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Integrating TTF and UTAUT to explain mobile banking user adoption

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ABSTRACT

Due to its advantages such as ubiquity and immediacy, mobile banking has attracted traditional banks' interests. However, a survey report showed that user adoption of mobile banking was much lower than that of other mobile services. The extant research focuses on explaining user adoption from technology perceptions such as perceived usefulness, perceived ease of use, interactivity, and relative advantage. However, users' adoption is determined not only by their perception of the technology but also by the task technology fit. In other words, even though a technology may be perceived as being advanced, if it does not fit users' task requirements, they may not adopt it. By integrating the task technology fit (TTF) model and the unified theory of acceptance and usage of technology (UTAUT), this research proposes a mobile banking user adoption model. We found that performance expectancy, task technology fit, social influence, and facilitating conditions have significant effects on user adoption. In addition, we also found a significant effect of task technology fit on performance expectancy.

1. Introduction

Mobile banking, also referred to as cell phone banking, is the use of mobile terminals such as cell phones and personal digital assistants (PDAs) to access banking networks via the wireless application protocol (WAP). Through mobile banking, users can access banking services such as account management, information inquiry, money transfer, and bill payment (Luarn & Lin, 2005). Compared with Internet-based online banking services, mobile banking is free of temporal and spatial constraints. Users can acquire real-time account information and make payments at anytime and anywhere. This helps traditional banks improve their service quality and reduce service costs. Thus, many banks such as the Industrialized and Commercial Bank of China (ICBC) and China Construction Bank (CCB), the two largest banks in China, have developed mobile banking services and tried to market them to mobile users.

However, a survey report by iResearch, a leading consulting company that focuses on the Internet sector in China, showed that only 14.3% of cell phone Internet users adopted mobile banking (iResearch, 2008). This figure was much lower than the adoption rate of other mobile value-added services such as mobile instant messaging (IM) (72%), image and ring tone download (48.4%), mobile games (43.8%), and mobile search (34.3%) (iResearch, 2008). By understanding the factors affecting user adoption and usage of mobile banking services, banks will be able to target bottlenecks that hinder user adoption and improve their services.

The extant research has tried to explain mobile user adoption based on user perceptions of the technology such as perceived usefulness and perceived ease of use (Aldas-Manzano, Ruiz-Mafe, & Sanz-Blas, 2009; Ha, Yoon, & Choi, 2007; Jung, Perez-Mira, & Wiley-Patton, 2009; Kuo & Yen, 2009; Mallat, Rossi, Tuunainen, & Oorni, 2009; Shin, 2009), relative advantage, compatibility (Chen, Yen, & Chen, 2009; Hsu, Lu, & Hsu, 2007; Wu & Wang, 2005), and interactivity (Lee, 2005). However, simply focusing on user perceptions of the technology may be not enough. The task technology fit (TTF) model argues that individuals will adopt a technology based on the fit between the technology characteristics and task requirements (Goodhue, 1995; Goodhue & Thompson, 1995). It is possible that, although users perceive a technology as being advanced, they do not adopt it if they think this technology is unfit with their tasks and cannot improve their performance (Junglas, Abraham, & Watson, 2008; Lee, Cheng, & Cheng, 2007). In other words, these users may be utilitarian, and their adoption is not only determined by their perception and attitudes toward the technology but also by a good task technology fit. This research integrates the unified theory of acceptance and usage of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) and TTF to explain user adoption of mobile banking from both perspectives including technology perception and task technology fit. Our results showed that user behavior is indeed significantly influenced by both types of factors.

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This research makes three contributions. First, the extant research on mobile user adoption focuses on user perception toward technology and rarely considers the effect of the task technology fit. This research tries to fill this gap and integrates both UTAUT and TTF to explain user adoption behavior. Second, this research found that task technology fit not only affects user adoption but also affects performance expectancy. This shows the importance of task technology fit. Third, compared with the individual TTF and UTAUT models, the integrated model explains more variance of user adoption, showing the explanation advantage of the integrated model.

2. Theoretical background and research model

Researchers have examined mobile banking, an emergent mobile service, from the perspectives of trust, the technology acceptance model (TAM), and the theory of planned behavior (TPB). Kim, Shin, and Lee (2009) examined the effect of initial trust on mobile banking user adoption. They identified the determinants of initial trust including relative benefits of mobile banking, structural assurances, firm reputation, and a user's trust propensity. TAM and TPB have been used to identify possible factors affecting mobile banking users' behavioral intention (Luarn & Lin, 2005). These factors include perceived usefulness, perceived ease of use, perceived credibility, self-efficacy, and perceived financial cost (Luarn & Lin, 2005). In addition to perceived credibility, facilitating conditions and demographic factors also have obvious effects on mobile banking adoption (Crabbe, Standing, Standing, & Karjaluoto, 2009).

