UNDERSTANDING THE ACCEPTANCE OF MOBILE HEALTH SERVICES: A COMPARISON AND INTEGRATION OF ALTERNATIVE MODELS

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ABSTRACT

The advancement of mobile technology and the increasing importance of health promote the boom in mobile health services (MHS) around the world. Although there have been several studies investigating the health technology acceptance behavior from a variety of theoretical perspectives, they have not provided a unified understanding. To fill this research gap, this paper: (1) reviews the health technology acceptance literature and discusses three prominent models (e.g., the technology acceptance model, the theory of planned behavior or the unified theory of use and acceptance of technology, and the protection motivation theory), (2) empirically compares the three models, and (3) formulates and empirically validates the unified model in the context of mobile health services. In the unified model of health technology acceptance, we propose that users' intention to use mobile health services is determined by five key factors: performance expectancy, effort expectancy, social influence, facilitating conditions, and threat appraisals. The results show that the unified model outperforms the three alternative models by significantly improving the R-squares. Finally, the implications for theory and practice are put forward.

Keywords: mobile health; technology acceptance model (TAM); protection motivation theory (PMT); theory of planned behavior (TPB); the unified theory of use and acceptance of technology (UTAUT)

1. Introduction

The advancement of wireless networks and mobile devices has driven the emergence of mobile health services (MHS) which can be defined as a variety of healthcare services, including health consulting, hospital registering, and location-based services delivered through mobile communications and network technologies [Istepanian et al. 2006; Ivatury et al. 2009]. Compared to the previous electronic health services which are based on the desktop computer and wired network, MHS enables users to access to health services more conveniently. For example, when a user suddenly suffers a heart attack in the suburbs where the wired network is not available, s/he can press an SOS button on the customized mobile device for MHS, and then the emergency center of the hospital will receive the message, identify the location of the user, and arrange for the aid.

The most important issue for mobile health service providers is to attract and keep their users, precipitating the understanding on users' mobile health service adoption behavior as a critical issue for researchers on this specific research area. However, despite numerous previous studies investigating the electronic health technology adoption behavior, most of these studies view this phenomenon from the perspective of *professionals or physicians* [e.g., Bhattacherjee et al. 2007; Chau et al. 2002; Klein 2007], focusing on the technologies used in the diagnosis process [Romanow et al. 2012] such as electronic medical records [e.g., Hennington et al. 2007] and computerized physician order entry (COPE) systems [e.g., Bhattacherjee et al. 2007]. In contrast, the studies on health technology adoption behavior from the perspective of *patients or consumers* are relatively rare. This lack is a mismatch for the increasing prevalence of health technology or services for consumers who receive medical care [Or et al. 2009]. Thus, our study fills the gap by examining the health technology acceptance behavior from the perspective of consumers rather than that of professionals.

Among the limited empirical studies on consumers' health technology adoption behavior, most studies view this issue from the *technology acceptance theories*. For example, Akter et al. [2010] investigate how users' perceptions of mobile health service quality influence their intentions to adopt the services from the information systems success model [DeLone et al. 2003]. Cocosila and Archer [2010] purport that users' intentions to adopt MHS are determined by their extrinsic motivation (e.g., the extent to which the services are useful) and intrinsic motivation (e.g., the extent to which the services are enjoyable) from the motivational model [Venkatesh et al. 2002]. Hung and Jen [2010] posit behavioral intention to be the result of perceived usefulness and perceived ease of use by drawing on the technology acceptance model (TAM) [Davis 1989].

Although these studies treating consumer health technology acceptance behavior as a special case of technology acceptance tell part of the whole story, these studies do not shed light on how users' decision making processes differ when the technology is for *healthcare* rather than for other objectives. According to Nutbeam [1998], health behavior is defined as "any activity undertaken by an individual, regardless of actual or perceived health status, for the purpose of promoting, protecting or maintaining health, whether or not such behavior is objectively effective towards that end" (p. 355). Regarding the adoption of health services as an activity to promote, protect or maintain health, health technology acceptance behavior should be considered health behavior [Laugesen et al. 2011; Scammon et al. 2011]. Therefore, a better understanding of the health technology acceptance behavior should be seen not only from a *technology acceptance perspective* but also as a *health behavior perspective*.

Treating health technology acceptance behavior as health behavior, a variety of *health behavior theories* can be used to explain this phenomenon. Among these theories, the protection motivation theory (PMT) is most widely used. This theory argues that individuals' evaluations on the severity and the vulnerability of the potential threats (i.e., threat appraisals) and the extent to which they can cope with the threats by conducting certain health behavior (i.e., coping appraisals) will determine their intentions to perform the health behavior [Rogers 1983]. Here, the health technology acceptance behavior is regarded as a behavior to cope with the potential threats to health.

Both the technology acceptance and the health behavior theories can be used to explain the health technology acceptance behavior. The question that follows then is whether or not one stream of theories can outperform another stream of theories in predicting the health technology acceptance behavior, and whether it is possible to integrate these two theoretical streams to formulate a unified model. Therefore, the research objective of the study can be clearly stated as: *to compare and integrate the alternative models to explain the health technology acceptance behavior*.

The remainder of the paper is organized as follows. The technology acceptance theories and the health behavior theories are first reviewed, after which the differences and the similarities between these theories are articulated and a unified model to integrate these theories is proposed. Next, the methods and procedures to collect the data are shown and the data analysis results are reported. Finally, the limitations, theoretical and practical implications of the study are discussed.

2. Literature Review and Theoretical Background

2.1. Technology Acceptance Theories

Technology acceptance is regarded as one of the most important research areas in the information systems (IS) research [Venkatesh et al. 2003]. It engages in understanding the variety of factors that determine users' intentions to adopt a technology and their actual technology usage behaviors. An overview of the literature relevant to the technology acceptance behavior is portrayed in Figure 1.

