Journal of Organizational and End User Computing
Volume 34 • Issue 4

Factors Affecting Customer Intention to Adopt a Mobile Chronic Disease Management Service:

Differentiating Age Effect From Experiential Distance Perspective

Zhangxiang Zhu, Hunan Normal University, China

https://orcid.org/0000-0002-4917-3274

Yongmei Liu, Central South University, China

Xianye Cao, Hunan University of Technology and Business, China

Wei Dong, Central South University, China

ABSTRACT

The Mobile Chronic Disease Management Service (MCDMS) is an emerging medical service for chronic disease prevention and treatment, but limited attention has been paid to the factors that affect users' intention to adopt the service. Based on the unified theory of acceptance and use of technology and the protection motivation theory, the authors built an MCDMS adoption model. The authors also verified the differentiating age effect on the service adoption intention from experiential distance perspective of the construal level theory. Empirical results showed that the young group focused more on the impact of effort expectancy, whereas the elderly group focused more on performance expectancy, imitating others, and perceived severity. Furthermore, the young group focused more on the impact of perceived vulnerability, and offline medical habits showed no significant influence on either group's intention to adopt, which were not consistent with the original hypotheses. The findings can aid MCDMS providers in selecting marketing strategies targeted toward different age groups.

KEYWORDS

Adoption Intention, Construal Level Theory, Experimental Distance, Mobile Chronic Disease Management Service, Mobile Health, Protection Motivation Theory, UTAUT 2

INTRODUCTION

According to the *Progress of Disease Prevention and Control in China (2015),* released by the National Health and Family Commission of the People's Republic of China, medical expenses for chronic diseases already represent nearly 70% of total medical costs in China. Disappointingly, the number of deaths caused by chronic diseases still account for 86.6% of all deaths, indicating that ideal chronic disease prevention and treatment have not been met. Fortunately, with the rapid development of information technology, the level of medical service informatization has increased (Shiau, Siau, Yu, & Guo, 2021). This has facilitated the development of the Mobile Chronic Disease Management Service (MCDMS) (Dou et al., 2017), which provides an opportunity to deal with this medical challenge. By

DOI: 10.4018/JOEUC.287910

using MCDMS, users can view medical examination reports and health promotion schemes anytime and anywhere. Daily physiological parameters are entered regularly through wearable devices, wireless Bluetooth technology, or manual approaches. When an abnormal physiological parameter occurs, the MCDMS will automatically inform patients or family members with a text message or phone call. With the help of MCDMS, chronic patients can obtain comprehensive, continuous, and active health management, and can realize various goals such as slowing disease progress, reducing complications and disability rates, improving quality of life, and prolonging life. However, the level of current intention to adopt is relatively low, and many studies on diabetic patients also show that the acceptance of diabetes management APP is low (Y. Zhang et al., 2019). Existing literature on technology adoption has shown the importance of understanding the factors that influence behavioral intention and facilitate system use. From a practical point of view, understanding the factors that influence patients' intent to use services will further increase the ability of service operators to apply proper, efficient strategies to improve the design of MCDMS and promote its use.

Previous studies on user adoption of mobile health (mHealth) services mostly focus on a certain type of service or chronic disease, while MCDMS integrates a variety of common chronic disease service modes and is mainly aimed at common chronic diseases, such as diabetes; chronic respiratory diseases; cardiovascular and cerebrovascular diseases, including hypertension, stroke, and coronary heart disease; and lung diseases. Furthermore, chronic diseases mainly affect middle-age and elderly people, who have a low penetration rate of information technology services and are in greater need of assistance from their families. Therefore, the potential users of MCDMS in this study include not only patients with common chronic diseases, but also patients' families and the general public with general health monitoring needs. In this way, the integration of service functions and the diversity of service objects are the characteristics of MCDMS. To our knowledge, relevant theoretical models have not been applied to the field of MCDMS.

Considering that the use of MCDMS is voluntary and that the patients are a general audience, the unified theory of acceptance and use of technology 2 (UTAUT2) proposed by Venkatesh, Thong, and Xu (2012) to explain common consumers' adoption behavior regarding information systems (IS) is a suitable way to explain the intention to adopt MCDMS in this study. Although a few scholars, including Dwivedi, Shareef, Simintiras, Lal, and Weerakkody (2016) and Duarte and Pinho (2019), comprehensively evaluated the characteristics of mHealth and proposed a generalized adoption model for that program mHealth based on UTAUT2, they did not consider any specific medical situation. Chronic diseases are often asymptomatic and can be involve such problems as long treatment cycles, complicated treatment regimens, and unsatisfactory treatment effects, which can have significant and long-lasting negative effects on patients' physiological and psychological well-being (Triantafyllidis et al., 2019). For this reason, the authors hold that adoption of MCDMS is not only a technology-acceptance behavior, but also a health-related behavior, and we should fully consider the influence of medical behavior and psychological factors born from long-term chronic medical treatment on the decision to adopt a given service. Then variables in the traditional IS adoption theory and health behavior theory should be considered and analyzed comprehensively in the study of MCDMS adoption (Zhao, Ni, & Zhou, 2018).

At present, although some researchers have combined IS adoption theory and the health belief model (HBM) to explore related issues, with the deepening of this research, some scholars have gradually found that the HBM is applicable only to research into health behaviors within a relatively short period of time, whereas most individual health behaviors come from dealing with ongoing chronic and noninfectious diseases. Protection motivation theory (PMT)(Prenticedunn & Rogers, 1986) is an extension of the HBM, which is used to explain how an individual's response to fear appeal affects his or her related health behaviors. Subsequent studies have also confirmed that PMT can more comprehensively and deeply analyze the behavioral intention of users of mHealth services (Guo, Han, Zhang, Dang, & Chen, 2015; X. Zhang, Liu, Wang, Zhang, & Wang, 2020), but it does not address mHealth services for chronic diseases. Given these considerations, the authors set out in this study to combine the service characteristics of MCDMS, integrate the UTAUT2 and PMT, and study the influencing factors of potential users' adoption intention.

In addition, although chronic patients are mainly the elderly, with the continued formation of poor lifestyles and environmental pollution, increasing numbers of young people have been suffering from chronic diseases in recent years. Chronic diseases require long-term care, and because of daily work pressure, young and elderly groups follow different medical behavioral modes. Therefore, exploring the differentiating age effect on the influencing factors constitutes another important aspect of this study. Many studies have explained different IS adoption and participation behavior of users of different types based on construal level theory (CLT) (Huang, Li, & Zhang, 2015). From the experiential distance perspective of CLT (Fiedler, 2007), we divided potential MCDMS users into an elderly group (older than 50) and a young group (younger than 50) and analyzed the differentiating age effect in factors affecting their intention to adopt MCDMS.

Based on unique/salient features of the MCDMS service, this study explored user adoption intentions in depth, and the results have allowed us to draw valuable conclusions through expansion of the application of UTAUT2 and PMT within a new research field. Our contributions not only extend the mHealth adoption literature by putting forward the relevant factors affecting willingness to adopt MCDMS but also to compare the differences in the influencing factors across age groups, and provide a theoretical explanation for the moderating effect of user age in the process of the MCDMS adoption decision. More important, this study also provides theoretical guidance for optimizing system functions and improving user experience, and help service operators put forward targeted marketing plans for users in different age groups.

The rest of this paper proceeds as follows. First, the authors review and discuss the existing literature on mHealth adoption. Next, the authors articulate the hypotheses and present the research model. This discussion is followed by our research method and results. Thereafter, the authors discuss results as well as the theoretical and practical implications. Limitations and future directions are also presented. The paper ends with the conclusions.

LITERATURE REVIEW

With respect to mHealth user adoption and usage behavior, most previous studies have been based on different types of mHealth services and different types of users. Some studies on adoption behavior have addressed mobile electronic medical record systems for medical personnel (Kuo, Liu, & Ma, 2013; C. Liu & Cheng, 2015), individuals' acceptance of mobile phones as they seek health information (Cilliers, Viljoen, & Chinyamurindi, 2018; Li & Wang, 2018), individuals' acceptance of medical wearable technology (Dai, Larnyo, Tetteh, Aboagye, & Musah, 2019; Pan, Ding, Wu, Yang, & Yang, 2019) and medical apps (Alaiad, Alsharo, & Alnsour, 2019; Nunes, Limpo, & Castro, 2019), patients' intention to adopt mobile clinic registration systems (Lai, Huang, & Yang, 2016) and mobile cloud medical systems for diabetes prevention (S. L. Wang & Lin, 2019), and mHealth service adoption for populations with specific health needs (e.g., weight loss, smoking cessation, and mobile phone addiction).