In this research, we focus on the TTF model. TTF argues that a user will only adopt an information technology when it fits his/her tasks at hand and improves his/her performance (Gebauer & Ginsburg, 2009; Goodhue, 1995; Goodhue & Thompson, 1995). Since its inception, TTF has been widely used and combined with other models such as TAM to explain user adoption of an information technology (Dishaw & Strong, 1999). Recently, TTF has been applied to explain user adoption of emerging Internet services such as blogs (Shang, Chen, & Chen, 2007). Empirical evidence shows that the interaction between task and technology characteristics affects users' evaluation of blogs, which further determines their usage (Shang et al., 2007). TTF has also been used to explain user adoption of mobile technologies such as location-based systems (LBS) (Junglas et al., 2008) and mobile insurance (Lee et al., 2007). Location sensitiveness (task characteristics), locatability, and mobility (technology characteristics) affect the task technology fit, which further determines individual performance while using LBS (Junglas et al., 2008). In addition to task and technology characteristics, individual differences such as computer experience and self-efficacy also affect the task technology fit of PDAs in insurance tasks (Lee et al., 2007). Fig. 1 shows the TTF model. As shown in the figure, both task characteristics and technology characteristics affect the task technology fit, which in turn determines individual performance and actual utilization.

As an extension to TAM, UTAUT was proposed by Venkatesh et al. in 2003. They found that user adoption and usage of an information technology are influenced mainly by four factors: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions* (Venkatesh et al., 2003). UTAUT was built on the following eight theories: the theory of reasoned action (TRA), TAM, the motivational model, TPB, the PC utilization model, the innovation diffusion theory (IDT), the social cognitive theory (SCT), and the integrated model of technology acceptance and planned behavior. Although UTAUT has not been as widely used as TAM, it has gradually drawn researchers' attentions and has been recently applied to exploring user acceptance of mobile technologies (Carlsson, Carlsson, Hyvonen, Puhakainen, & Walden, 2006; Min, Ji, & Qu, 2008; Park, Yang, & Lehto, 2007). Performance expectancy and effort expectancy are found to be the main determinants of behavioral intention in using mobile services in Finland (Carlsson et al., 2006). The UTAUT model has also been revised to study mobile commerce acceptance (Min et al., 2008). In addition to the original determinants, trust, privacy, convenience, and cost are also shown to affect the behavioral intention (Min et al., 2008). Moreover, gender and education have significant moderation effects on user adoption (Park et al., 2007).

Mobile banking is built on wireless networks using protocols such as general package radio service (GPRS) and code division multiple access (CDMA) (Junglas & Watson, 2006). One of the most significant advantages of mobile banking is that it provides users with ubiquitous and real-time services (Dahlberg, Mallat, Ondrus, & Zmijewska, 2008; Mallat, 2007). Thus, compared with traditional and Internet-based banking services, mobile banking is more advantageous for mobile users who are constantly on the go, resulting in a higher task technology fit. On the other hand, according to TTF, a complex task will decrease the task technology fit (Goodhue, 1995; Goodhue & Thompson, 1995). In other words, when tasks become more difficult, technologies will hardly meet task demands (Dishaw & Strong, 1999; Gebauer & Ginsburg, 2009; Junglas et al., 2008). For example, when users need to conduct a large number of payments (batch processing) simultaneously, mobile banking functions may be limited because of the small screen, inconvenient input, and slow processing speed (Chae & Kim, 2004). The effects of task and technology characteristics on task technology fit have been found in previous research. Lin and Huang (2008) noted that task tacitness and knowledge management system (KMS) characteristics determine perceived task technology fit. Dishaw and Strong (1999) found that tool functionality and task characteristics affect the task technology fit. Gebauer and Ginsburg (2009) showed that task characteristics and technology performance determine the task technology fit of mobile information systems.

A good task technology fit will promote user adoption of mobile banking. In contrast, a poor task technology fit will decrease users' adoption intention (Lee et al., 2007; Lin & Huang, 2008). For example, although mobile banking has many advantages such as ubiquity and immediacy, if users do not require mobile transactions (for example, they are mostly in the office and have a low demand for mobile payments), they will select traditional or online banking services rather than mobile banking. Previous research also suggests the importance of task technology fit on user adoption. Lin and Huang (2008) found that task technology fit affects KMS usage. Shang et al. (2007) noted that the interaction between task and technology characteristics will affect users' usage of blogs. Dishaw and Strong (1999) found that task technology fit affects users' utilization of information technology. Thus, we have:

H1: Task characteristics significantly affect the task technology fit.
H2: Technology characteristics of mobile banking significantly affect the task technology fit.
H3: Task technology fit significantly affects user adoption of mobile banking.