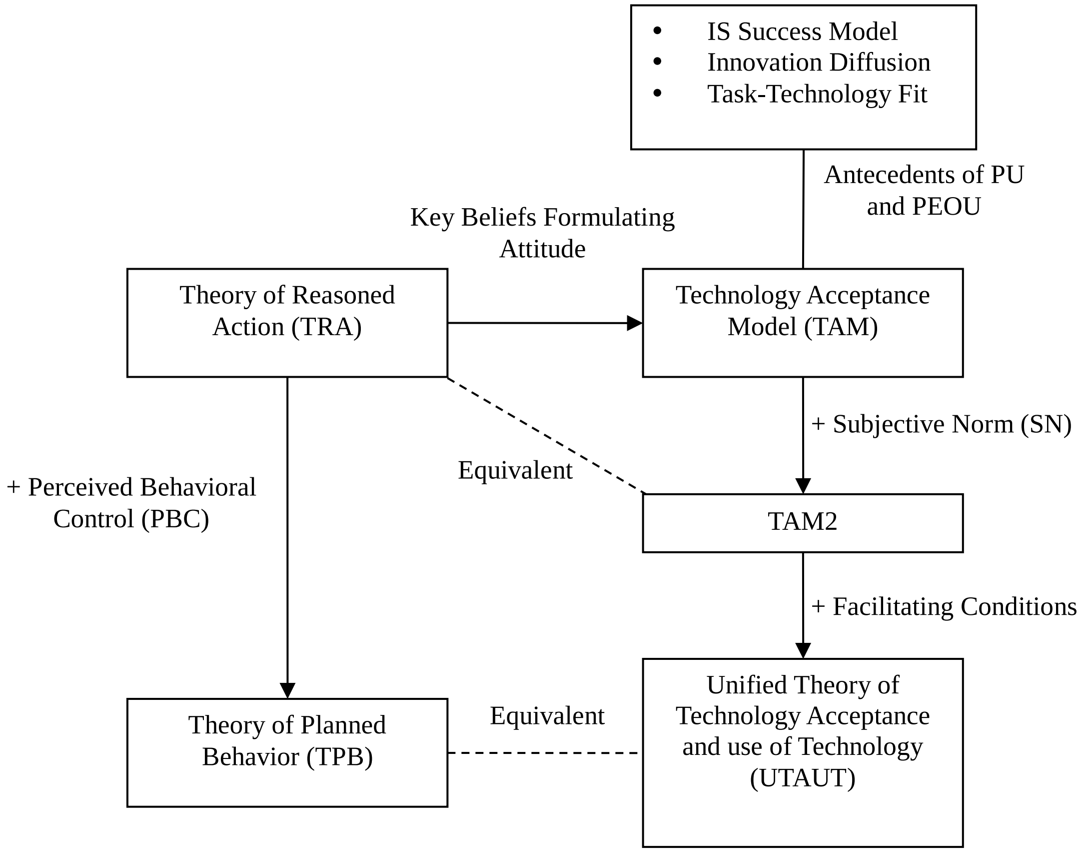

Figure 1: An Overview of Technology Acceptance Theories

The key theories used to explain the technology acceptance behavior and the relationships between these theories are shown in Figure 1. Among these theories, Davis' [1989] technology acceptance model (TAM) is most influential. This theory states that users' intention to adopt a new technology is determined by two key beliefs, namely, perceived usefulness and perceived ease of use. Perceived usefulness (PU) refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" [Davis 1989, p.320], while perceived ease of use (PEOU) refers to "the degree to which a person believes that using a particular system would be free of effort" [Davis 1989, p. 320]. This theory is derived from a more general theory to explain individual behavior, namely, the theory of reasoned action (TRA) [Fishbein et al. 1975], which argues that individual behavioral intention is determined by two key factors: attitude, which describes "an individual's positive or negative feelings (evaluative affect) about performing the target behavior" [Fishbein et al. 1975, p. 216] and subjective norm, which captures "the person's perception that most people who are important to him think he should or should not perform the behavior in question" [Fishbein et al. 1975, p. 302]. Attitude is formed based on an individual's beliefs about consequences of particular behavior (e.g., behavioral beliefs), and subjective norm is formed based on an individual's perceptions of social normative pressures (e.g., normative beliefs). The two important factors in TAM can actually be regarded as two beliefs resulting in attitude. Obviously, subjective norm is not considered in TAM. To fill this gap, Venkatesh and Davis [2000] extended TAM by including subjective norm as another important determinant of intention in the case of mandatory settings (e.g., TAM2). Thus, TAM2, in some sense, is equivalent to TRA.

The unified theory of acceptance and use of technology (UTAUT) is another widely used theory to explain technology acceptance [e.g., Fetscherin et al. 2008; Yu 2012; Zhou 2012]. In UTAUT, Venkatesh et al. [2003] - based on the comparison of the eight prominent theories - further extended TAM2 by reframing the concepts used in previous studies and including facilitating conditions as an additional predictor of intention. Specifically, perceived usefulness, perceived ease of use, and subjective norm are respectively represented by three new terms, namely, performance expectancy, effort expectancy, and social influence.

In greater detail, performance expectancy refers to "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" [Venkatesh et al. 2003, p. 447]. Effort expectancy refers to "the degree of ease associated with the use of the system" [Venkatesh et al. 2003, p. 450]. Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" [Venkatesh et al. 2003, p. 451]. The added construct - facilitating conditions - is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" [Venkatesh et al. 2003, p. 453]. This definition is very similar to the concept of perceived behavioral control (PBC) in the theory of planned behavior (TPB) [Ajzen 1991], which is an extension of TRA by including PBC. Therefore, UTAUT and TPB are equivalent regarding performance expectancy and effort expectancy as two components of attitude [Benbasat et al. 2007].

In addition to the relevant TAM theories, there are several other theories used to explain the technology acceptance behavior including the IS success model, innovation diffusion theory (IDT), and task - technology fit theory (TTFT). Specifically, DeLone and McLean's [2003] IS success model suggests that the technology acceptance behavior is determined by information quality, system quality, and service quality. The innovation diffusion theory argues that the adoption of innovation is determined by five factors: relative advantage, compatibility, triability, observability, and complexity

Table 1: Previous Studies on Health Information Technology Acceptance

Literature	User Type	Theory	Key Conclusion
[Hu et al. 1999]	Professionals	TAM	• PU is a significant determinant of attitude and intention, but PEOU is not.
[Chau et al. 2001]	Professionals	TAM, TPB, and IDT	• Compatibility has a positive effect on PU. • PU has positive effects on attitude and behavioral intention. • Attitude and PBC have positive effects on behavioral intention but SN does not.
[Chau et al. 2002]	Professionals	TAM and TPB	• TAM is more appropriate than TPB for examining technology acceptance by individual professionals.
[Yi et al. 2006]	Professionals	TAM and TPB	• PU has a positive effect on behavioral intention, but PEOU does not. • PBC and SN have positive impacts on behavioral intention. • Result demonstrability and image have positive effects on PU and PEOU.
[Bhattacherjee et al. 2007]	Professionals	TAM and IDT	• PU has a positive effect on intention, but PEOU does not. • Perceived compatibility has a positive effect on PU.
[Liang et al. 2010]	Professionals	UTAUT	• Performance expectancy and facilitating conditions have significant impacts on IT use, while effort expectancy and SN do not.
[Moores 2012]	Professionals	TAM and IS success model	• PU and PEOU have significant impacts on attitude towards technology adoption. • Information quality has a significant impact on PU but insignificant effect on PEOU.
[Hung et al. 2012]	Professionals	TAM and TPB	• Attitude, SN, PBC have positive effects on usage intention. • PU and PEOU have positive effects on attitude.
[Kim et al. 2007]	Consumers	TAM	• PU has a positive effect on satisfaction, while PEOU does not.
[Klein 2007]	Consumers	TAM	• PU has a positive effect on behavioral intention.
[Akter et al. 2010]	Consumers	IS success model	• Service quality has three dimensions, namely, platform quality, interaction quality, and outcome quality. • Service quality has positive effects on satisfaction and behavioral intention.

[Rogers 1995]. The task – technology fit theory postulates that when the task characteristic and technology characteristic are a good fit, an individual's technology utilization and his/her performance will increase [Goodhue et al. 1995]. These three theories are often used to explain the antecedents of TAM factors or TPB factors. For example, Wixom and Todd [2005] and Celik and Yimaz [2011] argue for information quality and system quality as the antecedents of PU and PEOU. Dishaw and Strong [1999] propose task-technology fit as the antecedent of PU and PEOU. Lau et al. [2001] suggest factors in the innovation diffusion theory, including compatibility and relative advantage, as the antecedents of attitude.

