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The Role of Decision Rationality on Users' Attitudes toward Utilitarian Mobile Service Usage

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Abstract:

Organizations in various industries have emphasized the need to use mobile information and communication technologies (mICTs) to deliver utilitarian services. Firms need to understand how users make routine and unexpected use decisions in order for their utilitarian mobile services (UMSs) to gain market acceptance. In this study, we empirically tested a theoretical model that examined how both affective attitude and cognitive attitude influence both routine and unexpected UMS use and the role of decision rationality in the process. We tested our model using two independent empirical studies. The results show that affective attitude had a stronger effect than cognitive attitude on routine use, while cognitive attitude had a stronger effect than affective attitude on the unexpected UMS use. Furthermore, decision rationality weakened the effects that affective attitude had on both routine use and unexpected use but strengthened the effects that cognitive attitude had on the routine use of UMSs. Our results advance knowledge on: 1) users' behaviors when they use UMSs, 2) the effect that attitude components have on use at different levels of decision rationality, and 3) the underlying mechanism for our mixed findings about the effect of both affective and cognitive attitudes. These findings also provide insights for practitioners on how to promote their services among consumers.

Keywords: Utilitarian Mobile Service, Routine Use, Unexpected Use, Affective Attitude, Cognitive Attitude, Decision Rationality.

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1 Introduction

Rapid developments in mobile information and communication technologies (mICTs) continue to enlarge the size and scope of mobile services (Jung, 2014). This transition to mobile services has noticeably changed the daily lives of many throughout the world (Shin & Koh, 2017). These changes have affected utilitarian-focused services in particular, such as mobile payments, mobile banking (mBanking), and mobile health services (mHealth). In comparison to hedonic services that provide excitement and entertainment, utilitarian mobile services (UMSs) provide consumers with functional capabilities to solve practical problems via mICTs (Hellén & Sääksjärvi, 2011). Such services offer advantages over Web-based services owing to their mobile capabilities, such as ubiquity, compatibility, and communicability (Kleijnen et al. 2004). Thus, users have increasingly integrated UMSs into their daily routines (Kleijnen, De Ruyter, & Wetzels, 2004).

Users need to routinely use such services for UMS providers to develop value from them in the long term. However, UMS providers face one major challenge: most users do not routinely use their services; instead, they only use a UMS occasionally, such as in an unexpected situation (Gumussoy, 2016). This phenomenon indicates that users can access these services in two forms: routine and unplanned use. Routine use suggests that one accesses a UMS each day for certain tasks (e.g., to monitor one's health, manage one's accounts, and communicate with others). Unplanned use occurs when unplanned situations arise (e.g., making an appointment with a physician, a bank transfer, or a mobile device-enabled purchase). These two-use patterns not only differentiate UMSs from online services or those online services that request users to make different use decisions but also complicate users' decision processes. Even users need to routinely use UMS for UMS providers to create value in the long term, the extant IS literature focuses predominantly on adoption decisions regarding UMS usage and pays little attention to addressing why users conduct different usage behaviors (Saeed & Abdinnour, 2013). As such, we need to explore how users make use decisions regarding UMSs by investigating how they form routine usage and unexpected usage behaviors. Thus, we examine the following research question (RQ):

RQ1: What factors influence users' decisions to use UMSs in a routine or unexpected manner?

In this study, we draw on the attitude literature to explore how users make different use decisions (i.e., routine and unexpected) regarding UMSs. Attitude is a key predictor of human behaviors and behavioral intentions (Fishbein & Ajzen, 1975), and researchers have widely studied it in information systems usage (Bhattacherjee & Premkumar, 2004) and service usage contexts (Wünderlich, Wangenheim, & Bitner, 2013). Previous literature has posited that attitude has both cognitive and affective components based on the information-processing process (Bagozzi & Burnkrant, 1979). Cognitive attitude builds on how individuals evaluate benefits and costs regarding their usage behavior, which relies on how they perceive whether they can benefit from using it; as such, it indicates a more rational assessment (Keer, van den Putte, Neijens, & de Wit, 2013). In contrast, affective attitude builds on individuals' subjective feelings about the usage process, such as pleasure and enjoyment, which relies on how they perceive whether they like using it; as such, it indicates a less rational assessment (Christensen, Moran, & Wiebe, 1999). As individuals form these attitude components through different decision processes, they may exert different effects on different use behaviors. For instance, when making some decisions, individuals may rely more on the "benefit" feeling, while, for other decisions, they may rely more on the "like" feeling. Even though previous empirical studies have verified the explanatory power that different attitude components have on human behaviors, we lack consensus on whether affective attitude or cognitive attitude has stronger effects in determining behaviors (Crites, Fabrigar, & Petty, 1994; Légaré et al., 2013; van Dongen et al., 2012), which has led many mixed findings on the relative effects that affective and cognitive attitudes have on human behaviors. To fill this research gap, we further test the relative importance of two attitude components in determining routine use and unexpected use in the context of UMSs. Thus, we examine the following research question

RQ2: What differential effects do affective and cognitive attitudes have on routine use and unexpected use decisions regarding UMSs?

Moreover, given that individuals develop cognitive and affective attitudes at different rationality levels, individuals' decision rationality can shape their decision-making behaviors. Cognitive attitude relies on a more analytic (and, thus, rational) evaluation process (Keer et al., 2013), while affective attitude relies more on intuitive or spontaneous (and, thus, less rational) approaches (Scott & Bruce, 1995). Thus, individuals' decision rationality can be the boundary condition that dictates whether individuals rely more on cognitive attitude or affective attitude. Given the mixed findings, we draw on the contingency theory

and argue that the effects of cognitive and affective attitudes depend on decision makers' rationality (Tosi & Slocum, 1984). Thus, we examine the following research question:

RQ3: Do the different effects that cognitive and affective attitudes have on routine and unexpected use depend on users' rationality?

We develop an integrative model based on human-ICT interactions, the attitude literature, and the rationality literature with two empirical studies to obtain answers to our research questions and develop several contributions. First, by investigating users' diverse UMS usage behaviors and their determinants, we advance knowledge on how users make different use decisions regarding UMSs, which provides an overall picture of human-UMS interactions. Second, we explain the relationships between different attitude components and UMS usage behaviors by identifying the relative influence that cognitive attitude and affective attitude have on usage behaviors, which offers new insights into the attitude-behavior relationship. Third, although researchers have extensively examined the effects that cognitive attitude and affective attitude have on user behavior, limited studies have investigated how strongly the two attitude types influence routine and unexpected use. This research, to the best of our knowledge, represents the first to examine whether the degree to which cognitive attitude and affective attitude influence routine and unexpected use depend on users' decision rationality, which sheds light on the underlying mechanisms regarding how attitude influences behavior differently. Finally, by precisely exploring the relative effects that attitude components have on users' use UMS the contingent effects that decision rationality play in that relationships, this research helps clarify the mixed findings in the literature.

This paper proceeds as follows. In Section 2, we discuss the study's theoretical foundation. In Section 3, we detail the research model and hypotheses. In Section 4, we explain how we tested the model in two studies. In Section 5, we discuss the study's key findings and implications. Finally, in Section 6, we conclude the paper.