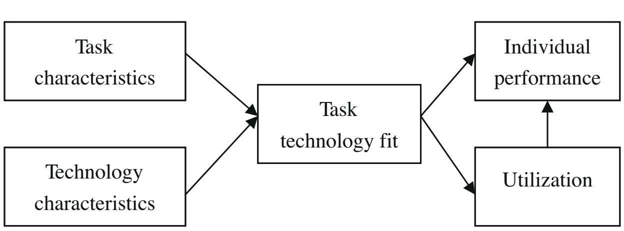

Fig. 1. TTF model by Goodhue and Thompson (1995).

Performance expectancy is similar to the perceived usefulness of TAM and the relative advantage of IDT (Venkatesh et al., 2003). It reflects user perception of performance improvement by using mobile banking such as convenient payment, fast response, and service effectiveness. Effort expectancy is similar to the perceived ease-of-use of TAM and the complexity of IDT (Venkatesh et al., 2003). It reflects user perception of how difficult it is to use mobile banking. According to UTAUT, effort expectancy positively affects performance expectancy (Venkatesh et al., 2003). When users feel that mobile banking is easy to use and does not require much effort, they will have a high expectation toward acquiring the expected performance. Otherwise, their performance expectancy will be low. Social influence is similar to subjective norm of TRA (Venkatesh et al., 2003) and reflects the effect of environmental factors such as the opinions of a user's friends, relatives, and superiors on user behavior (Lopez-Nicolas, Molina-Castillo, & Bouwman, 2008). Their opinions will affect this user's adoption and usage of mobile banking (Hong, Thong, Moon, & Tam, 2008). Facilitating conditions are similar to perceived behavioral control of TPB and reflect the effect of a user's knowledge, ability, and resources (Venkatesh et al., 2003). Mobile banking as a new service requires users to have certain skills such as configuring and operating mobile phones so as to connect to the wireless Internet. In addition, users need to bear usage costs such as data service and transaction fees when using mobile banking. If users do not have these necessary financial resources and operational skills, they will not adopt or use mobile banking. Much research has found the significant effect of perceived cost on mobile commerce adoption (Hong et al., 2008; Kuo & Yen, 2009; Shin, 2009; Shin, Lee, Shin, & Lee, in press). Previous research also reveals the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on users' behavioral intention (Carlsson et al., 2006; Park et al., 2007). Thus, we hypothesize:

H4: Performance expectancy significantly affects user adoption of mobile banking.
H5: Effort expectancy significantly affects user adoption of mobile banking.
H6: Effort expectancy significantly affects performance expectancy.
H7: Social influence significantly affects user adoption of mobile banking.
H8: Facilitating conditions significantly affect user adoption of mobile banking.

The technology characteristics of mobile banking will affect effort expectancy. Advantages of mobile banking such as ubiquity and immediacy will allow a user to make convenient payments and reduce his/her time and effort investments. Furthermore, compared with the complex interfaces of online banking, which provides many functions, mobile banking has fewer functions and clearer interfaces. This may simplify user operations. An ordinary user can easily use mobile banking. These advantages will affect the user's effort expectancy. In addition, task technology fit will affect a user's performance expectancy (Dishaw & Strong, 1999). Only when a user's tasks require fast, convenient, and ubiquitous payment will he/she feel that mobile banking is useful and improves his/her performance. Otherwise, he/she may adopt other substitute technologies such as Internet or traditional banking services.

H9: Technology characteristics significantly affect a user's effort expectancy.
H10: Task technology fit significantly affects a user's performance expectancy.

Fig. 2 shows the research model.

3. Research method

3.1. Instrument

Our research model includes eight constructs, each of which was measured with multiple items. Most of our items were adapted from the extant literature to preserve the content validity (Straub, Boudreau, & Gefen, 2004). Because there were no existing items for task characteristics and technology characteristics, we followed Churchill (1979) to develop new items for both constructs. First, we searched the relevant literature on mobile banking and generated the initial items for both constructs. Second, we asked three e-commerce experts to review these items. Based on their suggestions, we revised some items. Third, we collected data and conducted a confirmatory factor analysis (CFA) to purify the items. We also tested the reliability of both constructs. Following these three steps, we obtained three items for each construct.