Most previous empirical studies on health information technology (HIT) acceptance are built upon the technology acceptance theories (as shown in Table 1).

As shown in Table 1, most of these studies focus on investigating the professionals' technology acceptance rather than the patients' technology acceptance. One of the interesting findings of these studies is that perceived ease of use has no significant impact on behavioral intention, because professionals may exhibit considerable competence and adaptability to new technologies [Hu et al. 1999]. However, when examining the patients' technology acceptance behavior, the conclusion may not hold true, requiring further empirical examination. Further, among these studies, TAM and TPB are regarded as two of the most influential theories on technology acceptance behavior, and thus we compare these two models in our study.

2.2. Health Behavior Theories

To differentiate the acceptance behavior of *health* information technology from other technologies, researchers need to pay attention to adapting the model specifically to the health care context [Holden et al. 2010]. Therefore, despite the technology acceptance theories, the health behavior theories also need to be taken into account.

There are four major theories used to explain health behavior: health belief model (HBM), protection motivation theory (PMT), subjective expected utility theory (SEU), and theory of reasoned action (TRA) (see the review by Weinstein [1993]). HBM [e.g., Becker 1974] believes that a person makes a decision on whether or not to take a health-related action based on his/her evaluations on the perceived threat of not taking the action and the net benefits of taking the action. Specifically, perceived threat is assessed according to perceived susceptibility (i.e., one's opinion of chances of getting a condition) and perceived severity (i.e., one's opinion of how serious a condition and its consequences are). Net benefits are calculated based on perceived benefits (i.e., one's belief in the efficacy of the advised action to solve the threat) and perceived barriers (i.e., one's opinion of the tangible and psychological costs of the advised action). PMT [e.g., Rogers 1975] proposes a series of factors similar to HBM to explain health behavior. Specifically, PMT uses perceived vulnerability, perceived severity, response efficacy, and response costs to represent perceived susceptibility, perceived severity, perceived benefits, and perceived barriers in HBM. It includes a new factor, self-efficacy, to capture the degree to which one has the ability to perform the advised action [Bandura 1977]. Further, PMT classifies these factors into two categories according to individuals' decision making stages: the threat appraisals, including perceived vulnerability and perceived severity, and the coping appraisals, including response efficacy, response costs, and self-efficacy. PMT is generally regarded as a better theory than is HBM for explaining health behavior [Prentice-Dunn et al. 1986].

SEU and TRA are considered as more general theories on health behavior. SEU [e.g., Ronis 1992] postulates that an individual's behavior is determined by his/her evaluation of the expected utilities of alternative behaviors and the utilities of these behaviors. Similarly, TRA [e.g., Fishbein et al. 1975] articulates that individual behaviors are determined by attitude (i.e., the sum of the expected values of the behavioral consequences), and subjective norm (i.e., an individual's perception of whether people important to the individual think the behavior should be performed). SEU and TRA can be used to explain general individual behaviors but are not limited to health behavior.

As shown in Figure 2, all four health behavior theories are associated with the two fundamental principles: expectancy – value theory and cost – benefit analysis [Weinstein 1993]. For example, in PMT, perceived severity and perceived vulnerability are derived from the expectancy – value theory, and the response efficacy and response costs are derived from the cost – benefit analysis.

Regarding PMT's advantage over HBM and SEU for including the factor self-efficacy and that TRA is superior to other theories for including social influence (e.g., subjective norm), we take PMT and TRA (or its extension TPB) as the major theories for understanding health behavior.

Although PMT has been widely used as a theory to explain the adoption of health technology or services in health psychology (see the meta-analysis by Floyd et al. [2000]), in the literature its application in the mobile health context is rarely found. In our study, we thus examine whether PMT is an appropriate theory to explain the mobile health service adoption behavior and compare the predictive powers of PMT and technology acceptance theories.

2.3. Rationality for Theoretical Integration

Regarding mobile health service adoption behavior as both technology acceptance behavior and health behavior, a comprehensive understanding of the issue requires the integration of these two theoretical perspectives. To formulate a unified theory on health technology acceptance, the three prominent theories (e.g., TAM, TPB or UTAUT, and PMT) are compared in Table 2.

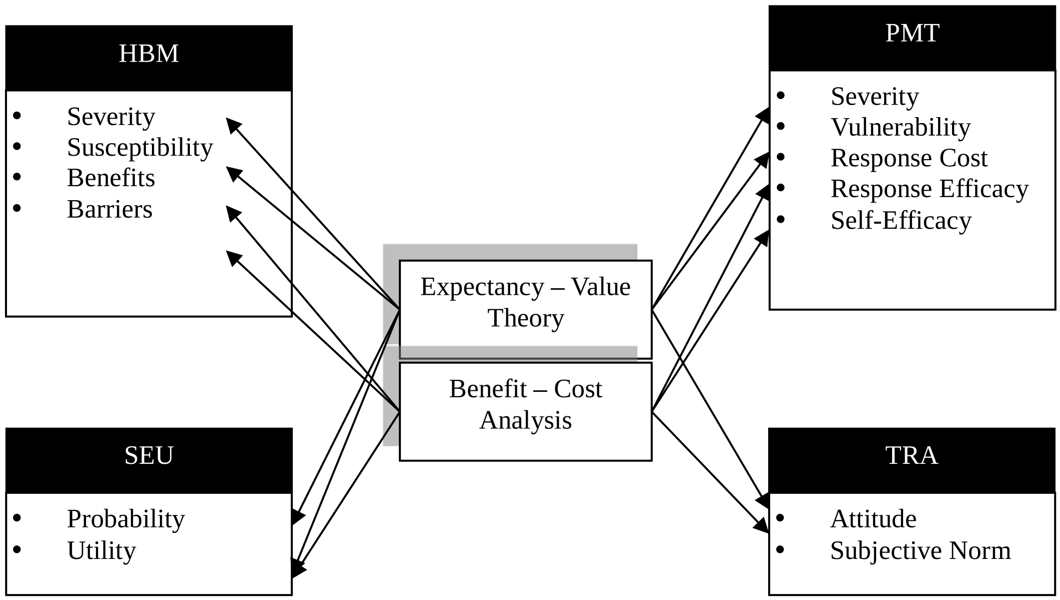

Figure 2: An Overview of Health Behavior Theories

As evident in Table 2, several different terms used in different theories share similar meanings. For example, perceived usefulness in TAM is similar to response efficacy in PMT, reflecting the degree to which using mobile health services can reduce the potential threats to health; self-efficacy and response cost in PMT can be respectively regarded as perceived internal and external behavioral control (PBC) in TPB or facilitating conditions in UTAUT. Further, perceived usefulness and perceived ease of use in TAM reflect TPB attitude. Thus, to formulate a unified theory, we need to deal with the conceptual overlaps in different theories.