In addition, there are also differences in the sample objects used in different studies. In addition to the mHealth adoption behaviors targeted at specific groups, such as medical personnel (Dai et al., 2019; Pan et al., 2019), patients (Balapour, Reychav, Sabherwal, & Azuri, 2019; Guo, Chen, Zhang, Ju, & Wang, 2020), family members (Jen, 2010), and the general public with health management or prevention needs, including students (Cho, Quinlan, Park, & Noh, 2014), women (Xue et al., 2012), and the elderly (Alsswey & Al-Samarraie, 2020), research samples also are targeted at specific countries or regions. The factors affecting individual adoption of mHealth care will be different in countries or regions with different levels of economic development (Alam, Hoque, Hu, & Barua, 2020). Other scholars have analyzed the characteristics of mHealth and explored users' adoption behavior from various perspectives, such as trust (Meng, Guo, Peng, Lai, & Zhao, 2019), service quality (Kim,

Kim, Lee, & Kim, 2019), service characteristics (L. Wang et al., 2018), technology transfer (Pan et al., 2019), privacy (Guo, Zhang, & Sun, 2016), security (Zhou, Bao, Watzlaf, & Parmanto, 2019), and resource competition (Ye et al., 2019).

Chronic disease is not specifically refer to a certain disease, but rather is a general term used to describe diseases with a hidden onset, long course, and no cure; diseases for which exact infectious biological etiology evidence and complicated etiology are unavailable; and some diseases that have not been completely confirmed. Although research on user adoption of mHealth services for chronic disease prevention and treatment has received attention, most studies have focused on a single type of chronic disease (Triantafyllidis et al., 2019; Zhu, Liu, Che, & Chen, 2018). With the acceleration of the pace of social life and the increase in personal work pressure, the trend of developing chronic diseases at younger ages is obvious, and attitudes toward chronic diseases and their treatment or prevention differ between the young and elderly. Even though most previous studies have explored the moderating role of user age in mHealth adoption (Yoo, Choi, Hwang, & Yi, 2021; Zhao et al., 2018)[REMOVED HYPERLINK FIELD], there is a lack of theoretical explanations for relevant research conclusions.

RESEARCH MODEL AND HYPOTHESIS

Hypothesis Development Based on UTAUT2

Venkatesh, Morris, Davis, and Davis (2003) formulated the unified theory of acceptance and use of technology (UTAUT), which integrates elements across eight prominent and competing models in IS adoption research. Specifically, performance expectancy, effort expectancy, and social influence directly affect behavioral intention while also facilitating conditions and behavioral intentions that directly affect user behavior. In the case of UTAUT, which originally was developed to explain employee technology adoption and use, it is reasonable to underestimate its explanatory power in the context of consumer technologies. In light of this, Venkatesh et al. (2012) proposed UTAUT2, which incorporated three constructs into UTAUT: hedonic motivation, price value, and habit. Furthermore, user age, gender, and experience were hypothesized to moderate the effects of these constructs on behavioral intention and technology use. UTAUT2 was found to outperform UTAUT in the context of consumer technologies, and accounted for 70% of the variance in usage intention.

The authors did not consider price value, hedonic motivation, and facilitating conditions in our research model for several reasons. First, the purpose of MCDMS is to enable the treatment of chronic diseases, so hedonic motivation was not suitable for this work. Second, price value was previously defined as consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost of using them (Alam et al., 2020). In this context, however, MCDMS vendors allowed users to operate the program during a free trial without considering price, so price value was not suitable for inclusion in this model. Furthermore, although UTAUT2 indicated that facilitating conditions act similarly to perceived behavioral control in the theory of planned behavior (TPB), Zhao et al. (2018) confirmed that perceived behavioral control had an insignificant influence on mHealth adoption in a meta-analysis about factors influencing the adoption of mHealth. Thus, the authors did not include facilitating conditions in our research model.

This study explored consumers' MCDMS adoption intention under voluntary situations from a personal perspective. The authors defined performance expectancy as the degree to which an individual believed that MCDMS would help them effectively attain autonomic chronic disease management; moreover, effort expectancy was defined as the degree of ease associated with MCDMS use. The authors theorized that the users' MCDMS adoption intention would be stronger if MCDMS usage was perceived to be helpful in effectively receiving chronic disease healthcare advice, remote monitoring, and other kinds of medical services received anytime and anywhere, as well as if the user interface was relatively simple to use. Thus, the authors assumed the following:

H1: Performance expectancy is positively associated with MCDMS adoption intention.
H2: Effort expectancy is positively associated with MCDMS adoption intention.

Previous studies have used network externality and subjective norms as influencing social factors. This paper, however, argues that social factors that affect MCDMS adoption may be embodied in herd behavior. Sun (2013) proposed "imitating others" as an alternative new concept to describe herd behavior in technology adoption, and confirmed that even if the adopted technology proved to be inefficient, it was still better than the situation in which a person became the only one making a poor decision and then suffering reputational damage for rejecting an efficient technology. Chronic disease is so intertwined with individual health that to reduce the risk of choice, individuals must refer to the behavior of other members of their community to determine whether or not to adopt MCDMS. Therefore, the authors chose imitating others as a social factor, and assumed the following:

H3: Imitating others is positively associated with MCDMS adoption intention.

According to path dependence theory (L. Chen, Su, & Zeng, 2016), a technical evolution or transition in human society is similar to inertia, in that dependent psychology will move toward an entered path whether the path is good or bad. Similarly, users' behavioral habits formed in offline medical channels would lead to hesitation when considering MCDMS adoption, which in turn would lead to the continuous self-reinforcement of previous habits because of inertia and the fall into path dependence. Therefore, it would be difficult to break through inertial behavior formed in offline environments and use MCDMS. Thus, the authors assumed the following:

H4: Offline medical habits are negatively associated with MCDMS adoption intention.

Hypothesis Development Based on Protection Motivation Theory

PMT accurately explains user medical service adoption behavior. It classifies various factors that affect health behavioral motivation into two categories according to decision-making stages: threat appraisals and coping appraisals. Threat appraisals, which consist of perceived vulnerability (one's judgment that their health is being threatened by chronic diseases) and perceived severity (the degree of physical and mental health harm caused if one refuses to accept chronic disease management services such as MCDMS), are used to assess the severity of the situation and check the seriousness of a given situation. Coping appraisals, which consist of response efficacy (one's belief in the efficacy of MCDMS to solve the chronic disease threat) and self-efficacy (the degree to which one has the ability to perform various advised health actions, such as adopting MCDMS), are used mainly to assess the response to the situation.

Coping appraisals were excluded in our research model because response efficacy in PMT is similar to performance expectancy in UTAUT2, whereas self-efficacy in PMT can be regarded as perceived behavioral control in TPB. MCDMS's main functions reflect its ability to help users anytime and anywhere, with access to medical services for chronic disease, as well as effective chronic disease surveillance and prevention. When users believe that they are more likely to suffer a chronic disease threat (e.g., high perceived vulnerability) or consider harm from the chronic disease threat to be serious (i.e., high perceived severity), they tend to adopt a health information system, such as MCDMS, to avoid or reduce the threat. Thus, the authors assumed the following:

H5: Perceived vulnerability is positively associated with MCDMS adoption intention.
H6: Perceived severity is positively associated with MCDMS adoption intention.

Cross-Age Comparison Hypothesis Development Based on CLT

Construal level theory proposes that psychological distance influences the way people think about or construe a target object or activity. Trope, Liberman, and Wakslak (2007) defined four dimensions of psychological distance: time/temporal, spatial, social, and hypothetical. When people perceive a low psychological distance from an object or event, they tend to form low-level mental representations or concrete mental construals that focus on contextual and incidental details about the object or event. Conversely, when a high psychological distance is perceived, people are likely to form high-level mental representations or abstract mental construals about the object or event that are more general and decontextualized. Fiedler (2007) considered a few other distance dimensions, such as experiential distance (e.g., experience versus no experience). Their findings also indicated that the various psychological distances are cognitively related to each other, and experiential distance and other various dimensions similarly influence and are influenced by the level of mental construal and similarly affect prediction, preference, and action.