Three items of task characteristics reflect three aspects of user task requirements: ubiquitous account management, money transfer and remittance, and real-time account information inquiry. Three items of technology characteristics reflect characteristics of mobile banking including ubiquity, immediacy, and security. The items measuring task technology fit were adapted from Lin and Huang (2008) to reflect the fit between mobile payment task requirements and mobile banking functions. The items measuring four factors of UTAUT and user adoption were adapted from Venkatesh et al. (2003). Items of performance expectancy reflect the improved payment efficiency and convenience when using mobile banking. Items of effort expectancy reflect the ease of learning to use or skillfully using mobile banking. Items of social influence show the influence of people important to the user on the adoption behavior. Items of facilitating conditions reflect the resources and knowledge owned by the user. Items of user adoption include the use of account management, money transfer, and payments.

Items were first translated into Chinese by one researcher. Then another researcher translated these Chinese items back into English to assure the consistency. After the questionnaire was formulated, it was tested among ten users with extended mobile banking usage experience. Based on their comments, we revised some items to improve the readability. The final items and their sources are listed in Appendix A. Each item was measured with a seven-point Likert scale, whose answer choices range from "strongly disagree" (1) to "strongly agree" (7).

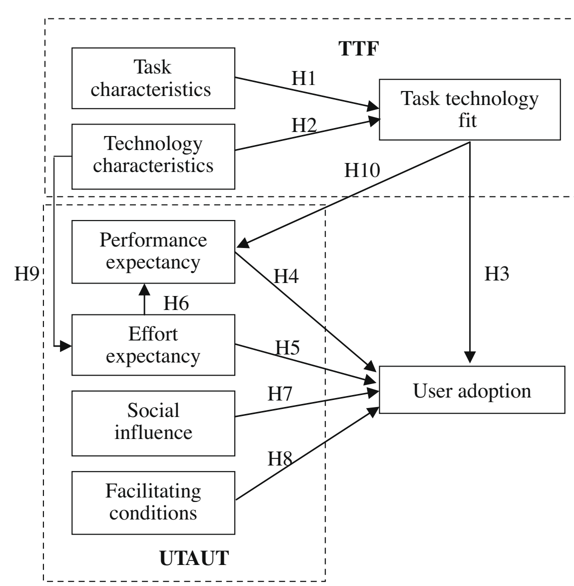

Fig. 2. The research model.

3.2. Procedures

Data were collected from universities and service halls of China Mobile and China Unicom branches. China Mobile and China Unicom are the two largest mobile telecommunications service providers in China. We used this convenience sample because there were many mobile phone users at these places and we could very quickly obtain a large sample size. It was also appropriate to include students in our sample because they represent the second largest group of mobile Internet users (19.2%) in China (CNNIC, 2009). We collected data from two universities and three service halls in a city located in eastern China, an area with more mature mobile commerce than other parts of China. Subjects were randomly intercepted in service halls and on campus, and they were asked whether they had experience with mobile banking. We then identified mobile phone users that had accessed banks' mobile sites and used mobile banking services through WAP rather than text messages. These mobile phone users were given the questionnaire and asked to fill them out based on their usage experience. Each user that completed the questionnaire was given a gift as a reward. We received a total of 265 questionnaires. After scrutinizing all collected questionnaires and removing those that had too many missing values or had the same answer to all questions, we obtained 250 valid responses. Among them, 83 were students and 167 were working professionals. With respect to gender and age, we found no significant differences between both samples. Thus we pooled them during subsequent data analyses.

Table 1
Demographics of our sample and the CNNIC (2009) sample.

	Option	Our sample (%)	CNNIC (2009) sample (%)	Differences
Gender	Male	63.2	74.6	$\chi^2(1) = 3.366$
	Female	36.8	25.4	
Age (years old)	<20	17.6	16.8	$\chi^2(3) = 4.355$
	20–29	61.2	66.3	
	30–39	11.2	13.7	
	>39	10.0	3.2	
Education	High school or below	26.1	50.9	$\chi^2(3) = 36.971^{***}$
	Associate's degree	10.3	23.1	
	Bachelor's degree	38.0	23.6	
	Master's degree or above	25.6	2.4	
Employment	Students	33.2	19.2	$\chi^2(1) = 5.094^{**}$
	Working professionals	66.8	80.8	
Months using mobile banking	<6	79.2	N/A	N/A
	6–12	10.4		
	12–24	6.0		
	>24	4.4		

** $p < .01$.
*** $p < .001$.

3.3. Participants

The sample demographics are listed in Table 1. We performed chi-square tests to compare the differences between our sample and the CNNIC (2009) sample. The results showed no significant differences between the two samples on gender and age. However, compared with the CNNIC sample, our sample was more educated and included more students. This was probably because we collected a proportion of our data from universities. Two of the most frequently used mobile banking sites were ICBC (wap.icbc.com.cn) and CMB (mobile.cmbchina.com).