Following the framework of UTAUT [Venkatesh et al. 2003], perceived usefulness or response efficacy can be seen as performance expectancy; perceived ease of use can be captured by effort expectancy; subjective norm can be represented by social influence. Self-efficacy and response cost can be interpreted by facilitating conditions. Further, we adapt the term, threat appraisals, in PMT to capture perceived vulnerability and perceived severity [Rogers 1975]. Through this reconceptualization in the unified model of health technology acceptance, five factors are taken as the determinants of health technology acceptance: performance expectancy, effort expectancy, social influence, facilitating conditions, and threat appraisals.

Table 2: A Comparison of the Three Prominent Theories

Unified Model	**Constructs**	**TAM**	**TPB/UTAUT**	**PMT**
Performance Expectancy	Perceived Usefulness / Response Efficacy	√	√	√
Effort Expectancy	Perceived Ease of Use	√	√	
Social Influence	Subjective Norm		√	
Facilitating Conditions	Self-Efficacy (Perceived Internal Behavioral Control)		√	√
	Response Cost (Perceived External Behavioral Control)		√	√
Threat Appraisals	Perceived Vulnerability			√
	Perceived Severity			√

Through the comparisons of the three prominent models, we can see that TAM captures only the components of performance and effort expectancy. TPB or UTAUT captures the first four components but does not consider the component of threat appraisals. In contrast, PMT does not include the components of effort expectancy and social influence. Therefore, the integrated model (see Figure 3) is expected to have greater predictive power than any of the alternative models.

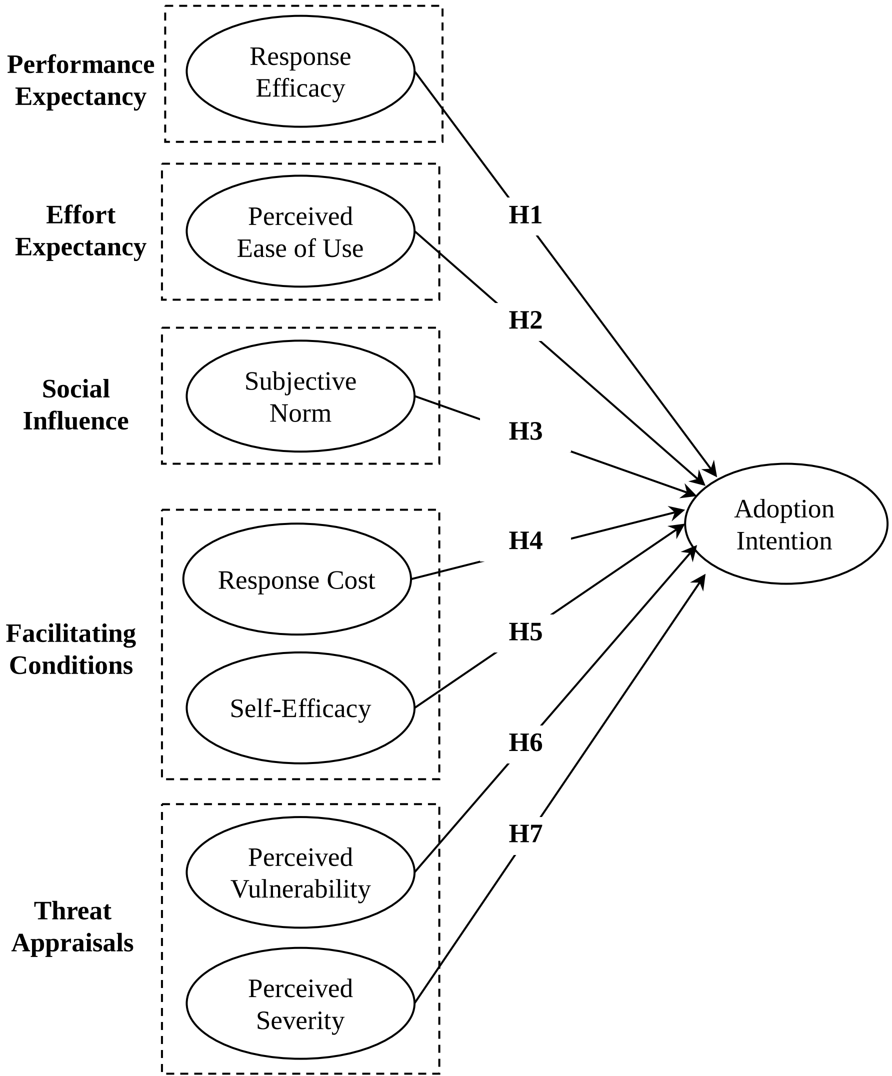

Figure 3: Research Model

3. Hypotheses

3.1. Performance Expectancy

Performance expectancy describes users' opinions of the effectiveness of using a technology [Venkatesh et al. 2003]. Within our research context where mobile health services (MHS) are the target technology, its effectiveness can be captured by the extent to which it can help users to reduce the health-relevant threat, and thus response efficacy in the PMT theory is treated as a proxy of performance expectancy. When users consider that using MHS can enable them to reduce the threats to health, they will be more likely to adopt this technology. This positive relationship can also be supported according to the positive effect of performance expectancy on behavioral intention in UTAUT [Venkatesh et al. 2003] and the positive effect of response efficacy on behavioral intention in PMT [Rogers 1975].We thus propose:

H1: Response efficacy is positively associated with MHS adoption intention.

3.2. Effort Expectancy

Effort expectancy describes users' opinion of the effort associated with the use of a technology [Venkatesh et al. 2003]. It can be represented by perceived ease of use in TAM. In previous studies on the professionals' technology acceptance behaviors, because most professionals have adequate competence to learn and operate the technology, perceived ease of use is found to have insignificant impact on behavioral intention [e.g., Hu et al. 1999]. However, within our research context regarding elderly users not being skilled users of new technologies, the elderly will not be likely to try a new technology which is perceived to be complex. In this situation, perceived ease of use should be a significant predictor of behavioral intention. This is supported by UTAUT, which argues that age moderates the relationship between perceived ease of use and intention, such that this relationship will be more salient for older users than for younger users [Venkatesh et al. 2003]. Therefore, we propose that:

H2: Perceived ease of use is positively associated with MHS adoption intention.

3.3. Social Influence

Social influence captures how users' decision making is affected by significant others' perceptions. It can be reflected by the subjective norm in TPB. Previous studies on professionals' health technology acceptance behavior have found that social influence does not play an important role [e.g., Chau et al. 2001] because most professionals are confident in their own decision making and are not concerned about others' opinions. However, in our study, because most elderly users tend to have their decision making reliant on others' suggestions, social influence should play a more important role. The UTAUT also states that the relationship between social influence and behavioral intention is stronger for older users [Venkatesh et al. 2003]. Thus, we propose that:

H3: Subjective norm is positively associated with MHS adoption intention.

3.4. Facilitating Conditions

Facilitating conditions describes the potential conditions that constrain or facilitate performing the behavior. This is similar to the concept of perceived behavioral control in TPB. According to TPB, perceived behavioral control is derived from two sources: *external* and the *internal* control [Ajzen 1991]. External control stresses the extent to which individuals have adequate external *resources* to perform a behavior, while internal control focuses on the extent to which individuals have the *ability* to undertake the behavior [Pavlou et al. 2006; Yang et al. 2009].