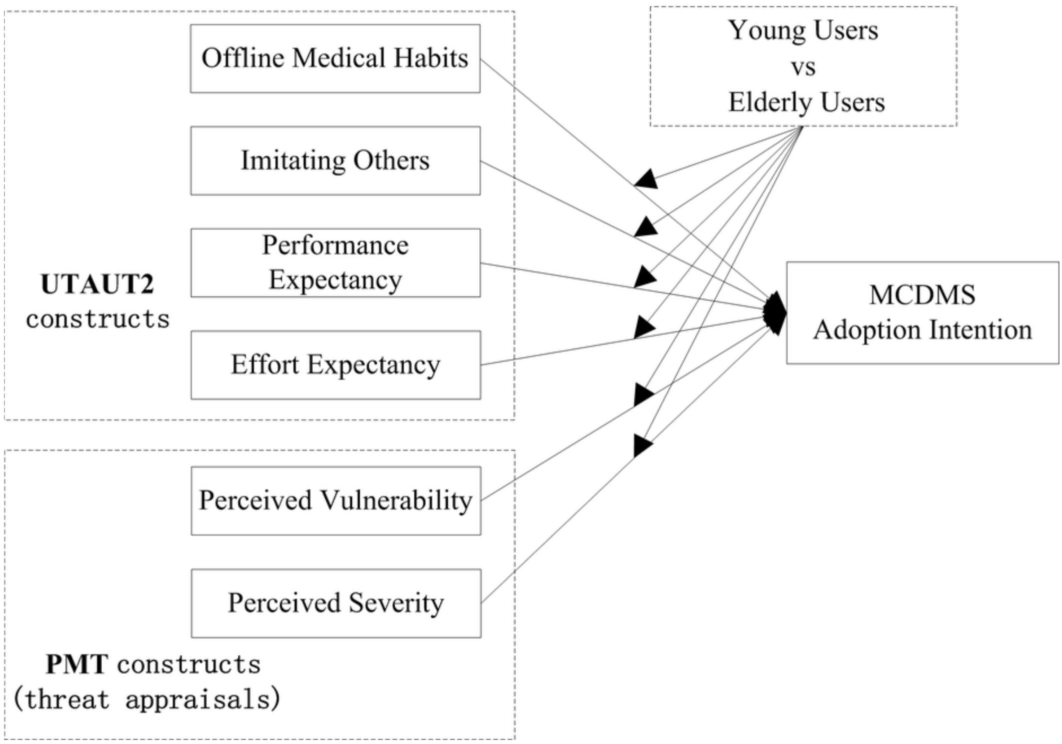
In CLT studies, a high-level construal has been found to emphasize the desirability (e.g., benefit, interest, or enjoyment) concerns of an individual, whereas a low-level construal focuses on feasibility (e.g., convenience and ease) concerns about performing an activity (in this case, MCDMS adoption). Thus, individuals considered desirability more important when the event was distant and considered feasibility as more salient when it was proximal. Similarly, the authors assumed that elderly users would place higher importance on desirability considerations (e.g., acquiring the effective chronic disease monitoring or treatment after adopting MCDMS) than young users (with more proximal perspective) because of their greater experiential distance stemming from a lack of direct experience with mobile applications). Thus, the authors posited the following:

H7: Performance expectancy is a stronger driver for the elderly groups' intention to adopt MCDMS than for young groups.
H8: Effort expectancy is a stronger driver for the young groups' intention to adopt MCDMS than for the elderly groups.

In addition, Eyal, Liberman, Trope, and Walther (2004) proposed that when considering a course of action, pros are high-level, superordinate construals, whereas cons are low-level, subordinate construals. After series of experimental studies, the authors confirmed that the number of pro arguments relative to con arguments increased with temporal distance and thus produced more favorable (or less unfavorable) attitudes and intentions regarding the more distant future options. Because of the lack of practical experience with mobile applications, the elderly group would place more importance on pros when considering MCDMS adoption when compared with the young group. Furthermore, with chronic diseases becoming increasingly more common, the elderly group's MCDMS adoption motivation would be stronger than that of the young group when they perceived themselves to be vulnerable to chronic disease and they would perceive the threat to be more serious. Additionally, Yang, Lu, and Chau (2013) argued that users' confirmations of offline channel service performance would negatively affect their relative benefit perception of online services, and when individuals formed offline medical habits, inertia would lead the individual to offline medical behavior, thus forming reasons against the use of the new medical service pattern.

Moreover, chronic disease is so intertwined with human health that users refer to the behavior of other members of their community when deciding whether or not to accept MCDMS. Users are more likely to make their choice in consensus with their community, thus engaging in herd behavior. Thus, the MCDMS adoption behavior of community members also constitutes supportive reasons for adopting MCDMS. Accordingly, the authors deduced that elderly users' MCDMS adoption intention would be more influenced by herd behavior than young users. Therefore, the authors hypothesized the following:

Figure 1. Research model



H9: Imitating others is a stronger driver for elderly groups' intention to adopt MCDMS than for young groups.
H10: Offline medical habits are a stronger driver for young groups' intention to adopt MCDMS than for elderly groups.
H11: Perceived vulnerability is a stronger driver for elderly groups' intention to adopt MCDMS than for young groups.
H12: Perceived severity is a stronger driver for elderly groups' intention to adopt MCDMS than for young groups.

Our proposed integrated model is shown in Figure 1.

METHODS

Measurement Development

The authors administered a cross-sectional questionnaire survey, including measurement items for all seven constructs of the conceptual model to test the proposed hypothesis in this study. This method was chosen because it is a suitable way to access performance expectancy, effort expectancy, imitating others, offline medical habits, perceived vulnerability, and perceived severity. Additionally, it can enhance the broader applications of the research findings.

The first part of the questionnaire consisted of questions based on the respondents' demographic profiles, and the second part included the measurement items of the seven latent variables featured in the model. To ensure the content validity of the scales, all measurement items were adapted or adopted from existing prevalidated instruments, with minor modifications in wording to make them more relevant in the MCDMS context. Specifically, the authors adapted adoption intention from the study by Dwivedi et al. (2016); performance expectancy, effort expectancy, and offline medical habits from the study by Venkatesh et al. (2012); imitating others from the study by Sun (2013); and perceived vulnerability and perceived severity from the study by Johnston and Warkentin (2010). As the original questionnaire was in English, the authors used a back-translation method (all items were translated and converted from the original English scale into Chinese, and then back into English) and consulted three doctoral students in information management to resolve any discrepancies between the two language versions.

Before the main survey, the authors conducted a pilot test of the questionnaire using a convenience sample of 32 college students who knew about the mHealth service. Suggestions about the structure and items of the instrument were requested. Finally, the authors revised or slightly adjusted the contents of the questionnaire according to the collected feedback to ensure the rationality of the questionnaire in terms of content validity, difficulty and layout. The details of the questionnaire are given in Table 1, and all items were measured using a five-point Likert scale (with anchors ranging from (1) "disagree" to (5) "agree").

Data Collection

The academic committee in "Mobile Health" Ministry of Education - China Mobile Joint Laboratory reviewed the project proposal and provided ethical approval to conduct a survey in the health management center of three large hospitals in China. These hospitals meet the health management needs of many patients with chronic diseases, as well as their families and the public. A convenience sampling method, which is cost effective and has been widely accepted in IS research, was used as the survey instrument. The authors asked respondents either waiting for a doctor or chatting with each other in the hospital waiting areas to complete our paper questionnaires.

Considering that the prevalence of chronic diseases in people age 30 or younger is much lower than in people over 30, and that people age 30 or younger tend to be less aware of chronic diseases, the authors used a judgment sampling method and did not include individuals in that age-range in the study sample. The authors asked individuals if they were older than 30, and if they were, the survey was conducted accordingly. The authors explained the purpose of the study, and all respondents were given informed consent. To ensure that the respondents had knowledge of MCDMS, our staff provided information about MCDMS, and every respondent was shown a picture or video of a sample system. As a reward, a small gift was sent to each participant after he or she filled out the questionnaire.

A total of 400 paper questionnaires were distributed and collected from June 1 to August 31, 2018, and after removing the invalid questionnaire with incomplete or identical answers, 305 usable responses were left and were subjected to further analysis. Generally speaking, the sample size for executing partial least squares (PLS) requires 10 times the number of indicators associated with the most complex construct or the largest number of antecedent constructs linked to an endogenous construct (Daradkeh, 2019). Furthermore, for statistical analyses such as structural equation modeling, a sample of 200 is considered a fair size and a sample size of 300 is considered good (Anderson & Gerbing, 1988; Hoelter, 1983). Therefore, the 305 samples used in this study met these requirements and were significant to obtain robust results after analysis. Table 2 shows the demographics of the respondents.