4. Results

Based on the two-step approach recommended by Anderson and Gerbing (1988), we first analyzed the measurement model to test the reliability and validity of the instrument, then we analyzed the structural model to test our research hypotheses.

First, we conducted a CFA to examine the reliability and validities including convergent validity and discriminant validity. Convergent validity shows whether each factor can be reflected by its own items (Campbell & Fiske, 1959; Gefen, Straub, & Boudreau, 2000). Table 2 lists the standardized item loadings, *t*-values, average variance extracted (AVE), composite reliability (CR), and Cronbach's Alpha values. As shown in the table, most item loadings were larger than 0.7 and significant at .001. All AVEs, CRs, and Alphas exceeded the recommended threshold values of 0.5, 0.7, and 0.7, respectively (Bagozzi & Yi, 1988; Gefen et al., 2000; Nunnally, 1978). This showed good convergent validity and reliability.

Discriminant validity reflects whether two factors are statistically different (Campbell & Fiske, 1959; Gefen et al., 2000). As shown in Table 3, for each factor, the square root of AVE was obviously larger than its correlation coefficients with other factors. Thus the scales had good discriminant validity (Boudreau, Gefen, & Straub, 2001; Fornell & Larcker, 1981). We also list the cross-loading matrix in Appendix B. Each item had a higher loading on its corresponding factor than the cross-loadings on other factors. Thus the items had a clear loading matrix.

Second, we used LISREL 8.72 to perform a path analysis and test model hypotheses. According to Gefen et al. (2000), at least 100–150 respondents are needed to conduct the structural equation model (SEM) using LISREL. We had 250 respondents, so the sample size was large enough for LISREL. The results are shown in Fig. 3. The actual and recommended values of model fit indices are listed in Table 4. Except for GFI, the actual values of other fit indices were better than the recommended values. This demonstrated a good fit between the model and the data (Gefen et al., 2000; Hau, Wen, & Chen, 2004). The squared multiple correlations (SMC), which were the explained variances of effort expectancy, performance expectancy, task technology fit, and user adoption, were 0.129, 0.432, 0.405, and 0.575, respectively.

We also performed two ad hoc analyses to compare the explained variances of the individual UTAUT and TTF models to that of the integrated model. The results showed that the explained variances of user adoption of the individual UTAUT and TTF models were 45.7% and 43.3%, respectively, both of which were lower than that of the integrated model (57.5%). This showed the explanation advantage of the integrated model over both individual models.

To test whether our results were consistent across different statistical methods, we also conducted a path analysis with partial least squares (PLS). Compared with LISREL, PLS is less restrictive on sample size and data distribution (Chin, Marcolin, & Newsted, 2003). It requires ten times the number of items in the most complex construct (Gefen et al., 2000). In our model, both performance expectancy and effort expectancy had the most items: four items. Thus it requires at least 40 respondents to conduct the PLS analysis. We had 250 respondents, which met the PLS requirement on sample size. The PLS results are listed in Table 5. As shown in the table, the results produced by LISREL and PLS were very similar, which demonstrated the consistency of our results.

Table 5 lists all path coefficients and their significance as estimated by LISREL and PLS. As shown in the table, except H5, all

Table 2
Standardized item loadings, *t*-values, AVE, CR, and Alpha.

Factor	Item	Standardized loadings	*t*-Value	AVE	CR	Alpha
Task characteristics (TAC)	TAC1	0.842	15.418	0.69	0.869	0.868
	TAC2	0.854	15.740			
	TAC3	0.793	14.228			
Technology characteristics (TEC)	TEC1	0.864	15.606	0.64	0.843	0.837
	TEC2	0.849	15.259			
	TEC3	0.682	11.527			
Task technology fit (TTF)	TTF1	0.843	16.201	0.78	0.913	0.912
	TTF2	0.955	19.889			
	TTF3	0.844	16.242			
Performance expectancy (PEE)	PEE1	0.703	12.177	0.62	0.869	0.866
	PEE2	0.824	15.268			
	PEE3	0.843	15.800			
	PEE4	0.783	14.177			
Effort expectancy (EFE)	EFE1	0.835	15.480	0.62	0.864	0.864
	EFE2	0.787	14.197			
	EFE3	0.811	14.808			
	EFE4	0.697	11.980			
Social influence (SOI)	SOI1	0.847	13.756	0.73	0.846	0.846
	SOI2	0.866	14.091			
Facilitating conditions (FAC)	FAC1	0.639	10.721	0.64	0.840	0.833
	FAC2	0.851	15.672			
	FAC3	0.890	16.683			
User adoption (USE)	USE1	0.832	15.443	0.68	0.862	0.857
	USE2	0.872	16.558			
	USE3	0.759	13.538			

Table 3
The square root of AVEs (shown in bold at diagonal) and factor correlation coefficients.