2 Theoretical Foundations

2.1 Utilitarian Mobile Services

Mobile services require mICTs to provide customers with benefits by delivering their services (Hellén & Sääksjärvi, 2011). Accordingly, UMSs constitute a kind of mobile service that provides instrumental and functional benefits for customers (Hellén & Sääksjärvi, 2011). Given that mICTs typically feature ubiquity, compatibility, and communicability, UMSs can offer advantages over offline and Web services by providing more personalized, timely, and continuous services (Akter, D'Ambra, & Ray, 2010). As an emerging service type, UMSs possess three unique characteristics: 1) users have exclusive access to the platform, 2) users can access the service free from temporal and geographical constraints, and 3) users can access a variety of services (Hong & Tam, 2006). With UMS, customers can now receive services related to health, banking, locations, shopping, payments, and so on through their mobile devices. Basically, these UMSs provide two types of features: general features to fulfill users' daily needs and special features to satisfy their needs in a particular context. Users can use the general features in their normal daily routines (e.g., using mobile devices to monitor their heartbeat and navigate). However, UMSs also allow users to perform special features for more unexpected situations, such as in using mobile devices for emergency alerts and dealing with unanticipated needs (e.g., when someone needs urgent care). The unique features make the UMSs more like the general services that users will encounter when they need them; however, the general features that users use to fulfill their daily needs make such services distinctive so that users need to use them more frequently.

Previous literature has extensively addressed UMS diffusion in a specific context by using the well-established technology acceptance model (TAM) (Lin & Bhattacherjee, 2010). For instance, research has used the TAM to study the diffusion of mobile banking (mBanking) (Karjaluoto, Riquelme, & Rios, 2010), the mobile Internet (Kim, Chan, & Gupta, 2007), mobile data services (Hong & Tam, 2006), and mobile ticketing services (Mallat, Rossi, Tuunainen, & Öörni, 2008). Research on UMS diffusion has also adopted the unified theory of acceptance and use of technology (UTAUT) to study mobile shopping service adoption (Yang, 2010; Yu, 2012), mBanking usage intention (Zhou, Lu, & Wang, 2010), and mobile government service adoption (Yfantis, Vassilopoulou, Pateli, & Usoro, 2013). Some other studies have focused on one core construct to explore UMS diffusion. For instance, Akter, D'Ambra, and Ray (2011) and Lowry et al. (2014) investigated how users develop trust in mHealth and how, in turn, that influences their decision making regarding whether to adopt it. Akter et al. (2010) and Akter, D'Ambra, Ray, and Hani

(2013) focused on service quality to explore mHealth diffusion, and Alalwan, Dwivedi, Rana, and Williams (2015) studied service quality in mBanking diffusion.

From the above review, we can identify two main research gaps. First, most previous studies on UMS diffusion have adopted a cognitive perspective by applying certain well-developed models or core constructs. Even though some studies involved one or two affective factors, such as satisfaction (Akter et al., 2013, 2010) and perceived enjoyment (Cocosila & Archer, 2010), the mechanism underlying their research models remains the cognitive decision. Prior literature has likely used cognitive-centric framing due to its strong relationship with goal-oriented activities in typical utilitarian service contexts (Lee, Kim, & Kim, 2005). Given that UMSs primarily focus on providing instrumental benefits (related closely to cognitive evaluation), using them can also induce affective evaluations, such as enjoyment when one finds a service suitable for various daily activities. However, research has largely ignored the role that affective factors play in the service-usage process. Accordingly, we explore whether affective feelings (manifested by affective attitude) from the usage process influence user behavior regarding whether UMSs incorporate affective factors in the utilitarian context.

Second, previous literature has treated UMSs as a general e-service and neglected their mobile property. Due to UMSs' mobility, portability, and flexibility, customers can use them on a much wider scope and for different situations (Mallat, Rossi, Tuunainen, & Öörni, 2009). Moreover, they can participate in different use behaviors regarding UMSs, such as habitually using them for routine inquiries or for occasional use in unexpected situations. A UMS's convenience and ubiquitous connectivity enables individuals to finish tasks virtually without temporal or geographical constraints, which makes a UMS fit better for both routine and unexpected situations (Mallat et al., 2009). As the use decisions in different situations are subject to different motivating factors (Li, Hsieh, & Rai, 2013), research needs to distinguish between these behaviors and explain their different forming processes. Identifying and exploring the different forms of UMS usage behaviors can help researchers understand whether UMS diffusion represents a unique phenomenon, which aligns with practical implications regarding how service providers can identify their target customers by designing different promotion strategies.

To narrow this void in the UMS literature, we investigate the determinants of different UMS usage behaviors from both the cognitive and affective perspectives. We employ routine use and unexpected use to capture the different types of usage behaviors and both affective and cognitive attitudes to manifest affective and cognitive decision processes.

2.2 Usage Behaviors

Based on UMSs' characteristics, we propose two usage behaviors: routine use and unexpected use. Routine use refers to the extent to which individuals use a UMS as a regular part of their daily lives (Li et al., 2013). Unexpected use refers to the extent to which individual use UMS to accomplish their unexpected tasks before having overall knowledge of the service (Saga & Zmud, 1994). These two usage behaviors fit the UMS usage behaviors well as they cover most usage patterns of the service, which includes using UMSs' general features routinely and their unique features in unexpected situations..

Implementing a service in personal settings involves three stages: acceptance, routinization, and infusion (Li et al., 2013). Acceptance refers to individuals' commitment to using the service. Routinization refers to the state when UMS usage becomes a normal part of individuals' daily lives and also becomes a normal activity (Cooper & Zmud, 1990), which induces routine use behavior. Finally, infusion refers to the situation in which the UMS has become deeply and comprehensively embedded in users' lives based on which they can have innovatively use the service. Both routinization and infusion are post-acceptance states. From the decision-making process, routinization can precede infusion as individuals obtain the latter via more comprehensively evaluating the service, which they can obtain from routinization behaviors (Cooper & Zmud, 1990). However, they can also occur in parallel, such as when routinization does not necessarily induce the infusion (Cooper & Zmud, 1990). Therefore, a service or technology diffusion can encompass both routinization and infusion.

Accordingly, as routine use means using a service as a regular part of their daily lives, users conduct it in the routinization stage (Cooper & Zmud, 1990). Unexpected use means using a service for unexpected tasks, which need a more comprehensive and innovative approach to make decisions. Thus, individuals make the unexpected use decision in the infusion stage (Li et al., 2013). Routine use and unexpected use differ in users' decision process. Routine use requires less cognitive effort because users do not need to make repeated decisions on whether to use a service or decide on whether it suits via repeatedly using it.

Thus, users' cognition is anchored in standardized ways when making decisions on routine use (Starbuck & Webster, 1991). On the other hand, since unexpected use occurs in the infusion rather than the routinization stage, users need to evaluate a service overall and a make a decision on whether it suits for the special situations beyond their routine needs (Jasperson, Carter, & Zmud, 2005). Thus, an unexpected use decision requires more cognitive-based effort. However, even though these two types of usage behaviors commonly occur with UMSs, little research has examined how UMS users develop these two stages differently.