As far back as 1875, in Britain, the Friendly Societies Act enacted the definition of old age as "any age after 50." In terms of users' intention to adopt and use a healthcare information application (Infohealth) with a mobile phone, Xue et al. (2012) defined women over 50 years old as elderly in Singapore. Furthermore, Guo et al. (2016) used 50 years old as the cutoff between elderly and young mHealth users in China for several reasons. First, according to relevant statistics from the *2013–2014 China Mobile Internet Investigation Research Report*, elderly mobile Internet users (over the age of 50) account for only 5.4% of all users in China. Second, most people over 50 in China lack a formal education in information technology. Thus, there was concern as to whether this age-group would

Table 1. Measurement items of variables

Variable	Measurement items
Performance expectancy (PE)	PE1: Using MCDMS would be useful in managing my health. PE2: Using MCDMS would improve my health management performance.
	PE3: Using MCDMS would enhance my health management effectiveness.
	PE4: Using MCDMS would be useful in obtaining required medical services anytime and anywhere.
Effort expectancy (EE)	EE1: Learning to use an MCDMS is easy for me.
	EE2: MCDMS operation is clear and easy for me to understand.
	EE3: MCDMS is easy for me operate skillfully.
Imitating others (IO)	IO1: MCDMS seems to be the mainstream option for chronic disease self-management services, so I will use it.
	IO2: If a lot of other members of my community use MCDMS, I would like to use it.
	IO3: Because many other people have used MCDMS, I will use it.
Offline medical habits (OMH)	OMH1: I am used to going to hospitals or clinics to seek medical advice.
	OMH2: It is a natural thing for me to go to a hospital or clinic to seek medical advice.
	OMH3: I am very dependent on outpatient services provided by hospitals or clinics in my daily life. (***Dropped***)
Perceived vulnerability (PV)	PV1: I am at risk of catching chronic diseases.
	PV2: It is likely that I will catch chronic diseases in the future. PV3: It is easy for me to catch chronic diseases.
Perceived severity (PS)	PS1: If I do not take any medical measures when suffering from chronic diseases, the condition will be serious.
	PS2: If I do not take any medical measures when suffering from chronic diseases, the disease will tend to get worse. PS3: If I do not take any medical measures when suffering from chronic diseases, physical damage will be inevitable.
Adoption intention (AI)	AI1: I plan to use MCDMS in the near future.
	AI2: I would like to use MCDMS in the near future.
	AI3: I would recommend MCDMS to my family and friends.
	AI4: I feel I will use MCDMS in the near future.

accept newly introduced technology such as mHealth. Third, the majority of patients with chronic diseases are those over 50 years of age. Considering our selected sample in this study included only people from China, the authors followed the age classification that Guo et al. (2016) proposed to divide the total sample into two sets: a young group (younger than 50; N = 172) and an elderly group (older than 50; N = 133).

A further independent-sample *t* test showed that the young groups' mobile application experience was significantly higher than that of the elderly group, thus verifying our rationale for exploring the age differentiation of influencing factors from an experiential distance perspective. In addition, the chronic disease and disease treatment experiences of the elderly group were significantly higher than that of the young group, whereas the young groups' MCDMS adoption intention was significantly higher than that of the elderly group.

Table 2. Descriptive statistics of respondents (sample size: 305)

Demographic characteristic		Frequency and percentage (%)		Demographic characteristic		Frequency and percentage (%)	
Gender	Male	154	50.4	**Mobile applications experience**	Never used	67	22.0
	Female	151	49.6		<1 year	34	11.1
Age	31–40	79	25.9		1-3 years	69	22.6
	41–50	93	30.5		3-5 years	77	25.3
	51–60	53	17.4		>5 years	58	19.0
	61–70	57	18.7	**Chronic disease experience**	No sickness	106	34.7
	>70	23	7.5		<1 year	21	6.9
Education	Junior high school and below	52	17.1		1–3 years	56	18.4
	High school	50	16.4		3–5 years	42	13.8
	College degree	72	23.6		5–10 years	45	14.7
	Bachelor’s degree	87	28.5		>10 years	35	11.5
	Master’s degree or above	44	14.4	**Chronic disease treatment experience**	No treatment	122	40.0
Monthly income (RMB)	<3000	92	30.2		<1 year	33	10.8
	3001–6000	116	38.0		1–3 years	52	17.1
	6001–10,000	52	17.0		3–5 years	34	11.1
	10,001–15,000	21	6.9		5–10 years	36	11.8
	>15,000	24	7.9		>10 years	28	9.2

RESULTS

Structural equation modeling (SEM) comprises covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). In this study, the authors predicted factors that could influence MCDMS adoption in a predictive model rather than in a theory confirmatory model. According to Hair, Risher, Sarstedt, and Ringle (2019) suggestions, when the analysis is concerned with testing a theoretical framework from a prediction perspective and the research objective is to better understand increasing complexity by exploring theoretical extensions of established theories, PLS is more appropriate. Furthermore, the sample objects in this study were mainly individuals with chronic disease management needs, and this cannot meet the requirements for normal distribution of samples. This study intends to carry out a comparative analysis of the structural equation path coefficients of the young group and elderly group, whereas the sample sizes of the two groups are both small. PLS-SEM has minimal restrictions in terms of distributional assumptions, suitability for models with formative constructs, and relatively small sample requests, which was the case in our study (Gefen, Rigdon, & Straub, 2011; Hair et al., 2019; Shiau, Sarstedt, & Hair, 2019). In addition, there were significantly more published articles with PLS-SEM than with CB-SEM in the past 20 years (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). Through a literature review, the authors found that the research on mHealth user adoption based on PLS accounts for the highest proportion of research. Given these considerations, the authors used PLS in this study to conduct data analysis.

As suggested by Anderson and Gerbing (1988), the authors used a two-step method to analyze the measurement model and the structural model. Specifically, the measurement model included reliability, convergent validity, and discriminant validity, and the authors subsequently tested the

Table 3. Reliability and convergent validity (young group|elderly group)

Construct	Item	Standard load	*t* value	α	CR	AVE
OMH	OMH1 OMH2	0.961|0.762 0.705|0.922	3.871|3.695 2.470|6.084	0.650|0.621	0.827|0.832	0.711|0.715
IO	IO1 IO2 IO3	0.739|0.703 0.866|0.892 0.819|0.829	4.131|7.530 6.529|26.727 4.983|13.154	0.736|0.751	0.850|0.852	0.655|0.659
PE	PE1 PE2 PE3 PE4	0.769|0.790 0.807|0.859 0.862|0.809 0.771|0.814	18.143|18.575 28.794|31.589 49.731|18.542 19.757|36.581	0.817|0.840	0.879|0.890	0.645|0.670
EE	EE1 EE2 EE3	0.841|0.722 0.707|0.761 0.820|0.904	26.747|8.028 8.705|10.672 25.793|46.261	0.708|0.733	0.834|0.840	0.627|0.639
PV	PV1 PV2 PV3	0.739|0.720 0.704|0.711 0.826|0.791	11.990|4.458 10.212|3.981 21.078|5.446	0.628|0.605	0.801|0.785	0.575|0.550
PS	PS1	0.812|0.942	15.963|66.704	0.763|0.927	0.859|0.954	0.671|0.873
	PS2	0.778|0.932	9.933|49.453			
	PS3	0.865|0.929	16.996|49.949			
AI	AI1 AI2 AI3 AI4	0.708|0.780 0.850|0.840 0.806|0.765 0.860|0.807	13.044|21.641 29.165|25.752 24.206|16.931 36.127|22.930	0.821|0.810	0.882|0.875	0.653|0.638

common method deviation. Then the authors verified the main effect of the model and the hypothesis of path coefficient difference.

Measurement Model

For the two sample groups, the authors adopted the SmartPLS 3.0 to test the measurement and structural models through a confirmatory factor analysis. Reliability was tested by composite reliability (CR) and Cronbach's α. Table 3 shows that all CR values of the constructs ranged from 0.785 to 0.954, and the Cronbach's α values ranged from 0.605 to 0.927, both of which exceeded the threshold levels of 0.7 and 0.6 recommended by previous researchers, respectively, thus suggesting adequate reliability (Fornell & Larcker, 1981; Zhu et al., 2018).

