affect usage intention as it means potential losses to users [13].

H5: Flow positively affects usage intention.
H6: Trust positively affects usage intention.
H7: Perceived risk negatively affects usage intention.

Figure 1 presents the research model.

4 Research method

The research model includes six factors. Each factor was measured with multiple items. We adapted all items from extant literature to improve content validity [49]. A researcher first translated these items into Chinese. Then, another researcher translated them back into English to ensure consistency. When the instrument was developed, we tested it among five users that had LBS usage experience. Then, according to their comments, we revised some items to improve the clarity and understandability. Appendix lists the final items and their sources.

Four items of privacy concern were adapted from Son and Kim [48] to reflect a user's concern about information storage and usage. Items of contextual offering were adapted from Lee [34] to reflect the timely, specific location and contextual information presented to users. Items of perceived risk were adapted from Xu et al. [55] to measure the potential losses and uncertainty associated with using LBS. Items of trust were adapted from Pavlou and Gefen [44] to reflect user beliefs in mobile service providers' ability, integrity and benevolence. We adapted three items of flow from Lee et al. [36] to measure users' concentration, perceived control and enjoyment. Since it is difficult to measure actual usage, we measured usage intention to

Table 1 Demographic information of our sample and CNNIC sample

	Option	Count	Percentage (%)	CNNIC sample (%)
Gender	Male	155	55.8	58.1
	Female	123	44.2	41.9
Age (years old)	<20	26	9.4	30.7
	20–29	241	86.7	36.0
	>29	11	3.9	33.3
Education	Middle school and below	4	1.4	76.2
	Associate degree	20	7.2	10.9
	Bachelor degree and higher	254	91.4	13.0
Mobile Internet usage history (years)	<1	12	4.3	NA.
	1–2	67	24.1	
	3–5	171	61.5	
	>5	28	10.1	
Mobile Internet usage frequency (average times each week)	1–2	12	4.3	NA.
	3–4	24	8.6	
	5–7	40	14.4	
	>7	202	72.7	

reflect user adoption. Items of usage intention were adapted from Lee [34] to reflect users' intention to use and continue using LBS.

We collected data at a university and two retail outlets of China Mobile, which is the largest telecommunication operator in China. The university and retail outlets are located in an eastern China city, where mobile Internet is relatively developed than other regions. We contacted users and inquired whether they had LBS usage experience. Then, we asked those users with positive answers to fill the questionnaires based on their usage experience. To encourage users' participation, we promised to send the research results to them by e-mail if they were willing to obtain the results. Most users completed the questionnaires and the response rate was 95 %. We scrutinized questionnaires and dropped seven responses with too many missing values. As a result, we obtained 278 valid responses. Table 1 lists the demographic information of our sample and CNNIC [9] sample.

To test the common method variance (CMV), we modeled all items as the indicators of a factor representing the method effect [41], and re-estimated the model. The results indicated a poor fitness. For example, the goodness of fit index (GFI) is 0.499 (<0.90). The root mean square error of approximation (RMSEA) is 0.243 (>0.08). This indicates that CMV is not a significant problem in our research.

Table 2 Standardized item loadings, AVE and CR

Factor	Item	Standardized item loading	AVE	CR
Privacy concern (PC)	PC1	0.768	0.70	0.90
	PC2	0.875		
	PC3	0.882		
	PC4	0.809		
Contextual offering (CO)	CO1	0.725	0.57	0.80
	CO2	0.804		
	CO3	0.741		
Flow (FLOW)	FLOW1	0.737	0.51	0.76
	FLOW2	0.662		
	FLOW3	0.739		
Trust (TRU)	TRU1	0.777	0.61	0.82
	TRU2	0.905		
	TRU3	0.644		
Perceived risk (RISK)	RISK1	0.657	0.61	0.83
	RISK2	0.855		
	RISK3	0.826		
Usage intention (USE)	USE1	0.825	0.74	0.90
	USE2	0.907		
	USE3	0.848		

5 Results

Following the two-step approach recommended by Anderson and Gerbing [2], we first examined the measurement model to test validity. Then, we examined the structural model to test research hypotheses and model fitness.

First, we conducted a confirmatory factor analysis (CFA) to examine the validity, which includes the convergent validity and the discriminant validity. The convergent validity measures whether items can effectively reflect their corresponding factor, whereas the discriminant validity measures whether two factors are statistically different. Table 2 lists the standardized item loadings, the average variance extracted (AVE), and the composite reliability (CR). Most item loadings are larger than 0.7 and the T values indicate that all loadings are significant at 0.001. All AVEs exceed 0.5 and CRs exceed 0.7. Thus, the scale has a good convergent validity [4, 17].