2.3 Attitude

Attitude is a function of how users evaluate a targeted object (or behavior) using a good or bad performance (Eagly & Chaiken, 1993). The prior literature has defined attitude from different perspectives. To study the role of attitude in behavioral decisions, Fishbein and Ajzen (1977) defined the attitude towards behavior as an individual's positive or negative feelings about conducting a particular behavior. Taking a cognitive perspective, Bagozzi and Burnkrant (1979) defined attitude as an individual's cognitive beliefs regarding a particular behavior or object. On its part, the social psychology literature posits that attitude should include both affective and cognitive components (Yang & Yoo, 2004); namely, that affective attitude and cognitive attitude should capture individuals' affective and cognitive evaluations, respectively. Accordingly, affective attitude refers to individuals' emotional feelings toward a targeted object (or behavior), while cognitive attitude refers to individuals' cognitive beliefs toward a targeted object (or behavior) (Yang & Yoo, 2004). In our study, we use affective attitude and cognitive attitude to manifest affective feelings and cognitive beliefs, respectively, on UMS usage.

Several studies have explored the role that affective and cognitive attitudes play in determining human behaviors. Bagozzi and Burnkrant (1979) tested the attitude-behavior relationship in a healthcare context and found that both affective attitude and cognitive attitude were positively related to behavior and that affective attitude had three times more powerful an effect than cognitive attitude (0.651 vs. 0.226). Lawton, Conner, and McEachan (2009) examined the role that affective attitudes play in predicting healthcare behaviors and found that affective attitudes more strongly predicted these behaviors than cognitive attitudes in most situations. Légaré et al. (2013) adopted both affective attitude and cognitive attitude to explain health providers' behavioral intentions and found that both influenced behavioral intentions positively (0.30 vs. 0.13 respectively). However, some other studies have discovered inconsistent results. In fact, van Dongen et al. (2012) found that cognitive attitude had a stronger effect on blood donating behavior than affective attitude did (0.61 vs. 0.24).

In the information systems (IS) field, Yang and Yoo (2004 introduced attitude components into technology acceptance research. They found that cognitive attitude positively influenced IS use while affective attitude did not. Conner, Godin, Sheeran, and Germain (2013) and Pi, Liao, and Liu (2016) found similar results. Besides findings on affective attitude's insignificant effects, Min and Lee (2009) found that both affective attitude and cognitive attitude had positive effects on technology use (though cognitive attitude had the stronger effect) (.349 vs. .216). Table 1 summarizes the literature related to the relative importance of affective attitude and cognitive attitude in previous empirical studies.

Based on the above literature review, we observe that we lack consensus on the effect that affective and cognitive attitudes have on behavior in two respects. First, previous literature has found that affective attitude and cognitive attitude have different and relatively stronger effects in different contexts. Second, some researchers have observed that both affective attitude and cognitive attitude have an insignificant effect on behaviors or behavioral intentions. These mixed findings suggest that the underlying mechanism of how attitude components determine human behaviors remains unclear and that we require further research. Therefore, with this paper, we focus on augmenting the mixed findings by investigating the relative effect that affective attitude and cognitive attitude have in determining different behaviors and the possible contingent factors underlying the attitude-behavior relationship.

Furthermore, research has regarded utilitarian services as more cognitively driven and goal oriented given that it has focused only on the cognitive process (Lee et al., 2005) based on the belief that affective attitude has more prominence in the utilitarian context. We draw on affective attitude to measure users' positive affective feelings on the usage process with the view that, while users use UMSs primarily for utilitarian purposes, they can still generate positive feelings from the usage process (Purani & Kumar, 2018). Studying the role that affective attitude has in the utilitarian context can advance our understanding about use decisions regarding UMSs from a combined cognitive and affective perspective.

Table 1. Studies on the Effects of Affective Attitude and Cognitive Attitude

Research context	Outcome of attitude	Behavior pattern	Relative effects (affective vs. cognitive)	Study
Religious behaviors	Self-reported behaviors	A mixed of routine and unexpected behaviors	0.651 vs. 0.226	Bagozzi & Burnkrant (1979)
Shared decision-making in healthcare	Intention to engage in shared decision making	Unexpected behavior	0.13 vs. 0.30	Légaré et al. (2013)
Blood donation	Intention to return for donation	Unexpected behavior	0.24 vs. 0.61	van Dongen et al. (2012)
IS use	Stable IS use	Routine use	-0.04 (ns) vs. 0.51	Yang & Yoo (2004)
Blood donation	Donation intention	Unexpected behavior	-0.037 (ns) vs. 0.188	Conner et al. (2013)
Electronic word-of-mouth	Share intention	A mixed of routine and unexpected behaviors	0.009 (ns) vs. 0.664	Pi et al. (2016)
Identity-reflecting IS	Continuous intention to use	A mixed of routine and unexpected behaviors	0.216 vs. 0.349	Min & Lee (2009)

Note: ns = not significant.

2.4 Decision Rationality

Decision rationality refers to individuals' personality regarding the rational level of their decisions and refers to the extent to which they use a systematic and analytical approach to make general decisions (Kandemir & Acur, 2012). Individuals with high decision rationality will likely make decisions based on searching for and cognitively evaluating all alternatives (Scott & Bruce, 1995). On the other hand, individuals with low decision rationality will likely rely more on their intuitions or feelings and less on cognitive evaluations (Scott & Bruce, 1995). Therefore, decision makers' rationality determines the extent to which they rely on the cognitive process.

To further explore the relationship between affective and cognitive attitudes and behavior, we consider individuals' decision rationality the contingent factor that influences the strength of such a relationship. Affective attitude refers to an individual's positive or negative feelings regarding a particular behavior (Fishbein & Ajzen, 1977)—a non-cognition evaluation. As we mention above, the extent to which one relies on cognitive evaluations when making behavioral decisions determines rationality. In making behavioral decisions based on the magnitude of affective attitude and cognitive attitude, individuals with varying levels of rationality will have different preferences. Therefore, decision rationality represents an important contingency factor for investigating the different effects of affective attitude and cognitive attitude. Accordingly, we can explain the mixed findings in the literature by indicating that users with different levels of decision rationality rely on cognitive and affective attitudes differently.

3 Research Model and Hypotheses

Based on the attitude literature and reviewing different user behaviors, we hypothesize the relative impacts of the two attitude components and explain the moderating effect that decision rationality has on the attitude-behavior relationship. We show our research model in Figure 1.

Prior literature posits that affective attitude and cognitive attitude can influence human behaviors simultaneously and that they play relatively significant roles in human behaviors in different situations (Edwards & Hippel, 1995). An affective attitude towards using a specific UMS denotes users' emotional feelings such as liking and enjoying experience. A positive cognitive attitude resulting from using a specific UMS transpires when the users perceive more benefits than costs from using it. Thus, both affective and cognitive attitudes can enhance how individual use a UMS in their daily lives routinely or for unexpected approaches (Yang & Yoo, 2004). However, their effects on different use behaviors show relatively different levels of importance.