Table 3 also shows the results of convergent validity. Specifically, all average variance extracted (AVE) values were above 0.5, and the item loadings of each construct were found to be significant and higher than the recommended value of 0.5. The values were much greater than the cross-loadings on other constructs, thus indicating good convergent validity (Fornell & Larcker, 1981; Y. C. Liu & Huang, 2016). The only exception was the single offline medical habit defined as "I am very dependent on outpatient services provided by hospitals or clinics in my daily life" (OMH3), which the authors deleted as a result of its low loading and high cross-loading.

The authors examined discriminant validity by checking whether the square root of the AVE of each construct was greater than all of the interconstruct correlations (Fornell & Larcker, 1981). The results of analysis given in Table 4 confirmed the discriminant validity of the data.

We further assessed discriminant validity using the Heterotrait-Monotrait Ratio Inference ($HTMT_{inference}$) criteria (Henseler, Ringle, & Sarstedt, 2015). As shown in Table 5, all the values were under heterotrait–monotrait values of 0.85, which indicated satisfactory discriminant validity.

Table 4. Discriminant validity (young group|elderly group)

Construct	AI	IO	PV	EE	OMH	PE	PS
AI	**0.808|0.799**						
IO	0.154|0.371	**0.810|0.812**					
PV	0.571|0.248	0.161|0.066	**0.758|0.742**				
EE	0.523|0.479	-0.015|0.345	0.345|-0.024	**0.792|0.800**			
OMH	-0.115|0.194	-0.137|0.058	-0.099|0.354	-0.007|0.146	**0.843|0.845**		
PE	0.683|0.697	0.058|0.223	0.574|0.268	0.502|0.485	-0.012|0.324	**0.803|0.819**	
PS	0.499|0.306	0.581|0.280	0.101|0.206	0.318|0.031	0.486|0.276	0.383|0.408	**0.819|0.934**

Note: Diagonal bold values are square roots of AVE.

Table 5. Heterotrait–monotrait

	AI	EE	IO	OMH	PE	PS
EE	0.650					
IO	0.830	0.703				
OMH	0.144	0.249	0.146			
PE	0.845	0.650	0.837	0.150		
PS	0.341	0.054	0.431	0.466	0.369	
PV	0.159	0.355	0.197	0.410	0.142	0.205

Common Method Bias Testing

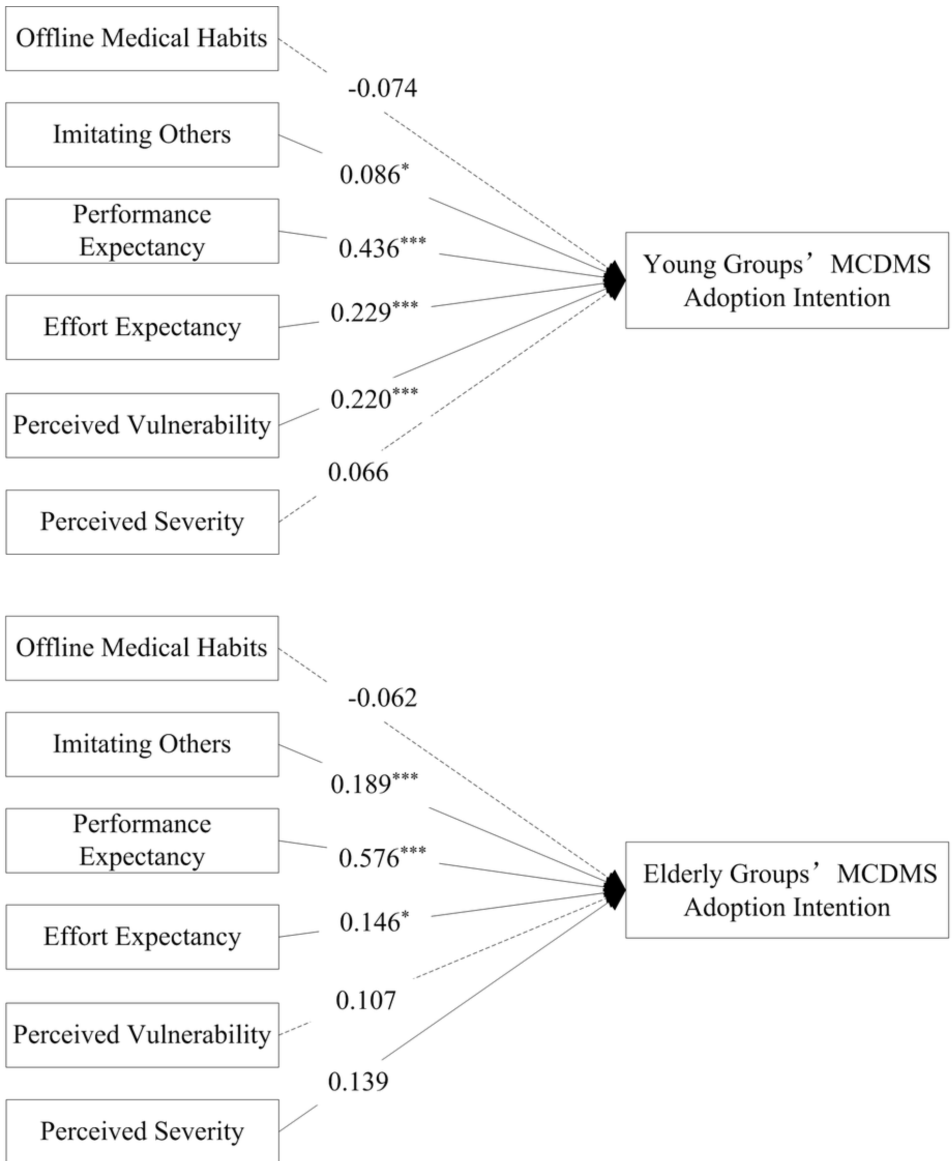
The authors conducted Harman' s one-factor test on the seven conceptually crucial variables in our theoretical model to address the possible common method bias problem. The results of unrotated principal components factor analysis showed that seven factors were present in both groups. Furthermore, covariances, as explained by the largest factor, accounted for 31.46% and 29.98% of the young and elderly groups, respectively, which were less than 50%. This suggested that common method biases likely did not contaminate the results.

Structural Model

The significance of each path coefficient was calculated by bootstrapping with 5000 samples using the replacement method, and the results are displayed in Figure 2. As for the basic model paths, performance expectancy, effort expectancy, and imitation of others exerted a significant positive influence on MCDMS adoption intentions for both the young and elderly groups. In contrast, perceived vulnerability positively affected only the young group, and perceived severity negatively affected only the elderly group. Counterintuitively, the impact of offline medical habits on MCDMS adoption intentions was not significant in either group.

Based on the proposed six factors that affect MCDMS adoption intention, the authors adopted a procedure proposed by Keil et al. (2000) to determine whether there was any differentiated impact. The authors tested H7–H12 by statistically comparing the path coefficients from six factors to adoption intention in the young group's structural model with the corresponding path coefficients in the elderly group's structural model. These statistical comparisons were conducted using the following procedure:

Figure 2. PLS results of model testing



$$S_{pooled} = \sqrt{\{[(N_1 - 1)/(N_1 + N_2 - 2)] * SE_1^2 + [(N_2 - 1)/(N_1 + N_2 - 2)] * SE_2^2\}}$$

$$t_{pooled} = (PC_1 - PC_2)/[S_{pooled} * \sqrt{(1/N_1 + 1/N_2)}].$$

Here, S_{pooled} is the pooled estimator for the variance; t_{pooled} is t-statistic with $N_1 + N_2 - 2$ degrees of freedom; N_i is the sample size of the data set for group i; SE_i is standard error of the path in the structural model of group i; and PC_i is the path coefficient in the structural model of group i.

Table 6 summarizes the test results for all of the hypotheses. Specifically, when deciding whether or not to adopt MCDMS, the young group placed more importance on effort expectancy compared with the elderly group, whereas the elderly group emphasized performance expectancy, imitation, and perceived severity, thus supporting H7, H8, H9, and H12. The young group, however, emphasized perceived vulnerability more than the elderly group, which was inconsistent with our original hypothesis. Thus, H11 was not supported. Regarding offline medical habits, the empirical results confirmed the insignificant path coefficients for both groups; therefore; it was not necessary to validate the differentiated impact of offline medical habits on MCDMS adoption intention. Thus, H10 was not supported.