Within our research context, response cost is regarded to be associated with external control because it is relevant to the resources (especially the money and effort) spent for learning and using the MHS. If users need to spend considerable money to pay for the services or much effort to learn the technology (i.e., high response cost), they may be unlikely to use the technology, indicating a negative relationship between response cost and adoption intention [e.g., Rogers 1975]. Further, for elderly users who care more about the value of expenditures, response cost should be an important factor influencing their decision making. For example, according to our initial interview with some of the elderly users, they gave raising their grandsons priority over other issues. Therefore, we propose that:

H4: Response cost is negatively associated with MHS adoption intention.

The internal control in our study refers to users' ability to learn and use mobile health services. When users are confident in their ability to use the technology, they will be more likely to use that technology. This relationship has been well established in previous studies on technology acceptance [e.g, Venkatesh et al. 2003]. Within our research context, lack of competence to use the technology may become a major barrier inhibiting the elderly users' new technology acceptance. As suggested by Morris et al. [2005], the relationship between perceived behavioral control and behavioral intention is stronger for older users. Thus, we propose that:

H5: Self-efficacy is positively associated with MHS adoption intention.

3.5. Threat Appraisals

The motivation theory postulates that any individual behavior is driven by the needs [Deci et al. 1985]. However, all of the aforementioned factors have focused mainly on what should be considered when an individual has identified certain needs to adopt a new technology, while how these needs are generated is not taken into consideration. According to PMT, a health behavior is induced not only by threat appraisals that assess the probability and severity of the threats (i.e., needs) but also by coping appraisals that assess how one responds to the situation [Rogers 1975]. Thus, beyond the aforementioned factors that capture only coping appraisals, the threat appraisals should also be considered.

According to PMT, threat appraisals include two constructs: perceived vulnerability and perceived severity. Perceived vulnerability refers to the probability that one will experience harm, while perceived severity refers to the degree of harm from unhealthy behavior [Rogers 1975]. When users consider that they are more likely to suffer a health-relevant threat (i.e., high perceived vulnerability) and/or the harm of the threat is serious (i.e., high perceived severity), they will tend to adopt the health technology that can avoid or reduce the threat [Rogers 1975]. Accordingly, we propose that:

H6: Perceived vulnerability is positively associated with MHS adoption intention.

H7: Perceived severity is positively associated with MHS adoption intention.

4. Methodology

4.1. Research Setting and Subjects

To test our proposed research model and hypotheses, a field survey was conducted with subjects who were the customers of a large company providing mobile health services (MHS) targeting elderly consumers in Harbin, China. This company is one of the biggest companies in China providing integrated health services for the elderly, and it is also the only company that obtains the ISO9001 certification in China to provide home healthcare services for the elderly, indicating that the target company is an appropriate site for collecting data. As to the subjects, elderly consumers were selected as the target subjects because the target company takes elderly consumers as target consumers, and this consumer group accounts for a vast proportion of the whole consumers of health services. However, this sampling strategy also limits the external validity of the research result and should be regarded as a limitation of the study.

The MHS was initiated by the target company in collaboration with the Harbin government and was first released to the market in February 2010. The target consumers of this service were the elderly of one million families in 500 communities in Harbin. When the study was conducted in June and July 2011, it was still not largely adopted by these potential consumers.

The characteristics of the MHS provided by this company can be described as follows. First, the *consulting and assistance center* provides the elderly with emergency aid through real time positioning techniques and refined daily information and consulting services. Second, the *customized terminal* is designed with larger font sizes, bigger buttons, and higher volume, as well as radio and other multimedia entertainment functions. Third, *remote positioning services*, with the help of Location Based Services (LBS) or Global Positioning System (GPS), can enable relatives of the elderly to achieve real-time positioning when the elderly are in an emergency. Additionally, it can facilitate the elderly to search for transportation routes by themselves.

The fees for the service were charged by two major components: the payment for the mobile terminal (about 159 USD) and the monthly fee for the services (about 3 USD per month). The fees for the service were relatively low because this project was supported by the government's provision of certain financial subsidies to the company.

4.2. Operationalization of Constructs

As most of the measures for the constructs in the research model are available in prior studies, we adapted these measures as the basis for developing our measures. To fit with our research context, we first stated the possible problems that might be encountered by users, including *(1) getting lost when not being familiar with the traffic, (2) suddenly requiring emergency aid, and (3) having little knowledge about self-care*. Then, in relation to these problems, we asked the subjects to evaluate perceived vulnerability and perceived severity. These two constructs were measured with the adjusted items of threat susceptibility and threat severity from Johnston and Warkentin [2010].

We then introduced the characteristics of the mobile health services provided by the target company, including: (1) the *consulting and assistance center* providing real time emergency aid services, (2) the *customized terminal* designed in terms of older people's usage habit, and (3) the *remote positioning services* based on the Location Based Services (LBS) and Global Positioning System (GPS). The pricing strategies and payment modes were also introduced. Next, the subjects were asked to answer the questions on response efficacy, self-efficacy, and response cost. The measures for response efficacy and self-efficacy were adapted from Johnston and Warkentin [2010]. The measures for response cost were developed in terms of the research context. To ensure the comprehensiveness of cost, response cost was measured with a formative construct with three dimensions: one dimension captures monetary cost, as suggested by Lee and Larsen [2009] (e.g., "Mobile health services are expensive to purchase"), while the other two dimensions capture learning cost (e.g., "I have to spend effort on learning how to use mobile health services") and switching cost (e.g., "Using mobile health services will change my prior life style").

Further, other questions on TAM and TPB factors and adoption intention were asked. Perceived usefulness and perceived ease of use were measured with the items adapted from Bhattacherjee et al. [2007]. The measures for TPB factors, including attitude, subjective norm, and perceived behavioral control, were adapted from Kim [2009]. The measures for the dependent variable, that is, intention to adopt MHS, were adapted from Johnston and Warkentin [2010]. A seven-point Likert scale was used for all items (see the Appendix A).

4.3. Data Collection Procedure

The target company helped to approach the potential consumers of the services and to collect the data through community service centers. As the company was also engaged in other businesses targeting older people, it had good relationships with many community service centers. In the community service centers, the company routinely provided training for its customers, about every 3 months. We requested the senior manager of the company to evenly distribute 250 questionnaires to the managers of its 12 service centers. These service centers were in charge of 372 communities among the total 500, representing a wide range of the geographical variety in Harbin. During the routine training and interaction, the company provided new product promotions when customers visited its service centers. In the company, each employee in the service centers was in charge of a specific group of customers. The manager in the service center randomly asked the employees in the center to distribute the survey to his/her customers. Further, to encourage the participation, we also provided ten eggs as the incentives for participation because older people always visited the service center when they went to the grocery shop; thus, using eggs as the incentive was consistent with their needs and could promote participation.

We believe this sampling and survey procedure is appropriate, given the characteristics of the elderly, who cannot be as easily accessed as ordinary people. The employees in service centers, in contrast, had established good relationships with their customers during their long time cooperation and could easily explain the survey to their customers using familiar approaches. All of this ensured the success of the data collection.

Among the 250 distributed questionnaires, 212 were returned with a response rate of 84.8%. The high response rate was due to the good relationships between the employees in the service centers and the potential consumers. After removing the incomplete cases and outliers, 204 valid responses were obtained. Among these subjects, female subjects occupy 46.6%, and over 80% of the subjects are over 40 years of age. The education level for 52.9% of the subjects is high school or below; approximately 51.5% have fewer than two years of computer experience, and about 70% of subjects have more than two years of mobile device usage experience.