To examine the discriminant validity, we compared the square root of AVE with factor correlation coefficients. As listed in Table 3, for each factor, the square root of AVE is significantly larger than its correlation coefficients with other factors, showing a good discriminant validity [16, 17].

Second, we adopted structural equation modeling software LISREL to estimate the structural model. Table 4 lists path coefficients and their significance. Table 5 lists the recommended and actual values of some fit indices. Each fit index has a better actual value than the recommended value. This indicates the good fitness of the research model [17]. The chi-square value for the structural model is 185.99 with

Table 3 The square root of AVE (shown as bold at diagonal) and factor correlation coefficients

	PC	CO	FLOW	TRU	RISK	USE
PC	**0.835**					
CO	0.055	**0.757**				
FLOW	−0.033	0.543	**0.714**			
TRU	−0.241	0.473	0.539	**0.783**		
RISK	0.490	0.004	−0.069	−0.249	**0.784**	
USE	−0.206	0.228	0.416	0.384	−0.207	**0.861**

Table 4 Path coefficients and their significance

Hypothesis	Path	Coefficient	Supported or not
H1.1	CO→FLOW	0.29^{**}	Yes
H1.2	CO→TRU	0.49^{***}	Yes
H1.3	CO→RISK	−0.06	No
H2.1	PC→FLOW	−0.07	No
H2.2	PC→TRU	-0.27^{**}	Yes
H2.3	PC→RISK	0.45^{***}	Yes
H3	TRU→FLOW	0.51^{***}	Yes
H4	TRU→RISK	-0.17^{*}	Yes
H5	FLOW→USE	0.30^{**}	Yes
H6	TRU→USE	0.16^{*}	Yes
H7	RISK→USE	-0.15^{*}	Yes

(Note: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$)

Table 5 The recommended and actual values of fit indices

Fit indices	chi^2/df	GFI	AGFI	CFI	NFI	SRMR	RMSEA
Recommended value [17]	<3	>0.90	>0.80	>0.90	>0.90	<0.05	<0.08
CFA	1.33	0.935	0.910	0.986	0.953	0.038	0.035
Structural model	1.33	0.934	0.910	0.986	0.952	0.041	0.034

(Note: chi^2/df is the ratio between Chi-square and degrees of freedom, GFI is Goodness of Fit Index, AGFI is the Adjusted Goodness of Fit Index, CFI is the Comparative Fit Index, NFI is the Normed Fit Index, SRMR is the Standardized Root Mean Square Residual, RMSEA is Root Mean Square Error of Approximation)

140 degrees of freedom. For CFA model, the chi-square value is 182.87 with 137 degrees of freedom. Both chi-square values are significant at 0.001. However, this may be caused by the sample size. The explained variance of flow, trust, perceived risk and usage intention is 48.5 %, 29.7 %, 26.3 %, and 21.8 %, respectively.

6 Discussion

As listed in Table 4, except H1.3 and 2.1, other hypotheses are supported. Contextual offering significantly affects flow and trust, but does not affect perceived risk. Privacy concern has significant effects on trust and perceived risk, but has no effect on flow. Trust affects flow and perceived risk, and these three factors determine usage intention.

The results indicated that contextual offering affects flow. Contextual offering enables users to receive personalized information and services from mobile service providers based on their location and preferences. This will significantly improve usage experience as it is difficult for users to search information with mobile terminals. Contextual offering reduces users' effort and time spent on information retrieval and brings more enjoyment to them. Contextual offering also has a strong effect on trust. This result is consistent with that of Lee [34]. Mobile service providers need to invest considerable resources and effort on presenting relevant and accurate information to users. When users obtain contextual information and services, they will form positive beliefs in the service provider's ability, integrity and benevolence. In contrast, if the information offered to users is irrelevant or inaccurate, they may doubt the service provider's trustworthiness. We did not find the direct effect of contextual offering on perceived risk. However, contextual offering indirectly affects perceived risk through trust. This demonstrates the mediation effect of trust.

Privacy concern has strong effects on trust and perceived risk. These results are consistent with extant findings [5, 29]. Privacy concern will affect users' evaluations on service providers' trustworthiness. They may doubt whether mobile service providers keep their promises to protect users' privacy. They may also doubt whether mobile service providers have enough technological ability to prevent personal information from unauthorized access. In addition, privacy concern will increase perceived risk. Users with high privacy concern may worry about the potential uncertainty associated with information disclosure, such as information leakage and sales to the third parties without their knowledge. To mitigate users' privacy concern, mobile service providers can post their privacy polices to inform users about their practices on information collection, storage and usage. They can also display privacy seals to demonstrate that their privacy practices are certified by the trusted third parties such as TRUSTe. In addition, they also need to acquire users' permission before collecting users' personal information. The results indicated that privacy concern has no effect on flow. However, it indirectly affects flow through trust.