Table 6. Hypothesis testing results

Hypotheses		(PE->AI)	(EE->AI)	(IO->AI)	(OMH->AI)	(PV->AI)	(PS->AI)
Path coefficient (standard error)	y	0.436*** (0.077)	0.229*** (0.075)	0.086* (0.049)	-0.074 ^{ns} (0.059)	0.220*** (0.064)	0.066 ^{ns} (0.079)
	e	0.576*** (0.056)	0.146* (0.079)	0.189*** (0.074)	-0.062 ^{ns} (0.066)	0.107 ^{ns} (0.075)	0.139* (0.073)
S_{pooled}		0.068	0.078	0.062	0.064	0.069	0.076
t_{pooled}		-17.761***	9.182***	-14.309***	-1.614 ^{ns}	14.098***	-8.275***
Conclusions		Supporting H1y, H1e, H7	Supporting H2y, H2e, H8	Supporting H3y, H3e, H9	Not supporting H4y, H4e, H10	Supporting H5y, but not supporting H5e and H11	Supporting H6e and H12, but not supporting H6y

Note: "y" stands for young group; "e" stands for elderly group; * P<0.1, ** P <0.05, *** P <0.01, ns = insignificant

DISCUSSION

This study provided early empirical support for a model that examines the predictors of MCDMS adoption intention based on integrated UTAUT2 and PMT. The authors clarified the differentiated impact of predictors from an experiential distance perspective. Our proposed model was empirically tested through a survey of 305 potential users, and the results showed certain theoretical and practical significance.

1. Most IS researchers have argued that the younger group placed more importance on perceived usefulness (perceived ease of use) than the elderly groups (Venkatesh et al., 2012). Under the mHealth service context, considering the fact that a person's physical and psychological activity change with age, which in turn affects an individual's health and decision-making ability, several studies have recognized that it is meaningful and important to explore age differences in mHealth adoption. Zhao et al. (2018) conducted a meta-analysis and confirmed that the effect of perceived ease of use on old and middle-age groups' adoption intention was greater than that of the young groups. Alsswey and Al-Samarraie (2020); Blut, Chong, Tsiga, and Venkatesh (2021); Hsiao and Tang (2015) all confirmed that the influence of perceived ease of use on the adoption intention of the elderly group was significantly greater than the influence of perceived usefulness.

Conversely, under the MCDMS context, our proposed hypotheses and empirical results revealed opposing research conclusions that were consistent with the conclusions reported by Hung and Jen (2012). Furthermore, Guo, Sun, Wang, Peng, and Yan (2013) also confirmed that in the adoption decision-making process of mHealth service for people over 40 years old, perceived usefulness had a greater influence on adoption intention than perceived ease of use. A possible explanation is that with users' increasing mobile applications experience, the importance of users' perception of ease of use weakens. Furthermore, MCDMS involves greater physical risk and longer treatment cycles, which leads older people to pay more attention to its effectiveness to treat or prevent chronic disease and to use MCMDS with the help of their family members.

2. In the context of mHealth services, the significant impact of subjective norms on users' adoption intentions has been confirmed by most research (Zhao et al., 2018). When age differences were considered, Hsiao and Tang (2015); Xue et al. (2012) confirmed that subjective norms had a significant impact on the willingness of elderly groups to adopt mHealth, whereas Deng, Mo, and Liu (2014) demonstrated that these results were not valid in the young group. These conclusions were consistent with those found by Venkatesh et al. (2012), to a certain extent, who observed that subjective norms had a greater impact on elderly groups' IS adoption behavior than on young groups' behavior.

Unlike subjective norms, herd behavior not only explained the influence of others' actions on individual behavior but also revealed that the number of referents can also affect people's decisions (Shen, Zhang, & Zhao, 2016). Although some studies have confirmed that age moderates the impact of herd behavior on user adoption of IS services, such as mobile payment (Handarkho & Harjoseputro, 2020) and social commerce platform (Handarkho, 2020), they have not fully considered elderly groups. After observing actual users' MCDMS actual adoption behaviors, potential consumers tended to give up perceptions about MCDMS that were formed in the initial adoption phase, and then exhibited some herd behavior. Few studies have explored the influence of herd behavior on mHealth service adoption. As a key dimension of herd behavior, in this study, imitating others proved to have greater impact on elderly groups' adoption intention than on young groups' intention. Generally, the elderly expressed obvious risk aversion (L. Zhang, Bi, Zhang, & Chen, 2015), and their decision-making behavior tended to be more consistent with that of other groups in their community.

3. Previous studies mainly focused on the positive impact of user habits on IS adoption under a single channel, and Duarte and Pinho (2019) confirmed the influence of mHealth service usage habits on adoption behavior. Limited attention has been paid to the negative effects of deep-seated habitual behavior toward an existing system with the intention to use a new system (C. C. Chen, Kuo-Lun, & Cheng-Han, 2019; Polites & Karahanna, 2012). Cao, Lu, and Yang (2013) confirmed that the habit of obtaining offline banking services negatively affected users' willingness to transfer to online banking services, but empirical results in the MCDMS context did not support the conclusions that offline medical habits exerted a significant impact on adoption intention, which was partially consistent with Zhu and Liu (2016) research that offline medical habits exerted no significant impact on the young group's intention to transfer usage from offline medical channels to mHealth. On one hand, according to path dependence theory, offline medical habits generated by potential users of traditional medical services could lead these individuals to unconsciously choose traditional medical services while ignoring other alternatives, such as mHealth, when making medical decisions, and this also explains why offline medical habits have a negative impact on intention to adopt MCDMS in this study. However, mobile applications are increasingly popular across all ages, and compared with traditional offline services, mobile applications provide more people with relative benefits when using various kinds of mobile services. Thus, the authors can safely argue that the long-term formation of offline medical

habits does not eliminate interest in the MCDMS. For this reason, the negative impact of offline medical habits on adoption intention is not significant in MCDMS context.

4. The significant effect of perceived vulnerability and perceived severity on mHealth users' intention to adopt has been confirmed in other studies (Dou et al., 2017; Gao, Li, & Luo, 2015; Guo et al., 2015; X. Zhang et al., 2020). Guo et al. (2015) confirmed that there were no age difference in these effects, but they noted that as a person gets older, he or she is more likely to suffer from diseases and deteriorating health. As a result, elderly people pay more attention to health problems and are more likely to take action to avoid disease and remain healthy (Guo et al., 2015). Through a meta-analysis, Zhao et al. (2018) also confirmed that compared with the young group, the elderly group's perceived vulnerability had a greater impact on mHealth users' intention to adopt. Therefore, it is necessary to consider specific service contexts when considering the age differences and the influencing factors of adoption intention.

When considering the MCDMS context, the authors found a meaningful conclusion that perceived vulnerability exerted a significant and positive influence only on the willingness to adopt MCDMS in the young group, but not in the elderly group, which was contrary to Deng (2013) findings as well as the assumed moderating role of user age. As a result of lifestyle and environmental changes, when those in the young group perceived themselves to be vulnerable to chronic disease threats, pressures from daily life and a receptive attitude to new things (Guo et al., 2016) could lead to a greater willingness to use the MCDMS, which is a more convenient and efficient service. Furthermore, perceived severity, which is opposite perceived vulnerability, exerted a significant and positive influence only on the elderly group's willingness to adopt MCDMS. In addition, the comparison hypothesis with respect to the relationship between perceived severity and service adoption intention was supported, which was consistent with Zhao et al. (2018) confirmation that perceived severity exerted a more positive influence on users' mHealth adoption intention with an increase in user age. When individuals perceived their illness would be more serious if they did not take any medical measures, the elderly group was more likely to consider their personal physical fitness and other factors and then to adopt medical services, such as MCDMS.

Theoretical Implications

The theoretical contributions of this study are focused on three main aspects. First, previous studies using UTUT2 or PMT to study the user adoption behaviors of different mHealth services rarely considered the context of chronic disease management. By integrating the core variables of UTAUT2 and PMT, this study explored the influencing factors of MCDMS adoption intention and expanded the application context of UTAUT2 and PMT with a new research field. Second, although the moderating effect of user age in the decision process of mHealth adoption has been confirmed by many studies, the related conclusions have not been explained using appropriate theories. This study accounted for the experience distance caused by differences in mobile application experience between the young and elderly group, which led to individuals' different behavioral responses and psychological processes when facing a target object or activity (MCDMS adoption in this study). Our empirical results confirmed most of the comparison hypotheses proposed from this experiential distance perspective. The conclusions of this study further broadened the application of CLT in IS adoption research. Third, this study confirmed that in the decision-making process of MCDMS adoption, the young group paid more attention to effort expectancy, whereas the elderly group paid more attention to performance expectancy. This notable empirical result was inconsistent with most previous studies about mHealth adoption. In addition, the moderating effect of user age on the relationships among other variables further enriched the research on IS adoption behaviour.