5. Data Analysis and Results

Partial Least Squares (PLS) was used to test the research model because of the several advantages of this technique. First, as a second-generation structural equation modeling technique, it can estimate the loadings (and weights) of indicators on constructs (hence, assessing construct validity) and the causal relationships among constructs in multistage models [Fornell et al. 1982; Gefen et al. 2011; Hair et al. 2011]. Second, in comparison with covariance-based structural equation modeling, PLS is robust with fewer statistical identification issues; moreover, it is most suitable for models with formative constructs and relatively small samples [Hair et al. 2011], which is the case in our study. Additionally, whereas covariance-based structural equation modeling is regarded as being more appropriate for theory confirmation, PLS does provide a good approximation of covariance-based structural equation modeling in terms of final estimates [Gefen et al. 2011; Hair et al. 2011]. Based on the above considerations, PLS was chosen for the current study.

The data analysis was conducted in two stages. In the first stage, the reliability and validity of the constructs were assessed to ensure the appropriateness of the measurement model; in the second stage, the structural model was assessed, and hypotheses were tested [Hair et al. 1998].

5.1. Assessment of the Measurement Model

Reflective constructs and formative constructs were assessed using different approaches. For the reflective constructs, the reliability, convergent validity, and discriminant validity were examined. Composite reliability (CR) and average variance extracted (AVE) were used to assess the reliability of reflective constructs [Fornell et al. 1981; Hsu et al. 2008]. With the exception of perceived behavior control, all other constructs were with adequate CR (ranged from .880 to .901) and AVE (ranged from .695 to .747), considerably above the suggested value of .70 and .50 [Fornell et al. 1981; Hsu et al. 2008]. After a careful check of the construct, perceived behavioral control, it was found that the loading of the second item was only .415 ($t=1.564$). After removing this item, the CR and AVE increased to .891 and .804, respectively, thus satisfying the criteria for reliability (see Table 3).

The convergent validity of reflective constructs was assessed by seeing if the loadings on the expected constructs were high enough [Anderson et al. 1988; Jiang et al. 2002]. As shown in the Appendix, all item loadings were higher than 0.70 and significant ($p<.001$), suggesting good convergent validity of constructs. The discriminant validity can be assessed by testing whether the square roots of AVEs are greater than the correlations [Fornell et al. 1981]. As shown in Table 3, all correlations were below the square roots of AVEs, indicating that the constructs had good discriminant validity.

The formative construct – response cost in our study – can be assessed by checking its item weights and loadings, which, respectively, represent the relative and absolute importance of these items [Cenfetelli et al. 2009]. As shown in Table 1, the weights for RC1 and RC3 were significant, while RC2 was not. However, the item loading for RC2 was 0.516 ($t=3.790$), suggesting that although RC2 was not as important as RC1 and RC2, it was still with important absolute value [Cenfetelli et al. 2009]. In accordance with Cenfetelli and Bassellier [2009], RC2 was still included in the analysis in order to keep the completeness of formative constructs.

Because our data were collected from a single source at the same time point, common method variance might be a concern [Podsakoff et al. 2003]. We used the method suggested by Liang et al. [2007] to examine this issue. The results showed that the trait factors (e.g., the proposed constructs) explained 72.5% of the variance, while the method factors explained only less than 1% of the variance, indicating that common method bias was not a threat to the present study.

Table 3: Correlations and Discriminant Validity

	Mean	Std. Dev	CR	AVE	AI	ATTD	SN	PBC	PU	PEOU	PV	PS	RC	RE	SE
AI	3.77	0.75	.898	.747	***.864***										
ATTD	3.94	0.68	.901	.695	.482	***.834***									
SN	3.95	0.77	.871	.772	.451	.603	***.879***								
PBC	3.61	0.81	.891	.804	.368	.429	.409	***.897***							
PU	4.10	0.68	.909	.715	.545	.729	.658	.440	***.846***						
PEOU	3.60	0.82	.919	.740	.398	.487	.387	.518	.458	***.860***					
PV	3.74	0.92	.887	.723	.344	.348	.393	.141	.331	.098	***.850***				
PS	4.21	0.70	.888	.725	.227	.460	.334	.174	.419	.230	.573	***.851***			
RC	2.72	0.78	NA	NA	-.314	-.345	-.257	-.371	-.331	-.314	-.164	-.149	***NA***		
RE	3.95	0.71	.880	.710	.478	.391	.287	.236	.348	.179	.432	.311	-.309	***.843***	
SE	3.68	0.75	.890	.730	.424	.454	.339	.503	.342	.593	.156	.150	-.368	.215	***.854***

Note: AI=Intention to adopt, ATTD=Attitude, SN=Subjective norm, PBC=Perceived behavioral control, PU=Perceived Usefulness, PEOU=Perceived Ease of Use, PV=Perceived vulnerability, PS=Perceived severity, RE=Response efficacy, SE=Self-efficacy, RC=Response cost. Diagonal elements denote the square root of AVE. As response cost is taken as a formative construct, the CR and AVE for this construct is not available.

5.2. Assessment of the Structural Model

The structural model was assessed by checking the significance of path coefficients (β) between different factors. As illustrated in Figure 4, the results showed that except for the relationship between perceived severity and adoption intention, all other proposed relationships were significant.

Specifically, the results indicated that response efficacy had a significant positive effect on intention (β=.297, t=6.097), lending support to H1. Perceived ease of use was found to have a significant effect on intention (β=.150, t=2.217), and thus H2 was supported. Subjective norm was found to be significantly related to intention (β=.192, t=2.934), supporting H3. Two factors of facilitating conditions, self-efficacy and response cost, were found to have significant positive (β=.161, t=3.000) and negative (β=-.111, t=2.243) impacts on intention, respectively. For the two factors of threat appraisals, perceived vulnerability had a significant effect on intention (β=.120, t=2.104), while perceived severity did not (β=-.042, t=0.825). These factors fully explained 43.6% of the variance of intention.