	EFE	PEE	TEC	TAC	TTF	SOI	FAC	USE
EFE	**0.78**							
PEE	0.527***	**0.79**						
TEC	0.317***	0.324***	**0.80**					
TAC	−0.303***	0.287***	−0.149*	**0.83**				
TTF	0.489***	0.643***	0.491***	−0.44***	**0.88**			
SOI	0.235**	0.388***	0.24**	−0.219**	0.403***	**0.86**		
FAC	0.565***	0.282***	0.155*	−0.214**	0.429***	0.417***	**0.80**	
USE	0.432***	0.647***	0.313***	−0.198**	0.667***	0.538***	0.511***	**0.82**

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

other hypotheses were supported. These path coefficients were significant at either .01 or .001.

5. Discussions

We used a questionnaire survey to test an integrated model of TTF and UTAUT that explains mobile banking user adoption. Our results show that all hypotheses of TTF are supported by the data. Both task characteristics and technology characteristics strongly affect the task technology fit, which further determines user adoption. This provides support for previous research's findings (Junglas et al., 2008; Lee et al., 2007; Lin & Huang, 2008). Thus, when banks promote their mobile banking services, they need to consider the fit between users' task requirements and mobile banking functions. For example, mobile banking is probably more appropriate for those traveling frequently than those always staying in the office. For the former group of users, mobile banking is a convenient way for them to acquire banking services at anytime and anywhere. For the latter group of users, they are more likely to choose online or traditional banking services rather than mobile banking. Thus, banks need to conduct market segregation and analyze the demand characteristics of different user groups. Then they can dif-

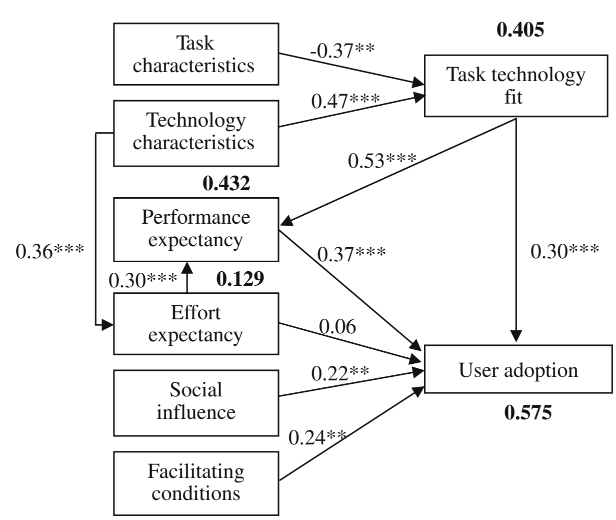

Fig. 3. Model estimation results by LISREL (*Note.* ***$p < .001$; **$p < .01$; bold figures are SMC).

Table 4
The recommended and actual values of fit indices.

Fit index	χ^2/df	GFI	AGFI	CFI	NFI	NNFI	RMSEA
Recommended value	<3	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
Actual value	2.19	0.846	0.807	0.963	0.935	0.957	0.069

Note. χ^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, NNFI is the Non-Normed Fit Index, RMSEA is the Root Mean Square Error of Approximation.

Table 5
Path coefficients and their significance.

Hypothesis	Path	Path coefficient by LISREL	Path coefficient by PLS	Supported or not
H1	TAC → TTF	−0.37***	−0.37***	Yes
H2	TEC → TTF	0.47***	0.38***	Yes
H3	TTF → USE	0.30***	0.28***	Yes
H4	PEE → USE	0.37***	0.30***	Yes
H5	EFE → USE	0.06	0.01	No
H6	EFE → PEE	0.30***	0.25***	Yes
H7	SOI → USE	0.22**	0.18**	Yes
H8	FAC → USE	0.24**	0.20**	Yes
H9	TEC → EFE	0.36***	0.28***	Yes
H10	TTF → PEE	0.53***	0.46***	Yes

** $p < 0.01$.
*** $p < 0.001$.

ferentiate their products and services to users, and acquire a good task technology fit. In turn, user adoption and usage behavior can be promoted.