Trust has a strong effect on flow. This demonstrates that users need to build trust in mobile service providers before they expect to obtain a good experience in future. Trust will increase users' perceived control and this may help generate a good experience. The results indicated that flow, trust and perceived risk affect usage intention. Among them, flow has a relatively larger effect. This may be good news for mobile service providers. Although perceived risk negatively affects users' behavior, service providers can improve users' experience to facilitate their usage intention.

7 Theoretical and managerial implications

From a theoretical perspective, this research examined LBS user adoption from the perspectives of flow and perceived risk. As noted earlier, extant research has focused on the effect of privacy risk on user adoption of LBS. However, LBS can present users with a good experience, which may also affect their adoption. To more fully reflect LBS user behavior, it is necessary to combine both perspectives of enablers such as trust and flow and inhibitors such as perceived risk to examine user adoption. Our results indicated that both flow and perceived risk have significant effects on usage intention. Furthermore, the effect of flow on usage intention outweighs that of perceived risk. This advances our understanding of LBS user behavior. Future research can include other enablers such as satisfaction and inhibitors such as switching cost into the model. In addition, while extant research has examined flow experience in various contexts such as online shopping and mobile TV, it has seldom been tested in the context of LBS, which represents an emerging mobile service. We extend flow to LBS context and found that contextual offering has a significant effect on flow. This enriches extant literature on flow, which has found the effects of perceived complexity and content quality on flow [21, 26].

From a practical perspective, our results imply that mobile service providers need to be concerned with both perspectives of enablers and inhibitors in order to facilitate user adoption of LBS. On one hand, they need to deliver an optimal experience to users. This requires service providers to present users with relevant and personalized information and services, which mean continuous effort and resources investment. However, this investment may be worthwhile as contextual offering not only improves user experience but also increases his or her trust. On the other hand, they need to mitigate users' perceived uncertainty and risk. They should obtain users' permission before pushing location-based information and services to users. Otherwise, users' privacy concern may be aroused, which will increase their perceived risk.

8 Conclusion

As an emerging service, LBS have not received wide adoption among mobile users. Integrating both perspectives of flow and perceived risk, this research examined user adoption of LBS. The results indicated that flow, trust and perceived risk have significant effects on usage intention. In addition, contextual offering affects trust and flow, whereas privacy concern affects trust and perceived risk. The results imply that mobile service providers need to concern both perspectives of enablers such as flow and inhibitors such as perceived risk in order to facilitate user adoption of LBS.

There are some limitations within this research. First, we conducted this research in China, where mobile commerce is developing rapidly but is still in its early stage. Thus, our results need to be generalized to other countries that had developed mobile commerce. Second, besides flow, trust and perceived risk, there exist other factors such as satisfaction and perceived usefulness that possibly affect user behavior. Future research can test their effects. Third, our sample is mainly composed of young adults that had received university education. The CNNIC report indicates that a majority of mobile Internet users held lower education level (middle school and below) [9]. Future research needs to generalize our results to these samples.

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Appendix: Measurement scales and items

Privacy concern (PC) (adapted from Son and Kim [48])

PC1: I am concerned that the information I disclosed to this service provider may be misused.
PC2: I am concerned that a person can find private information about me on the Internet.
PC3: I am concerned about providing personal information to this service provider, because of what others might do with it.
PC4: I am concerned about providing personal information to this service provider, because it could be used in a way I did not foresee.

Contextual offering (CO) (adapted from Lee [34])

CO1: This service provider presents real-time information to me.
CO2: This service provider presents specific location information to me.
CO3: This service provider can present the optimal information and services to me based on my interests and location.

Perceived risk (RISK) (adapted from Xu et al. [55])

RISK1: Providing this service provider with my personal information would involve many unexpected problems.
RISK2: It would be risky to disclose my personal information to this service provider.
RISK3: There would be high potential for loss in disclosing my personal information to this service provider.

Trust (TRU) (adapted from Pavlou and Gefen [44])

TRU1: This service provider is trustworthy.
TRU2: This service provider keeps its promise.
TRU3: This service provider keeps customer interests in mind.

Flow (FLOW) (adapted from Lee et al. [36])

FLOW1: When using this service, my attention is focused on the activity.
FLOW2: When using this service, I feel in control.
FLOW3: When using this service, I find a lot of pleasure.

Usage intention (USE) (adapted from Lee [34])

USE1: Given the chance, I intend to use this service.
USE2: I expect my use of this service to continue in the future.
USE3: I have intention to use this service.

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