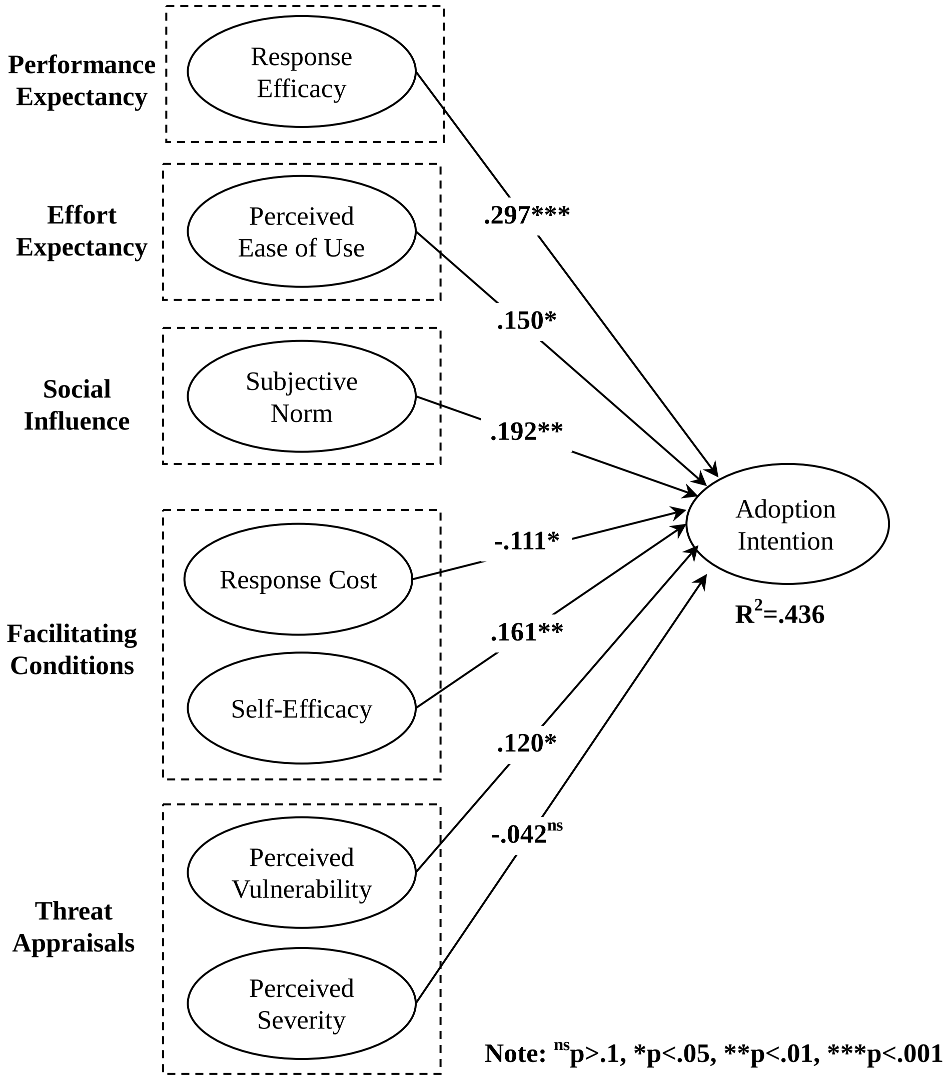

Figure 4: PLS Results

With regards to whether or not the proposed research model can be seen as an improvement over the alternative models, the PLS results for the three alternative models (e.g., TAM, TPB and PMT) are shown in Table 4. The results indicate that TAM and TPB, respectively, explain 32.6% and 32.7% of the total variance of intention, while the PMT explains 38.8% of the total variance of intention. Although PMT has greater R-square than the other two alternatives, it is still less powerful than the proposed unified model, which explains 4.8% more variance, validating the value of the theoretical integration.

6. Discussion and Implications

6.1. Key Findings

This study based on theories of technology acceptance and health behavior develops a unified model to explain the health information technology acceptance behavior. There are three key findings of the study.

First, through the comparisons between the three alternative models and the unified model, this study shows that the unified model outperforms its competing models by providing higher R-squares. Specifically, TAM and TPB, which focus on the general technology acceptance issues, are with weaker predictive powers than is PMT, which stresses health behavior. All of these three models are not as effective as the unified model, indicating that a comprehensive understanding of health technology acceptance behavior should consider both technology acceptance behavior as well as health behavior.

Table 4: PLS Results for the Three Alternative Models

Models	**Independent Variables**	**R^2**	**Beta**
TAM	Perceived Usefulness (PU)	.326	.456***
	Perceived Ease of Use (PEOU)		.189*
TPB	Attitude (ATTD)	.327	.251**
	Subjective Norm (SN)		.188*
	Perceived Behavioral Control (PBC)		.247**
PMT	Perceived Vulnerability (PV)	.388	.150*
	Perceived Severity (PS)		$.013^{ns}$
	Response Efficacy (RE)		.312***
	Response Cost (RC)		-.146*
	Self-Efficacy (SE)		.287***

Note: ^{ns}p>.1, *p<.05, **p<.01, ***p<.001.

Second, the results show that the factors relevant to coping appraisals are more important than are the factors associated with threat appraisals in predicting health technology acceptance. Specifically, response efficacy is found to be the most influential factor, followed by subjective norm, self-efficacy, and perceived ease of use. All of these factors are relevant to the coping stage. However, the factors relevant to threat appraisals have only relatively weak (e.g., perceived vulnerability) or no (e.g., perceived severity) effects on behavioral intention. This is consistent with the meta-analysis results of Floyd et al. [2000], suggesting that coping appraisals should be paid more attention in the study on health behavior.

Third, this study reveals that subjective norm and perceived ease of use have significant impacts on adoption intention. This is contrary to the findings in previous studies on professionals' technology acceptance behavior [e.g., Chau et al. 2002; Hu et al. 1999]. This can be explained by the distinctions between professional users and consumer users. Because professional users generally have adequate competency to learn and use a new technology, they will tend to rely on their own judgment in their decision making, and the technology complexity will not be a barrier inhibiting their technology acceptance [Hu et al. 1999]. However, for consumer users, especially the elderly users in our study who are not so skilled in learning and using a new technology, the ease of use of the technology and others' opinions becomes important. This indicates that effort expectancy and social influence should be taken into account when investigating consumer health technology acceptance.

It is worth noting that perceived severity is found to have insignificant impact on adoption intention, suggesting that the effect size of perceived severity is limited. According to previous literature, coping appraisals can achieve medium effect size, while threat appraisals can achieve only small effect size [Floyd et al. 2000]. The meta-analysis also indicates that perceived vulnerability often has stronger impact than does perceived severity [Milne et al. 2000]. In this case, when more influential predictors exist, the impact of perceived severity becomes unobservable. This is induced by its low relative value rather than its absolute value [Petter et al. 2007]. A good indicator of its absolute impact on intention is its correlation with intention. As shown in Table 3, the correlation between perceived severity and intention is 0.227, suggesting that its absolute value is significant at the significant level of p<.01.

6.2. Theoretical Implications

The study can contribute to the health information technology literature in several ways. First, this study provides a unified model of health technology acceptance by considering both the technology acceptance and health behavior theories. It amends the previous studies that investigate health technology acceptance behavior solely based on the general technology acceptance theories without considering the distinctions between *health* technology and other technologies [e.g., Hu et al. 1999]. In this paper, the acceptance of health technology is regarded as both a technology acceptance behavior and a health behavior, providing a more comprehensive understanding on this specific technology acceptance behavior. It can be regarded as a response to the call that encourages developing a technology acceptance model adapted to the health care context [Holden et al. 2010]. It also suggests future research on health technology acceptance to draw upon the theoretical underpinnings from these two research streams.

Second, this study proposes a model to understand the acceptance of *consumer* health technology rather than *professional* health technology, identifying the distinctions between the acceptance behavior of these two types of users. Most previous studies on health technology acceptance focus on understanding the factors enabling or inhibiting the physicians or professionals' health technology adoption [e.g., Bhattacherjee et al. 2007] but pay less attention on the technology acceptance behavior of consumers [Or et al. 2009]. Regarding the increasing importance of consumer health technologies, this study provides certain initial exploration of this new type of technology acceptance behavior. Specifically, the study shows that subjective norm and self-efficacy, which are identified as insignificant in previous studies on professional health technology acceptance [e.g., Hu et al. 1999], become significant in the context of consumer health technology. This suggests that future research should take the distinctions between professional and consumer health technologies into account when proposing research models.