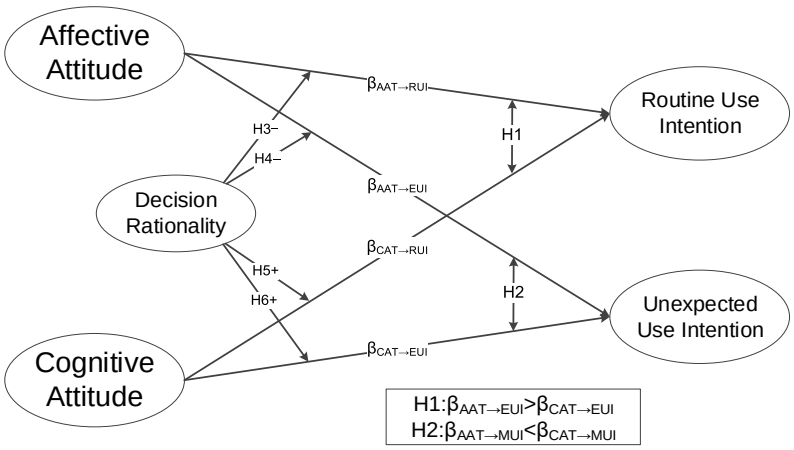


Figure 1. Research Model

Routine use refers to individuals' using UMSs in a standardized manner in their daily lives (Li et al., 2013). Whether an individual uses an UMS or not constitutes a personal decision. Compared with services or technologies from workplaces, a UMS can induce more hedonic outcomes (Venkatesh & Brown, 2001), such as enjoyment in finishing a task using a more convenient approach. According to affective-cognitive theory, such affective evaluations can positively induce human behavior together with cognitive evaluations when they have the same valence (Shiv & Fedorikhin, 1999). Routine use requires less cognition effort because users do not need to make repeated decisions on whether to use a service repetitively, and, thus, their cognition is anchored in standardized ways when making such decisions (Starbuck & Webster, 1991). Furthermore, existing literature has shown that inner affective feelings have stronger effects on long-term behaviors relative to cognitive benefits (Curry, Wagner, & Grothaus, 1991; Scott, Pereira, & Oakley, 2014). Therefore, when form routine use intentions on whether to use a UMS without also stimulating their routinization decisions, individuals will rely more on affective evaluations. Thus, we propose that:

H1: An affective attitude has a stronger effect than a cognitive attitude on UMS users' routine use intentions.

Unexpected usage occurs when the UMS is used to accomplish an unexpected task (Saga & Zmudm 1994). As a kind of use decision in the infusion stage, an unexpected use decision is developed from a comprehensive and integrated evaluation of the service and this requires a choice of whether the service is suitable for special situations (Cooper & Zmud, 1990). When facing unexpected tasks, individuals first need to evaluate the tasks to decide what functions are required to perform these tasks, which requires more cognitive-based efforts. Following this, they need to evaluate the service to decide whether the service can be used for these unexpected tasks, such as what functions the service can provide and whether these functions are suitable for the required tasks. Thus, when making unexpected use decisions, users need to exert more cognitive thinking on their unexpected situations. Therefore, they will rely more on their cognitive attitudes than on affective attitudes. While their adopting affective attitude also induces unexpected use, the effects of affective attitude can be weaker in comparison to that of cognitive attitude. Thus, we posit that:

H2: A cognitive attitude has a stronger effect than an affective attitude on UMS users' unexpected use intentions.

Decision rationality refers to the extent to which users make rational decisions based on their cognitive evaluations. Individuals with high decision rationality will tend to make decisions by completely searching for and logically evaluating all alternatives, and individuals with low decision rationality rely more on intuitive decision making (Scott & Bruce, 1995). Thus, individuals with different levels of decision rationality will exhibit different reliance on their decision making. Affective attitude relies on users' subjective feelings about using a service such as pleasure and enjoyment. Using these affective feelings in decision making will induce an individual's intuitive information process, which, in turn, leads to less rational decisions (Forgas, 2000). Thus, when users have high decision rationality, they will rely less on their affective attitude in decision making. In contrast, in the presence of low decision rationality, users will rely more on the intuitive information processing, such as whether they feel good when using a service,

rather than resorting to a complicated cognition process. Thus, users with high decision rationality will rely less on their affective attitude towards using the UMS in both routine and unexpected use decisions in contrast to those with lower decision rationality. Therefore, we hypothesize that:

H3: Decision rationality weakens the positive relationship between affective attitude and UMS users' routine use intentions.

H4: Decision rationality weakens the positive relationship between affective attitude and UMS users' unexpected use intentions.

Individuals with high decision rationality will make decisions through exhaustively searching for and logically evaluating all alternatives (Scott & Bruce, 1995). The logical evaluation relies on a cognition process that individuals reach by evaluating the gains and costs of all alternatives and figuring out the overall value of each one (Kim & Kankanhalli, 2009). Based on this process, users will cognitively evaluate all the alternatives. Further, in these situations, users will cognitively evaluate the different usage patterns. As cognitive attitude represents a kind of cognitive evaluation that involves making decisions on how to use a UMS with high decision rationality, users will rely more on their cognitive attitudes than using a systematic and analytical approach for evaluating the benefits and costs of whether and how to use a service (Kandemir & Acur, 2012). However, users with low decision rationality will rely more on intuitive feelings and less on the complicated cognition approach. Thus, users with low decision rationality will depend less on their cognitive attitude towards using the UMS in both routine and unexpected use decisions in contrast to those with higher decision rationality. Therefore, we posit that:

H5: High decision rationality strengthens the positive relationship between cognitive attitude and UMS users' routine use intentions.

H6: High decision rationality strengthens the positive relationship between cognitive attitude and UMS users' unexpected use intentions.

4 Research Methodology

We tested our model with two independent studies. As the UMS constitutes a general concept that covers many different types of services, users' decision processes may vary with different services. Thus, we decided to use two unrelated services (an mHealth monitoring service (MMS) and mobile banking (mBanking) to test our model for two reasons. First, as emerging UMSs, both services can provide two different research contexts. As users at the adoption and post-adoption stages may vary in their responses to IT-related services (Khalifa & Liu, 2003), they may make different use decisions. Second, both services provide different features for users that they can use routinely or only in unexpected situations. We further tested our model among potential MMS and mBanking users in the two studies. We used two different services and two different diffusion stages to enhance our findings' reliability and generalizability.

4.1 Development of Measures

As existing research has already measured and explored most of the constructs we examine well, we adopted their measures and adapted them according to our research contexts. Specifically, we adopted measures for affective attitude from Kim (2009) and Yang and Yoo (2004), and the measures for cognitive attitude from Yang and Yoo (2004). We measured routine use intention following Sundaram, Schwarz, Jones, and Chin (2007) and the unexpected use intention following Li et al. (2013). We adapted the measures for decision rationality from Kaufmann, Kreft, Ehrgott, and Reimann (2012). We first developed the measures in English and then translated them into Chinese. IS researchers and students checked the content validity. We conducted a pilot test with 40 masters' degree students to identify Chinese text problems and measure the validity of our measures. The Appendix shows the measures and their sources.