For the UTAUT model, except for effort expectancy, the other three factors – performance expectancy, social influence, and facilitating conditions – have significant effects on user adoption. In addition, effort expectancy strongly affects performance expectancy. These results are consistent with those of previous research (Carlsson et al., 2006; Park et al., 2007). Among factors affecting user adoption, the effect of performance expectancy is relatively large. Therefore, when banks develop mobile banking functions, they need to consider user expectations toward these functions. They can improve their products based on users' suggestions to better meet users' performance expectations. In addition, banks need to run marketing campaigns to enhance users' knowledge about mobile banking and skills in using it. Thus users' perceptions of facilitating conditions can be improved. The effect of social influence also deserves further attention. Traditional banks can take advantage of earlier adopters of mobile banking, whose opinions and reviews may generate positive word-of-mouth effects on subsequent adoption behavior (Wiedemann, Haunstetter, & Pousttchi, 2008). Publicizing such testimonials and obtaining celebrity endorsements will help promote user adoption. Although effort expectancy has no direct effect on the usage behavior, its indirect effect on user adoption through performance expectancy should not be ignored. Banks should fully consider the negative effects of difficult input and small screen of mobile phones, and design usable and easy-to-use mobile banking interfaces.

The results also show that there exist correlations between TTF constructs and UTAUT ones. Technology characteristics strongly affect effort expectancy and the task technology fit has an obvious effect on performance expectancy. Mobile banking needs to further improve its technological aspects such as security. Compared with Internet banking that builds on wired networks, mobile banking that builds on wireless networks will be more vulnerable to security attacks and interceptions (Crabbe et al., 2009; Kim et al., 2009). This may result in users' anxiety about mobile banking security and severely influence their effort expectancy. Mobile banking can use wireless encryption technologies to enhance its security and provide reliable, secure, and real-time services to users. Then users' effort expectancy can be improved. In addition, an important way to enhance performance expectancy is a good task technology fit. If users get services that are unfit with their needs, they will perceive these services to be of low usefulness and form low performance expectancy. For example, mobile banking may provide LBS services such as nearby automated teller machine (ATM) locations. Most users will consider these services as useful, but there may be some users arguing that these services violate their privacy rights (Junglas & Watson, 2008; Sheng, Nah, & Siau, 2008). For these users, LBS services are unfit with their requirements and will even result in negative attitude toward mobile banking. Hence, mobile banking service providers should first get users' permissions before providing LBS services.

6. Theoretical and practical implications

From a theoretical perspective, this research integrates TTF and UTAUT to explain user adoption of mobile banking. We found that, in addition to technology perceptions such as performance expectancy, task technology fit also has a significant effect on user adoption. This shows that, when examining the factors affecting mobile commerce users' adoption, we need to not only be concerned with technology perceptions based on TAM, IDT, and UTAUT but also pay attention to the effect of a good task technology fit. Moreover, the interaction between both perspectives including technology perceptions and task technology fit deserves further attention. For example, our research found that there exist correlations between task technology fit and performance expectancy. Our results also showed that, compared with the individual UTAUT and TTF models, the integrated model provides more explanation on user adoption. Thus future research can combine both perspectives to examine user adoption of other mobile services such as mobile purchase and mobile search. We believe that, compared with each individual research perspective, integrating both perspectives will provide richer insights.

From a practical perspective, our research showed that both performance expectancy and task technology fit have significant effects on user adoption of mobile banking. In addition, we found that task technology fit has an obvious effect on performance expectancy. Thus service providers need to improve the task technology fit. They can segregate the market and provide differentiated services to niche users. For example, student users may be more concerned with the usage cost and variety of functions, whereas working professionals may focus more on the reliability and ease-of-use of mobile banking. Thus service providers can provide different services to meet different group's task demands so as to improve user adoption of mobile banking. In addition to the task technology fit, mobile banking service providers also need to improve mobile users' technology perceptions such as performance expectancy. They can achieve this by presenting an ease-of-use interface, thus reducing effort expectancy and enhancing performance expectancy.

7. Conclusion

Building on wireless networks, mobile banking can provide ubiquitous and real-time services to users. Based on these advantages, traditional banks expect that mobile banking will acquire a wide user adoption. However, the reality is that the current user adoption level of mobile banking is much lower. By integrating UTAUT and TTF, this research analyzed factors determining user adoption of mobile banking from these two perspectives. Our results showed that users' adoption of mobile banking is affected not only by their perception toward the technology but also by the fit between their tasks and mobile banking technology.

This research has the following limitations. First, we mainly explained mobile banking user adoption using UTAUT and TTF. Future research may draw on other theories such as perceived value theory and explore the effects of other factors such as cost and trust. Second, user behavior is dynamic and constantly changing. We only collected cross-sectional data. A longitudinal research may provide more insights on how user adoption behavior changes over time. Third, we conducted this research in China, a country whose fast-developing mobile commerce is still in its infancy. Our results may not generalize to other countries with relatively mature mobile commerce. Fourth, compared with the rich services and functions offered by online banking, mobile banking offers fewer services and simplified functions. This may also affect user adoption. Future research can investigate their differences in more detail.