Third, this study also extends the traditional protection motivation theory (PMT) by pointing out the role of social influence and effort expectancy. Traditional PMT takes response efficacy, self-efficacy, response cost, perceived vulnerability, and perceived severity as five key determinants of health behavior [Floyd et al. 2000]. However, several other important factors associated with the technology acceptance process have been neglected. Specifically, although PMT has recognized the role of effectiveness of technology (e.g., response efficacy), it does not take into consideration the effort relevant to technology use (i.e., effort expectancy or perceived ease of use). Further, PMT assumes that users make decisions based on their own evaluations, ignoring the fact that that users' decision making can also be affected by social influence. Therefore, an improvement of the traditional PMT is to include social influence and effort expectancy in the model.

6.3. Practical Implications

Several practical implications can be derived from the study. First, response efficacy is found to be the most important factor in the mobile health service adoption, and thus service providers should try their best to improve their service quality in order to attract more consumers. Second, since social influence can positively affect user behavior, service providers should carry out certain promotion strategies to obtain early adopters and then expand the consumer scale through the social influence (e.g., word of mouth). Third, perceived ease of use and self-efficacy are two important factors influencing user behavior; for this reason service providers should adopt a user-centric service design method to ensure not only that the services can be easily learned and used, but also that service providers provide trainings for the potential consumers. Fourth, regarding the negative effect of response cost on adoption intention, service providers should set an appropriate service price, one which would be accepted by potential users. This can be achieved through a marketing survey. Finally, as perceived vulnerability has significant impact on adoption intention, service providers should identify the target market by analyzing not only the threats that the services could reduce but also the people who are more likely to experience the threats.

6.4. Limitations

Despite the theoretical and practical implications of the study, our findings should be interpreted in the light of the limitations. First, elderly users were taken as the sample in the study because elderly users account for a vast proportion of the whole MHS users. With the increase of people's health concerns, MHS providers should also begin to target other populations as potential customers. Thus, the conclusions of the current study should be applied with caution when the sampling population changes (e.g., the role of self-efficacy may not be as salient for college students). Second, because the study was conducted in China, which has a collectivistic culture, applying the conclusions to other cultural societies should be further examined in future research. Finally, while the explanatory power of the model (43.6% for intention) was acceptable, it could potentially be enhanced through the inclusion of additional factors in future research.

7. Conclusion

Previous literature on health technology acceptance focuses on professional health technology and relies heavily on the general technology acceptance theories; however, the consumer health technology acceptance behavior is less discussed. In this study concerning consumer health technology acceptance behavior as both a technology acceptance behavior as well as a health behavior, we propose a unified model that integrates the technology acceptance theories and health behavior theories. Through comparing the technology acceptance model, the theory of planned behavior, the protection motivation theory, and the unified model, the superiority of the unified model is confirmed. This study suggests that future research on health technology acceptance should consider the distinctions between professional and consumer health technology and take both the technology acceptance theories and the health behavior theories into account.

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APPENDIX A. Measures, Loadings and Weights

Measures	Loading	T-statistics
Intention to Adopt (AI): Adapted from [Johnston et al. 2010]		
AI1. I intend to use mobile health services in the next 3 months.	.799	19.262
AI2. I predict I will use mobile health service in the next 3 months.	.895	56.678
AI3. I plan to use mobile health services in the next 3 months.	.895	52.832
Attitude (ATTD): Adapted from [Kim 2009]		
ATTD1. Using mobile health services is a bad/good idea.	.788	20.663
ATTD2. Using mobile health services is a foolish/wise idea.	.833	33.502
ATTD3. I dislike/like the idea of using mobile health services.	.877	53.969
ATTD4. Using mobile health services is unpleasant/pleasant.	.834	43.891
Subjective Norm (SN): Adapted from [Kim 2009]		
SN1. People who influence my behavior think that I should use mobile health services.	.898	46.095
SN2. People who are important to me think that I should use mobile health services.	.858	27.323
Perceived Behavioral Control (PBC): Adapted from [Kim 2009]		
PBC1. I have control over using mobile health services.	.910	67.471
[a]PBC2. I have the resources necessary to use mobile health services.	NA[a]	NA
PBC3. I have the knowledge necessary to use mobile health services.	.883	43.243
Perceived Usefulness: Adapted from [Bhattacherjee et al. 2007]		
PU1. Using mobile health services will improve my life quality.	.802	32.662
PU2. Using mobile health services will make my life more convenient.	.873	45.544
PU3. Using mobile health services will make me more effective in my life.	.867	33.864
PU4. Overall, I find mobile health services to be useful in my life.	.837	38.258
Perceived Ease of Use: Adapted from [Bhattacherjee et al. 2007]		
PEOU1. Learning to operate mobile health services will be easy for me.	.870	39.803
PEOU2. I can easily become skillful at using mobile health services.	.838	27.201
PEOU3. I can get mobile health services to do what I want them to do.	.859	45.811
PEOU4. Overall, mobile health services are easy to use.	.872	46.693
Perceived Vulnerability (PV): Adjusted according to Threat Susceptibility in [Johnston et al. 2010]		
Please answer the following questions in terms of these problems: (1) getting lost for not being familiar with the traffic; (2) suddenly requiring emergency aid; (3) having little knowledge about self-care.		
PV1. I am at risk for suffering the stated problems.	.831	20.851
PV2. It is likely that I will suffer the stated problems.	.864	29.872
PV3. It is possible for me to suffer the stated problems.	.856	24.026
Perceived Severity (PS): Adjusted according to Threat Severity in [Johnston et al. 2010]		
Please answer the following questions in terms of these problems: (1) getting lost for not being familiar with the traffic; (2) suddenly requiring emergency aid; (3) having little knowledge about self-care.		
PS1. If I suffered the stated problems, it would be severe.	.802	23.446
PS2. If I suffered the stated problems, it would be serious.	.874	33.113
PS3. If I suffered the stated problems, it would be significant.	.877	40.041
Response Efficacy (RE): Adapted from [Johnston et al. 2010]		
RE1. Mobile health services work for solving these problems.	.785	20.359
RE2. Mobile health services are effective for solving these problems.	.841	26.020
RE3. When using mobile health services, solving these problems is more likely to be guaranteed.	.898	50.588
Self-Efficacy (SE): Adapted from [Johnston et al. 2010; Lee et al. 2009]		
SE1. It is easy for me to use mobile health services.	.874	39.765
SE2. I have the capability to use mobile health services.	.823	26.997
SE3. I am able to use mobile health services without much effort.	.867	35.582
Response Cost (RC): Adapted from [Lee et al. 2009]	*Weights*	*T-statistics*
RC1. Mobile health services are expensive to purchase.	.834	7.215
RC2. I have to spend effort on learning how to use mobile health services.	-.007	0.043
RC3. Using mobile health services will change my life style.	.341	2.463

[a] This item was removed from the analysis due to the low loading.