4.2 First Study

An MMS involves using mobile ICTs to provide end-users with health-monitoring services, which can manage and deliver health services free of temporal and geographical constraints and in an ubiquitous manner (Consulting, 2009). For users, our service represents a typical UMS that can help users to manage and monitor their daily health matters. Typically, this UMS can provide two different aspects of

functions: features for daily health monitoring and features for unexpected purposes such as hospital appointments and doctors' consultations. As such, users can choose to use the UMS routinely or in unexpected situations. Respondents in the first study were potential MMS users. We measured their cognitive and affective evaluations about using the services in the future and their intentions prior to adoption. It is appropriate and valid to measure potential users' decision processes when they recognize that they feel positive towards performing a usage behavior (Sussman & Siegal, 2003). Thus, we conducted a survey to test our study's guiding model and excluded individuals who had previously used an MMS. We designed the questionnaire to have three sections: 1) a section that introduced how the service works and its benefits (with a colored page introducing the service and the app used), 2) a section with measures of the constructs to reflect users' responses to the service, and 3) a section with questions about their demographic characteristics. We recruited the respondents in an online health community (for chronic diseases) because this portal is especially designed for individuals with poor health conditions. We posted the link of our online questionnaire in the community to invite the users to complete our survey. We offered an incentive of 20 Yuan (about US$3) to individuals who completed the survey.

A total of 250 respondents completed the survey from which we obtained 213 valid questionnaires. Among the respondents who provided valid questionnaires, 128 were males, and 85 were females. Most of them ranged in age from 41 to 50 years (77.4%), 35 ranged from 51-60 years, and seven were more than 60 years of age. Further, 209 of them had two or more years' experience in using smartphones. The majority also had a college-level qualification at minimum (77.4%).

We used partial least squares (PLS) to test the measurements and the structural model. We examined the reliability and validity of the measures in the first study. Tables 2 and 3 show the results.

The composite reliabilities exceeded 0.846, significantly above the suggested cut-off 0.707, which indicates good composite reliability (Chin, 1998; Jiang & Benbasat, 2007). Further, most loadings exceeded 0.700, above the suggested cut-off 0.600 (Barclay, Higgins, & Thompson, 1995; Chin, 1998; Jiang & Benbasat, 2007), which indicates convergent validity (Chin, 1998). Moreover, the factor loadings of each construct were much greater than the cross-loadings on other constructs, and the correlations of any two constructs were much smaller than the square root of the AVEs correspondingly, which indicates discriminant validity (Chin, 1998).

Table 2. Loadings and Cross Loadings for First Study

	AAT	CAT	DRT	UUI	RUI
AAT1	**0.884**	0.662	0.503	0.379	0.633
AAT2	**0.782**	0.647	0.488	0.375	0.576
AAT3	**0.798**	0.588	0.485	0.384	0.524
CAT1	0.637	**0.823**	0.494	0.375	0.637
CAT2	0.658	**0.841**	0.508	0.406	0.555
CAT3	0.680	**0.900**	0.563	0.470	0.599
DRT1	0.422	0.372	**0.710**	0.308	0.426
DRT2	0.471	0.446	**0.769**	0.377	0.447
DRT3	0.457	0.480	**0.737**	0.397	0.436
DRT4	0.466	0.494	**0.762**	0.416	0.458
DRT5	0.462	0.512	**0.827**	0.441	0.431
UUI1	0.171	0.229	0.216	**0.795**	0.155
UUI2	0.377	0.400	0.437	**0.845**	0.398
UUI3	0.467	0.474	0.495	**0.892**	0.477
RUI1	0.602	0.583	0.504	0.397	**0.869**
RUI2	0.583	0.629	0.510	0.441	**0.845**
RUI3	0.607	0.565	0.448	0.361	**0.830**

Note: AAT= affective attitude, CAT= cognitive attitude, DRT= decision rationality, UUI= unexpected use intention, RUI= routine use intention.

Table 3. Correlation Matrix for First Study

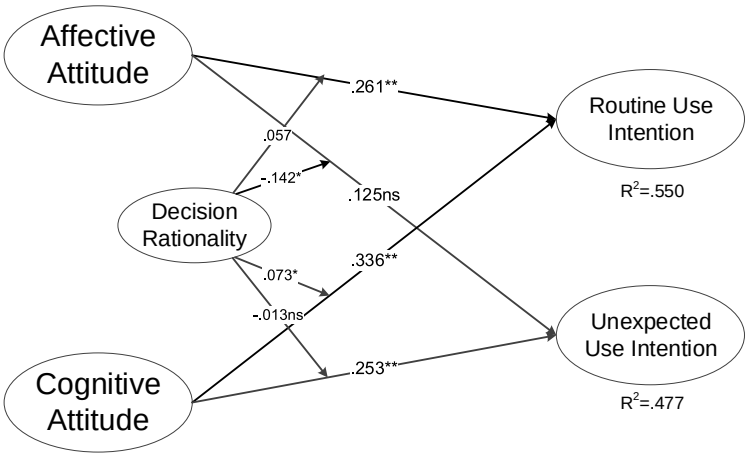
	AVE	C.R.	AAT	CAT	DRT	UUI	RUI
AAT	0.650	0.847	**0.806**				
CAT	0.709	0.879	0.746	**0.842**			
DRT	0.546	0.857	0.555	0.589	**0.739**		
UUI	0.592	0.808	0.523	0.577	0.615	**0.769**	
RUI	0.680	0.864	0.647	0.574	0.570	0.546	**0.825**

Note: AVE= average variance explained; C.R.= composite reliability; the bold diagonally presented data refer to the square roots of AVEs (average variance extracted)

Given that we obtained rather high correlations for affective attitude, cognitive attitude, perceived enjoyment, and routine use, a multicollinearity issue potentially existed. As such, we tested the constructs' variance inflation factors (VIFs) to examine the issue's seriousness. The results showed that all VIFs were less than 2.6, far lower than the recommended cut-off 10 (Cohen, Cohen, West, & Aiken, 2013; Kutner, Nachtsheim, & Neter, 2004), which indicates multicollinearity did not pose an issue in our study.

We tested the structural model in two stages. First, we verified the basic model without including the moderating effects to test H1 and H2. The results indicate that affective attitude significantly influenced routine use intention ($\beta = 0.328$, $t = 3.85$, $p < 0.01$) and unexpected use intention ($\beta = 0.211$, $t = 2.64$, $p < 0.01$), while cognitive attitude significantly influenced routine use intention ($\beta = 0.229$, $t = 5.58$, $p < 0.01$) and unexpected use intention ($\beta = 0.421$, $t = 5.49$, $p < 0.01$). We further tested affective attitude's and cognitive attitude's relatively stronger effects on the two intentions according to Cohen et al.'s (2013) procedures. The results indicate that affective attitude had a relatively stronger effect on routine use intention ($\beta = .328$ vs. $\beta = .229$, $t = 14.2$, $p < 0.01$) and that cognitive attitude had a relatively stronger effect on unexpected use intention ($\beta = .421$ vs. $\beta = .211$, $t = -29.2$, $p < 0.01$) than affective attitude. Thus, we found support for H1 and H2.

Second, we tested the full model for decision rationality's moderating role by testing the interaction effects. Figure 2 shows the results.



Note: ns $p > 0.05$; * $p < 0.05$; ** $p < 0.01$.

Figure 2. The Structural Model Results of First Study

From the results, we can perceive that decision rationality did not weaken the effect that affective attitude had on routine use intention ($\beta = 0.057$, $t = 1.09$, $p > 0.05$) but that it did weaken the effect that affective attitude had on unexpected use intention ($\beta = -0.142$, $t = 2.05$, $p < 0.05$) and strengthen the effect that cognitive attitude had on routine use intention ($\beta = 0.073$, $t = 2.26$, $p < 0.05$). The moderating effect that decision rationality had on the relationship between cognitive attitude and unexpected use intention lacked significance ($\beta = -0.013$, $t = 0.194$, $p < 0.05$). In total, the model explained 55 percent of the variance in routine use intention and 47.7 percent of the variance in unexpected use intention. Therefore, we found support for H4 and H5 but not for H3 and H6.