Practical Implications

This study offered new insight for MCDMS service providers. First, measures, such as live stream, greater promotion of existing mature MCDMS products on the market, authoritative expert recommendations, and free experiential services, should be considered by MCMDS providers to preferentially enhance the elderly group's perception of performance expectancy. In addition, appropriate measures, such as training, real-time feedback for operation issues, design of a popular system interface style, and one-click functions, should be preferentially available for the young group to enhance their effort expectancy of MCDMS. Second, service providers can mine the existing MCDMS users' consumption data to determine target groups, and then preferentially orientate elderly groups through social networks. Then, priority can be given to implement accurate marketing and recommendations to this orientated elderly group and promote their imitation of others' behavior to improve their MCMDS adoption intention. Furthermore, offline medical habits did not have a negative impact on the adoption willingness of the two groups. Doctors with good offline reputations could provide different medical services through MCDMS while also offering traditional services. This could further encourage and promote the transfer of potential users from traditional offline outpatient service to MCDMS. Third, popularization and propaganda of chronic diseases should be emphasized by MCDMS providers, especially to help young individuals realize that more young people have begun to suffer from chronic diseases. Then, providers should facilitate the formation of consciousness regarding chronic disease prevention and combine this with young group's rich mobile application experience to enhance their willingness to adopt MCDMS. In addition, MCDMS providers also should preferentially help elderly groups realize the severity and harmfulness of ignoring chronic disease treatment and then should promote MCDMS.

Limitations and Future Work

There were unavoidable limitations in this study that should be considered in future work. First, our data were gathered within a single time period and collected from individuals with a self-report questionnaire. Although the statistical results showed that the common method bias problem was not serious in this study, the conclusion validity was still affected. Second, considering that nonpatients with health management needs and patients' families are also potential users of the MCDMS, a significant number of the respondents had no previous experience with chronic disease. If the participants in the study included only respondents who had experience with chronic disease, the findings likely would be very different. Therefore, subsequent studies will further compare and analyze the differences in influencing factors of adoption intention based on whether or not potential users suffer from chronic diseases. Third, considering that no expert questionnaire was designed to evaluate the rationality of the questionnaire during the process of questionnaire design in this study, the content validity of the questionnaire in this study could not be evaluated according to the content validity index (Singun, 2018), and this needs to be given more attention in future studies. This study only considered the differences among different age groups. The economic level, innovation level, and cultural differences in different countries can also lead to differences in the adoption of MCDMS (Jadil, Rana, & Dwivedi, 2021), which should be explored further in combination with the above-mentioned moderators in the future.

CONCLUSION

According to the MCDMS service characteristics and Chinese medical situation, this study investigated the factors affecting customers' adoption intention of MCDMS. It also examined the possible cross-age differences that exist with respect to influencing factors that have not been addressed sufficiently, to facilitate chronic patients to adopt new technology to improve their level of health management. A key contribution of this study was to confirm user age as significant moderators that affected the relationships among some predictors proposed in this study and adoption intention of MCDMS from an experimental distance perspective of the construal level theory. A prominent counterintuitive finding showed that in the decision-making process of MCDMS service adoption, the young group paid more attention to effort expectancy, and the elderly group paid more attention to performance expectancy, which enriched the theoretical contributions of construal level theory to IS adoption research. As a whole, our findings were conducive to future research on mHealth service adoption. These finding also made important contributions by highlighting the role of an integrated model of UTAUT2 with PMT to explain the users' adoption of the MCDMS, which offer scholars a theoretical direction for further research. Accordingly, this study provided instrumental insight for practitioners to fully understand the key factors of mHealth user adoption behavior and to improve service quality to meet the different needs of actual users.

ACKNOWLEDGMENT

This research was supported by the Humanity and Social Science Youth Foundation of Ministry of Education of China [Grant number 18YJC630275].

REFERENCES

Alaiad, A., Alsharo, M., & Alnsour, Y. (2019). The determinants of m-health adoption in developing countries: An empirical investigation. *Applied Clinical Informatics*, *10*(05), 820–840. doi:10.1055/s-0039-1697906 PMID:31667819

Alam, M. Z., Hoque, R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management*, *50*, 128–143. doi:10.1016/j.ijinfomgt.2019.04.016

Alsswey, A., & Al-Samarraie, H. (2020). Elderly users' acceptance of mHealth user interface (UI) design-based culture: The moderator role of age. *Journal on Multimodal User Interfaces*, *14*(1), 49–59. doi:10.1007/s12193-019-00307-w

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. doi:10.1037/0033-2909.103.3.411

Balapour, A., Reychav, I., Sabherwal, R., & Azuri, J. (2019). Mobile technology identity and self-efficacy: Implications for the adoption of clinically supported mobile health apps. *International Journal of Information Management*, *49*, 58–68. doi:10.1016/j.ijinfomgt.2019.03.005

Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2021). Meta-Analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its Validity and Charting a Research Agenda in the Red Ocean. *Journal of the Association for Information Systems*.

Cao, Y., Lu, Y., & Yang, S. (2013). A Study on the Factors Influencing Consumers' Usage Transfer Behavioral Intention from Offline to Online Environment. *Chinese Journal of Management*, *10*(3), 404–412.

Chen, C. C., Kuo-Lun, H., & Cheng-Han, H. (2019). Understanding Usage Transfer Behavior of Two Way O2O Services. *Computers in Human Behavior*, *100*, 184–191. doi:10.1016/j.chb.2018.07.009

Chen, L., Su, Z. X., & Zeng, X. (2016). Path dependence and the evolution of HRM in China. *International Journal of Human Resource Management, 27*(18), 2034-2057.

Cho, J., Quinlan, M. M., Park, D., & Noh, G.-Y. (2014). Determinants of adoption of smartphone health apps among college students. *American Journal of Health Behavior*, *38*(6), 860–870. doi:10.5993/AJHB.38.6.8 PMID:25207512

Cilliers, L., Viljoen, K. L.-A., & Chinyamurindi, W. T. (2018). A study on students' acceptance of mobile phone use to seek health information in South Africa. *The HIM Journal*, *47*(2), 59–69. doi:10.1177/1833358317706185 PMID:28537211

Dai, B., Larnyo, E., Tetteh, E. A., Aboagye, A. K., & Musah, A.-A. I. (2019). Factors affecting caregivers' acceptance of the use of wearable devices by patients with dementia: An extension of the unified theory of acceptance and use of technology model. *American Journal of Alzheimer's Disease and Other Dementias*, *35*, 1–11. PMID:31679390

Daradkeh, M. (2019). Determinants of Self-Service Analytics Adoption Intention: The Effect of Task-Technology Fit, Compatibility, and User Empowerment. *Journal of Organizational and End User Computing*, *31*(4), 19–45. doi:10.4018/JOEUC.2019100102

Deng, Z. (2013). Understanding public users' adoption of mobile health service. *International Journal of Mobile Communications*, *11*(4), 351–373. doi:10.1504/IJMC.2013.055748

Deng, Z., Mo, X., & Liu, S. (2014). Comparison of the middle-aged and older users' adoption of mobile health services in China. *International Journal of Medical Informatics*, *83*(3), 210–224. doi:10.1016/j.ijmedinf.2013.12.002 PMID:24388129

Dou, K., Yu, P., Deng, N., Liu, F., Guan, Y., Li, Z., Ji, Y., Du, N., Lu, X., & Duan, H. (2017). Patients' acceptance of smartphone health technology for chronic disease management: A theoretical model and empirical test. *JMIR mHealth and uHealth*, *5*(12), e177. doi:10.2196/mhealth.7886 PMID:29212629

Duarte, P., & Pinho, J. C. (2019). A mixed methods UTAUT2-based approach to assess mobile health adoption. *Journal of Business Research*, *102*, 140–150. doi:10.1016/j.jbusres.2019.05.022

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., & Weerakkody, V. (2016). A generalised adoption model for services: A cross-country comparison of mobile health (m-health). *Government Information Quarterly*, *33*(1), 174–187. doi:10.1016/j.giq.2015.06.003

Eyal, T., Liberman, N., Trope, Y., & Walther, E. (2004). The pros and cons of temporally near and distant action. *Journal of Personality and Social Psychology*, *86*(6), 781–795. doi:10.1037/0022-3514.86.6.781 PMID:15149255