Due to the limitations in our research, there exist some future research directions. First, we focused on mobile banking and a portion of our samples were students. Future research can examine other mobile services such as mobile purchase or replicate our results with samples of working professionals. Second, researchers can also examine if our results can be generalized to countries with relatively mature mobile commerce. This may provide richer insights on user adoption around the world. Third, a longitudinal research is needed to examine the dynamics of user adoption of mobile banking.

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Appendix A. Scales and items

Task characteristics (TAC) (new scale).

TAC1: I need to manage my account anytime anywhere.
TAC2: I need to transfer money anytime anywhere.
TAC3: I need to acquire account information in real time.

Technology characteristics (TEC) (new scale)

TEC1: Mobile banking provides ubiquitous services.
TEC2: Mobile banking provides real-time services.
TEC3: Mobile banking provides secure services.

Task technology fit (TTF) (adapted from Lin and Huang (2008)).

TTF1: In helping complete my payment tasks, the functions of mobile banking are enough.
TTF2: In helping complete my payment tasks, the functions of mobile banking are appropriate.
TTF3: In general, the functions of mobile banking fully meet my payment needs.

Performance expectancy (PEE) (adapted from Venkatesh et al. (2003)).

PEE1: I feel mobile banking is useful.
PEE2: Mobile banking improves my payment efficiency.
PEE3: Mobile banking improves my payment convenience.
PEE4: Mobile banking lets me make payments more quickly.

Effort expectancy (EFE) (adapted from Venkatesh et al. (2003))

EFE1: Skillfully using mobile banking is easy for me.
EFE2: I find that using mobile banking is easy.
EFE3: Learning how to use mobile banking is easy for me.
EFE4: My interaction with mobile banking is clear and understandable.

Social influence (SOI) (adapted from Venkatesh et al. (2003)).

SOI1: Those people that influence my behavior think that I should use mobile banking.
SOI2: Those people that are important to me think that I should use mobile banking.

Facilitating conditions (FAC) (adapted from Venkatesh et al. (2003))

FAC1: I have the necessary resources to use mobile banking.
FAC2: I have the necessary knowledge to use mobile banking.
FAC3: If I have difficulty using mobile banking, there will be professionals to help me.

User adoption (USE) (adapted from Venkatesh et al. (2003))

USE1: I often use mobile banking to manage my account.
USE2: I often use mobile banking to transfer and remit money.
USE3: I often use mobile banking to make payments.

Appendix B. Cross-loading matrix

	PEE	EFE	TAC	TEC	USE	FAC	TTF	SOI
TEC1	.184	.110	−.050	**.859**	.079	.075	.049	.116
TEC2	.063	.104	−.089	**.892**	.100	−.021	.071	−.045
TEC3	.032	.066	.042	**.775**	.041	.034	.229	.112
TAC1	−.070	−.077	**.866**	.042	−.092	−.066	−.153	−.061
TAC2	−.063	−.103	**.891**	−.069	−.001	.002	−.082	−.064
TAC3	−.116	−.066	**.842**	−.065	−.002	−.109	−.130	−.030
EFE1	.321	**.723**	−.151	.158	.145	.222	.057	−.024
EFE2	.223	**.786**	−.187	.066	.021	.189	−.068	.061
EFE3	.095	**.825**	−.091	.058	.049	.196	.197	.084
EFE4	.073	**.773**	.066	.098	.179	.113	.203	−.002
PEE1	**.780**	.101	.001	.065	.044	.077	.269	.070
PEE2	**.830**	.155	−.113	.119	.192	−.017	.095	.080
PEE3	**.771**	.135	−.115	.056	.302	.080	.163	.058
PEE4	**.714**	.268	−.108	.103	.225	.012	.065	.166
TTF1	.226	.261	−.256	.159	.243	.210	**.718**	.033
TTF2	.331	.152	−.199	.297	.291	.154	**.715**	.111
TTF3	.278	.112	−.222	.176	.198	.122	**.762**	.167
USE1	.227	.105	.006	.151	**.776**	.171	.136	.225
USE2	.255	.057	−.090	.076	**.811**	.167	.204	.189
USE3	.285	.251	−.026	.058	**.700**	.200	.208	.074
SOI1	.109	−.002	−.054	.130	.167	.191	.070	**.872**
SOI2	.165	.091	−.103	.045	.196	.088	.114	**.871**
FAC1	.007	.128	−.060	.041	.093	**.784**	.198	.016
FAC2	.040	.241	−.066	.052	.148	**.848**	.035	.114
FAC3	.096	.271	−.066	−.009	.218	**.778**	.070	.223

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