4.3 Second Study

Since the two attitudes may have a different effect on behavioral intention for potential and actual users, we considered actual users in the second study. We further engaged mBanking users in the second study to test the model again. For these users, this service represents a typical UMS that can help them to manage their financial affairs (Kim, Shin, & Lee, 2009). The mBanking UMS also provides both general features to fulfill users' daily needs and special features to satisfy their needs in a particular context (e.g., account-management features, mobile payments, money transfers). We conducted a survey with the help of a bank in northeast China. The bank has launched a mobile app to help its customers to use bank services on their mobile phones. The bank sent the link of our survey to their app users as a follow-up user survey. We offered an incentive of 20 Yuan (about US$3) to individuals who completed the survey.

In total, 280 respondents completed the survey from which we obtained 251 valid questionnaires. Of the respondents who completed valid surveys, 100 were males and 151 were females. Most were 29 to 40 years of age (83.3%), while 18 were over 40. In addition, 240 participants had used smartphones for two or more years. Most had a college education (96.4%).

We used partial least squares (PLS) to test the measurement and structural models. We examined the reliability and validity of the measures in the second study. Tables 4 and 5 show the results.

Composite reliabilities exceeded 0.880, significantly above the suggested cut-off 0.707, which indicates composite reliability. Further, most of the items' loading exceeded 0.780, above the suggested cut-off 0.600 (Barclay et al., 1995; Chin, 1998; Jiang & Benbasat, 2007), which indicates convergent validity (Chin, 1998). Moreover, each construct's factor loadings exceeded the cross-loadings of other constructs, and the correlations of any two constructs were much smaller than the square roots of the AVEs, which indicates discriminant validity (Chin, 1998).

Table 4. Loadings and Cross Loadings for Second Study

	AAT	CAT	DRT	UUI	RUI
AAT1	**0.865**	0.688	0.223	0.199	0.193
AAT2	**0.893**	0.705	0.169	0.189	0.264
AAT3	**0.889**	0.698	0.205	0.206	0.221
CAT1	0.738	**0.896**	0.209	0.295	0.205
CAT2	0.656	**0.879**	0.183	0.216	0.199
CAT3	0.674	**0.850**	0.180	0.142	0.225
DRT1	0.179	0.187	**0.887**	-0.016	0.365
DRT2	0.204	0.227	**0.897**	0.014	0.441
DRT3	0.253	0.244	**0.900**	0.046	0.434
DRT4	0.166	0.161	**0.870**	0.048	0.420
DRT5	0.186	0.149	**0.878**	0.014	0.415
UUI1	0.191	0.212	0.012	**0.946**	-0.036
UUI2	0.215	0.250	0.025	**0.963**	-0.005
UUI3	0.233	0.269	0.034	**0.958**	-0.019
RUI1	0.228	0.194	0.406	-0.020	**0.864**
RUI2	0.238	0.235	0.398	-0.022	**0.888**
RUI3	0.215	0.197	0.434	-0.012	**0.884**

Note: AAT= affective attitude, CAT= cognitive attitude, DRT= decision rationality, UUI= unexpected use intention, and RUI= routine use intention.

Table 5. Correlation Matrix for Second Study

	AVE	C.R.	AAT	CAT	DRT	UUI	RUI
AAT	0.767	0.908	**0.876**				
CAT	0.778	0.913	0.789	**0.882**			
DRT	0.786	0.948	0.218	0.224	**0.887**		
UUI	0.852	0.945	0.462	0.367	0.232	**0.923**	
RUI	0.772	0.910	0.238	0.257	0.470	0.477	**0.879**

Note: AVE= average variance explained; C.R.= composite reliability; the bold diagonally presented data refer to the square roots of AVEs (average variance extracted)

Given that we obtained rather high correlations for affective and cognitive attitudes, a multicollinearity issue potentially existed. As such, we tested the items' variance inflation factors (VIFs) for multicollinearity. We found that all VIFs were less than 2.70, far below the recommended cut-off 10 (Cohen et al., 2013; Kutner et al., 2004), which indicates multicollinearity did not pose an issue in our study.

We tested the structural model in two stages. First, we verified the baseline model without the moderating effects to test H1 and H2. We found that affective attitude significantly influenced routine use intention ($\beta = 0.201$, $t = 2.72$, $p < 0.01$) but did not influence unexpected use intention ($\beta = 0.095$, $t = 1.17$, $p > 0.05$), while cognitive attitude significantly influenced both unexpected use intention ($\beta = 0.198$, $t = 2.58$, $p < 0.01$) and routine use intention ($\beta = 0.182$, $t = 1.98$, $p < 0.05$). We further tested affective attitude's and cognitive attitude's relatively stronger effects on two dependent variables according to Cohen et al.'s (2013) procedures. We found that affective attitude had a relatively stronger effect on routine use intention than cognitive attitude did ($\beta = 0.201$ vs. $\beta = 0.182$, $t = 2.33$, $p < 0.05$) and that cognitive attitude had a relatively stronger effect on unexpected use intention than affective attitude did ($\beta = 0.198$ vs. $\beta = 0.095$, $t = -15.21$, $p < 0.01$). Thus, we found support for H1 and H2.

Second, for the full model, we confirmed decision rationality's moderating role by testing the interaction effects. Figure 3 presents the results.

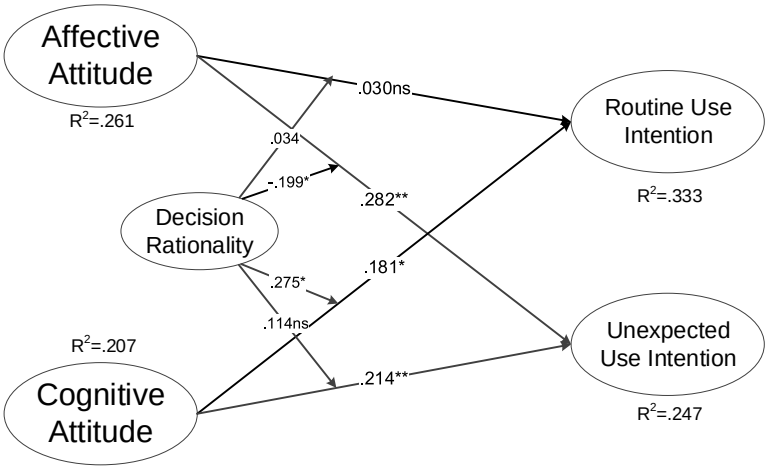


Figure 3. Structural Model Results of Second Study

From the results, we can perceive that the effect that the interaction between decision rationality and affective attitude had on unexpected use intention was negatively significant ($\beta = -0.199$, $t = 2.07$, $p < 0.05$) and the effect that the interaction between decision rationality and cognitive attitude on routine use intention was positively significant ($\beta = 0.275$, $t = 2.27$, $p < 0.05$). The effect that the interaction between decision rationality and affective attitude had on routine use intention ($\beta = 0.034$, $t = 0.290$, $p > 0.05$) and the effect that the interaction between decision rationality and cognitive attitude had on unexpected use intention ($\beta = 0.034$, $t = 1.19$, $p > 0.05$) were not significant. In addition, the model explained 33.3 percent of the variance in routine use intention and 24.7 percent of the variance in unexpected use intentions. Therefore, we found support for H4 and H5 but not for H3 and H6.

5 Discussion

We investigated the relative effect that affective attitude and cognitive attitude had on two usage behaviors (i.e., routine use and unexpected use) and decision rationality's contingency role. Specifically, we developed a theoretical model based on the effect that affective and cognitive attitudes have on individuals' use behaviors and decision rationality's moderating role in those relationships. We conducted two studies to test the model. Table 6 summarizes the results we obtained from testing our hypotheses. We discuss our key findings in Section 5.1.

Table 6. Hypothesis Testing Overall

Hypothesis	First study	Second study
H1: An affective attitude has a stronger effect than a cognitive attitude on UMS users' routine use intentions.	Supported	Supported
H2: A cognitive attitude has a stronger effect than an affective attitude on UMS users' unexpected use intentions.	Supported	Supported
H3: Decision rationality weakens the positive relationship between affective attitude and UMS users' routine use intentions.	Not supported	Not supported
H4: Decision rationality weakens the positive relationship between affective attitude and UMS users' unexpected use intentions.	Supported	Supported
H5: High decision rationality strengthens the positive relationship between cognitive attitude and UMS users' routine use intentions.	Supported	Supported
H6: High decision rationality strengthens the positive relationship between cognitive attitude and UMS users' unexpected use intentions.	Not supported	Not supported

5.1 Key Findings

First, affective attitude and cognitive attitude had different effects on different usage behaviors in the UMS context. In the first study, both affective and cognitive attitudes had significant effects on routine and unexpected UMS use. Further, affective attitude had a stronger effect on routine use intention than on unexpected use intention (0.328 vs. 0.211); however, cognitive attitude exerted a weaker effect on the unexpected use intention than on routine use intention (0.421 vs. 0.229). In the second study, affective attitude influenced only routine use, and its effect on the unexpected use was not significant ($\beta = 0.095$, $t = 1.117$, $p > 0.05$). Cognitive attitude had a stronger effect on unexpected use than on routine use (0.198 vs. 0.182). These findings indicate that affective attitude has a greater explanatory power for routine use, while cognitive attitude has more explanatory power for unexpected use in UMSs. One reason why may be that individuals develop affective attitude early on when interacting with UMSs, which influences their early use decisions more than their later decisions (Shiv & Fedorikhin, 1999). Therefore, for different use behaviors, affective and cognitive attitudes have different effects on users' decision making.

Second, affective attitude had a stronger effect on routine use intention compared with cognitive attitude. We found that the impact that affective attitude had on routine use intention was stronger than the impact that cognitive attitude had on routine use intention in both studies. This finding indicates that, when deciding whether to use a UMS in their daily routine, users rely more on their affective evaluations and less on their cognitive evaluations. As for why, individuals develop cognitive attitude in the later stage of interacting with a UMS; thus, it has a weaker effect on user decisions in the earlier stages (Shiv & Fedorikhin, 1999). This finding concurs with behavioral research in personal settings that has found individuals make decisions according to their own preferences (Lawton et al. 2009; Légaré et al., 2013). Therefore, affective attitude has a relatively stronger effect on routine UMS use.

Third, cognitive attitude had a stronger effect on the unexpected use intentions compared with affective attitude. The results from our two studies indicate that cognitive attitude had a stronger on the unexpected use than affective attitude did. This finding means that, when deciding whether to use a UMS for unexpected situations, users rely more on cognitive evaluations and less on their affective evaluations. One reason why may be that users make unexpected use decisions at later stages when interacting with a UMS; since they develop cognitive attitude in this stage, it plays a more significant role. This finding concurs with technology acceptance research in workplaces that has found cognitive evaluations play a major role (Yang & Yoo, 2004). Therefore, cognitive attitude has a stronger effect on the unexpected UMS use.

Finally, the effect that affective and cognitive attitudes have on UMS users' use behaviors depends on their decision rationality. We found that decision rationality weakened the relationship between affective attitude and unexpected use but strengthened the relationship between cognitive attitude and routine use. This finding can arise due to the underlying mechanism of how different attitude components predict usage behaviors differently. For instance, affective attitude has a relatively weaker effect on unexpected use as this decision process relies more on affective, but high decision rationality, which makes users more cognitively driven, can further weaken this effect. When making use decisions based on cognitive attitude, users will rely more on the cognition-based process. High decision rationality can enhance this effect by making users become more cognitively driven.

We found that the moderating effect that decision rationality had on the relationship between cognitive attitude and unexpected UMS usage was not significant. One reason why may be that, when relying more on cognitive attitude to make unexpected UMS use decisions, users are more rational as they have to determine whether the UMS suits their situation. Thus, whether they possess a high or low rationality lacks significance in such situations. We also found that the moderating effect that decision rationality had on the relationship between affective attitude and routine use was not significant in both studies possibly because a routine use decision needs less cognitive effort (Starbuck & Webster, 1991) and because the level of cognitive efforts in the decision process does not affect the relationship as much since affective attitude relies on affective efforts.

Our findings show why previous studies have found mixed results about affective attitude's and cognitive attitude's relative importance in determining user behaviors. The different service types (utilitarian or hedonic), use patterns (routine or unexpected), and the levels of decision rationality can all bring about different effects for affective and cognitive attitude.

5.2 Theoretical Implications

With this study, we provide several contributions to the current literature. First, by investigating the diverse UMS usage behaviors and their determinants, we review how users make different use decisions regarding UMSs. While research has widely explored UMS usage behaviors (Akter et al., 2013, 2015; Baptista & Oliveira, 2017; Yfantis et al., 2013), most have focused on generic use behaviors. As users can use UMSs for both daily routines and unexpected situations, they have two different usage behaviors (i.e., routine use and unexpected use.) For the different usage behaviors, users may respond to different evaluating processes when making their decisions. Drawing on the different attitude components, we found that affective attitude has a stronger effect on routine use than on unexpected use and that cognitive attitude has a stronger effect on unexpected use than on unexpected use. This finding enhances our understanding about how users make different UMS use decisions based on a unified affective and cognitive process, which can also explain users' different behaviors regarding UMSs. This research, to the best of our knowledge, represents one of the first studies to investigate how users make routine and unexpected use decisions regarding UMSs from a unified affective and cognitive process perspective. As a result, we encourage researchers to conduct future research on the determinants of different user behaviors to precisely explain users' decision making in the UMS context.

Second, we provide fresh insight by exploring the role that affective attitude plays in a UMS context. While extant empirical research has widely studied different kinds of utilitarian services, it has mostly adopted a cognitive perspective (Alalwan et al., 2015; Cheng, Lee, & Choi, 2019; Karjaluoto et al., 2010; Kim et al. 2007; Lin & Bhattacherjee, 2010; Lowry, Zhang, & Wu, 2014). Accordingly, research has largely neglected the affective perspective. Drawing on affective responses to the usage process, we specifically propose and empirically verify that affective attitude in using UMSs can also influence user behavior. Our research findings identify affective factors that influence UMS usage behavior and provide insights for future research.

Third, we also advance knowledge of the relationships between different attitude components and usage behaviors in human-service interactions by identifying the relative influence that cognitive attitude and affective attitude have on user behaviors. We found that affective attitude was the key predictor of routine use decisions and cognitive attitude was the key predictor of unexpected use decisions. This finding indicates that, when forming different use behaviors in using UMSs, users rely on different decision processes (i.e., via either affective or cognitive processes). Such findings provide insights on how users can make different use decisions based on two different decision-making mechanisms (Bagozzi & Burnkrant, 1979; Légaré et al., 2013; Pi et al., 2016; Yang & Yoo, 2004) and the relative importance of both affective and cognitive attitudes in shaping usage behaviors in human-UMS interaction. We also

provide motivation for researchers to conduct additional research on the interplay between cognitive attitude and affective attitude in decision making to better explain the attitude-behavior linkage.

Fourth, our work possibly represents the first study to examine whether the magnitude between cognitive and affective attitudes depends on users' decision rationality and to identify the mechanisms under which attitude influences different behaviors explicitly. Although research has extensively explored the effect that cognitive attitude and affective attitude have on human behavior (Bagozzi & Burnkrant, 1979; Cohen et al., 2013; Saeed & Abdinnour, 2013; Tosi & Slocum, 1984), few studies have investigated the magnitude between them according to different decision characteristics. In this study, we propose new insights into the effect that attitude has on human behavior at different levels of decision rationality. We encourage researchers to explore other individual differences as the contingent factors, such as personalities, preferences, and cultural differences.

Finally, we explain the different effects that affective and cognitive attitudes have on human behaviors for making decisions about using UMSs. We lack consensus on the relative effects that affective attitude and cognitive attitude have in determining human behavior, and, thus, we highlight the need to illuminate this research black box (Cohen et al., 2013; Conner et al., 2013; Karjaluoto et al., 2010; Légaré et al., 2013; Min & Lee, 2009; Sussman & Siegal, 2003). We found that, for different UMS use behaviors (routine or unexpected), affective attitude and cognitive attitude exert different relative effects and that effects depend on the decision makers' rationality. Therefore, we partially explain the mixed findings in the literature on the relative effect that attitude components have on human behavior in the attitude literature. In analyzing the role that affective and cognitive attitudes have on user behavior, one needs to consider different outcome variables and contingent factors. Thus, we anticipate further work that investigates how affective and cognitive attitudes play different roles in determining different behaviors on the decisions users make in deciding whether to use other services or technologies and whether these roles differ among users in different research contexts.

5.3 Practical Implications

We also consider some implications for UMS practitioners and users. Concerning the relative effect that affective and cognitive attitudes have in determining routine use and unexpected use, we advise UMS providers to devise better ways of promoting their services according to their different goals. If they seek to recruit more routine users or increase their current users' daily usage, they can increase users' positive affective responses to the service, such as by improving their services' design and performance. If they seek to recruit more users for certain occasions or to increase their current users' innovative usage, they can increase the benefits that users perceive they will gain from using the service, such as by including more useful features and promoting these features to both their existing and potential users. To strengthen users' affective and cognitive attitudes, we advise providers to take measures to promote their users' enjoyment and usefulness perceptions and also to alleviate their anxiety perceptions.

Furthermore, regarding decision rationality's contingent effects, if UMS providers seek to recruit more routine users or to increase their current users' daily usage, we advise them to try decreasing the influence of users' rationality, such as by shortening their decision-making time. If they seek to recruit more users for a certain occasion or to increase their current users' innovative usage, UMS providers should try to increase the influence of users' rationality, such as by providing them with more information and time to facilitate their decisions.

Potential UMS users and actual users can also benefit from our findings. When making routine use decisions on a UMS in which affective attitude plays a key role, we advise users to increase their decision rationality and conduct cognitive evaluations to make more rational decisions on whether they need to routinely use the service.

5.4 Limitations

As with any study, our study has several limitations. First, while routine and unexpected use represent two UMS use patterns, other use behaviors, such as extended use and selective use, that we need to consider in this context exist as well. Second, we found that decision rationality had a non-significant effect on the relationship between affective attitude and routine use and on the relationship between cognitive attitude and unexpected use. While this research explains such differences, no empirical evidence supports this observation. Future research could investigate the relative effect of attitude components among other different use behaviors and other related contingencies. Third, we explored the

determinants of routine use and unexpected use from the attitude perspective. In the future, research could explore factors such as habits for routine use (Limayem, Hirt, & Cheung, 2007; Soror, Hammer, Steelman, Davis, & Limayem, 2015) in terms of different user behaviors. Finally, as our main theoretical constructs concern behavioral intentions and attitudes, they were highly correlated with each other in the two studies. We encourage further research to adopt users' actual usage experiences to better measure use behaviors.

6 Conclusion

Using mICTs to deliver utilitarian services has become increasingly popular in recent years. Indeed, UMS users can switch between routine use and unexpected use behaviors. However, inadequate research has examined how users make decisions on the different use behaviors. On the other hand, the prior literature on the effects of attitude components implies that affective and cognitive attitudes have different relative effects on human behavior. Drawing on these gaps in research, we developed a model that tested the relative effect that affective attitude and cognitive attitude have on routine and unexpected UMS use and decision rationality's contingent effects. We tested the model among potential MMS users and actual mBanking users. We found that affective attitude had a stronger effect than cognitive attitude on routine use intention, while cognitive attitude had a stronger effect than affective attitude on unexpected use intention. Moreover, decision rationality weakened the effects that affective attitude had on routine use intention, and decision rationality strengthened the effects that cognitive attitude had on the unexpected use intentions. This study explains how users undertake different usage behaviors regarding UMSs, how affective and cognitive attitudes influence the different use behaviors, and whether the effect that affective and cognitive attitudes have on use decisions depends on decision rationality. It also explains the relative effects that affective and cognitive attitudes have on users' UMS use decisions. Practically, this research provides suggestions for UMS providers on how to promote their services and for UMS users on how to make use decisions based on their affective and cognitive attitudes.

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Appendix

Table A1. Measurements

Construct	Item
Affective attitude (Kim, 2009; Yang & Yoo, 2004)	I like the idea of using [] services.
	Using [] services would make me feel good.
	Using [] services would make me feel positive.
Cognitive attitude (Yang & Yoo, 2004)	Using [] service is a wise instrument in protecting my health.
	Using [] service is a beneficial instrument in protecting my health.
	Using [] service is a valuable instrument in protecting my health.
Routine use intention (Sundaram et al., 2007)	I predict to incorporate [] services into my regular life schedule.
	The [] services will be pretty much integrated as part of my normal life routine.
	[] services will be a normal part of my life.
Unexpected use intention (Li et al., 2013)	I will find ways to use [] in case of an emergency.
	I will use [] in new ways to support the unexpected [] situations.
	I plan to use [] under urgent [] requirements.
Decision rationality (Kaufmann et al., 2012)	My decision process regarding [] are mostly analytical.
	I look extensively for information in order to make a [] related decision.
	Quantitative analyses are important in making a [] decision.
	The entire selection of [] choices is very effective at focusing on important information.
	I extensively analyze relevant information before making a [] decision.

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