Fiedler, K. (2007). Construal level theory as an integrative framework for behavioral decision-making research and consumer psychology. *Journal of Consumer Psychology*, *17*(2), 101–106. doi:10.1016/S1057-7408(07)70015-3

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservables and measurement error. *JMR, Journal of Marketing Research*, *18*(2), 39–50. doi:10.1177/002224378101800104

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, *115*(9), 1704–1723. doi:10.1108/IMDS-03-2015-0087

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An Update and Extension to SEM Guidelines for Administrative and Social Science Research. *Management Information Systems Quarterly*, *35*(2), A1–A7. doi:10.2307/23044042

Guo, X., Chen, S., Zhang, X., Ju, X., & Wang, X. (2020). Exploring Patients' Intentions for Continuous Usage of mHealth Services: Elaboration-Likelihood Perspective Study. *JMIR mHealth and uHealth*, *8*(4), e17258. doi:10.2196/17258 PMID:32250277

Guo, X., Han, X., Zhang, X., Dang, Y., & Chen, C. (2015). Investigating m-Health acceptance from a protection motivation theory perspective: Gender and age differences. *Telemedicine Journal and e-Health*, *21*(8), 661–669. doi:10.1089/tmj.2014.0166 PMID:25919800

Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The dark side of elderly acceptance of preventive mobile health services in China. *Electronic Markets*, *23*(1), 49–61. doi:10.1007/s12525-012-0112-4

Guo, X., Zhang, X., & Sun, Y. (2016). The privacy-personalization paradox in mHealth services acceptance of different age groups. *Electronic Commerce Research and Applications*, *16*, 55–65. doi:10.1016/j.elerap.2015.11.001

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*(5), 616–632. doi:10.1007/s11747-017-0517-x

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. doi:10.1108/EBR-11-2018-0203

Handarkho, Y. D. (2020). The factors influencing customer loyalty in social commerce platform: Variety-seeking and social impact perspective. *International Journal of Web Information Systems*, *16*(4), 369–386. doi:10.1108/IJWIS-04-2020-0021

Handarkho, Y. D., & Harjoseputro, Y. (2020). Intention to adopt mobile payment in physical stores. *Journal of Enterprise Information Management*, *33*(2), 285–308. doi:10.1108/JEIM-06-2019-0179

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8

Hoelter, D. R. (1983). The analysis of covariance structures: Goodness-of-fit indices. *Sociological Methods & Research*, *11*(3), 325–344. doi:10.1177/0049124183011003003

Hsiao, C. H., & Tang, K. Y. (2015). Examining a model of mobile healthcare technology acceptance by the elderly in Taiwan. *Journal of Global Information Technology Management*, *18*(4), 292–311. doi:10.1080/1097198X.2015.1108099

Huang, J., Li, Y., & Zhang, H. (2015). The application and development of Construal Level Theory. *Xinli Kexue Jinzhan*, *23*(1), 110–119. doi:10.3724/SP.J.1042.2015.00110

Hung, M., & Jen, W. (2012). The adoption of mobile health management services: An empirical study. *Journal of Medical Systems*, *36*(3), 1381–1388. doi:10.1007/s10916-010-9600-2 PMID:20878452

Jadil, Y., Rana, N. P., & Dwivedi, Y. K. (2021). A meta-analysis of the UTAUT model in the mobile banking literature: The moderating role of sample size and culture. *Journal of Business Research*, *132*, 354–372. doi:10.1016/j.jbusres.2021.04.052

Jen, W., & Hung, M.-C. (2010). An empirical study of adopting mobile healthcare service: The family's perspective on the healthcare needs of their elderly members. *Telemedicine Journal and e-Health*, *16*(1), 41–48. doi:10.1089/tmj.2009.0093 PMID:20070162

Johnston, A. C., & Warkentin, M. (2010). Fear appeals and information security behaviors: An empirical study. *Management Information Systems Quarterly*, *34*(3), 549–566. doi:10.2307/25750691

Keil, M., Tan, B. C. Y., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *Management Information Systems Quarterly*, *24*(2), 299–325. doi:10.2307/3250940

Kim, K.-H., Kim, K.-J., Lee, D.-H., & Kim, M.-G. (2019). Identification of critical quality dimensions for continuance intention in mHealth services: Case study of onecare service. *International Journal of Information Management*, *46*, 187–197. doi:10.1016/j.ijinfomgt.2018.12.008

Kuo, K., Liu, C., & Ma, C. (2013). An investigation of the effect of nurses' technology readiness on the acceptance of mobile electronic medical record systems. *BMC Medical Informatics and Decision Making*, *13*(1), 1–14. doi:10.1186/1472-6947-13-88 PMID:23938040

Lai, Y.-H., Huang, F.-F., & Yang, H.-H. (2016). A study on the attitude of use the mobile clinic registration system in Taiwan. *Technology and Health Care*, *24*(s1, S1), S205–S211. doi:10.3233/THC-151076 PMID:26444802

Li, Y., & Wang, X. (2018). Seeking Health Information on Social Media: A Perspective of Trust, Self-Determination, and Social Support. *Journal of Organizational and End User Computing*, *30*(1), 1–22. doi:10.4018/JOEUC.2018010101

Liu, C., & Cheng, T. (2015). Exploring critical factors influencing physicians' acceptance of mobile electronic medical records based on the dual-factor model: A validation in Taiwan. *BMC Medical Informatics and Decision Making*, *15*(1), 1–12. doi:10.1186/s12911-014-0125-3 PMID:25889506

Liu, Y. C., & Huang, Y.-A. (2016). Factors Influence Intention to Adopt Internet Medical Information on Bulletin Boards: A Heuristic-Systematic Perspective. *Journal of Organizational and End User Computing*, *29*(1), 23–41. doi:10.4018/JOEUC.2017010102

Meng, F., Guo, X., Peng, Z., Lai, K.-H., & Zhao, X. (2019). Investigating the Adoption of Mobile Health Services by Elderly Users: Trust Transfer Model and Survey Study. *JMIR mHealth and uHealth*, *7*(1), e12269. doi:10.2196/12269 PMID:30622092

Nunes, A., Limpo, T., & Castro, S. L. (2019). Acceptance of mobile health applications: Examining key determinants and moderators. *Frontiers in Psychology*, *10*, 2791. doi:10.3389/fpsyg.2019.02791 PMID:31920836

Pan, J., Ding, S., Wu, D., Yang, S., & Yang, J. (2019). Exploring behavioural intentions toward smart healthcare services among medical practitioners: A technology transfer perspective. *International Journal of Production Research*, *57*(18), 5801–5820. doi:10.1080/00207543.2018.1550272

Polites, G. L., & Karahanna, E. (2012). Shackled to the status quo: The inhibiting effects of incumbent system habit, switching costs, and inertia on new system acceptance. *Management Information Systems Quarterly*, *36*(1), 21–42. doi:10.2307/41410404

Prenticedunn, S., & Rogers, R. W. (1986). Protection Motivation Theory and preventive health: Beyond the Health Belief Model. *Health Education Research*, *1*(3), 153–161. doi:10.1093/her/1.3.153

Shen, X.-L., Zhang, K., & Zhao, S. J. (2016). Herd behavior in consumers' adoption of online reviews. *Journal of the Association for Information Science and Technology*, *67*(11), 2754–2765. doi:10.1002/asi.23602

Shiau, W.-L., Sarstedt, M., & Hair, J. F. (2019). Internet research using partial least squares structural equation modeling (PLS-SEM). *Internet Research*, *29*(3), 398–406. doi:10.1108/IntR-10-2018-0447

Shiau, W.-L., Siau, K., Yu, Y., & Guo, J. (2021). Research Commentary on IS/IT Role in Emergency and Pandemic Management: Current and Future Research. *Journal of Database Management*, *32*(2), 67–75. doi:10.4018/JDM.2021040105

Singun, A. P. (2018). Heuristics as Mental Shortcuts in Evaluating Interactive Systems. *International Journal of Engineering Pedagogy*, *8*(4), 143–152. doi:10.3991/ijep.v8i4.8054

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *Management Information Systems Quarterly*, *37*(4), 1013–1042. doi:10.25300/MISQ/2013/37.4.02

Triantafyllidis, A., Kondylakis, H., Votis, K., Tzovaras, D., Maglaveras, N., & Rahimi, K. (2019). Features, outcomes, and challenges in mobile health interventions for patients living with chronic diseases: A review of systematic reviews. *International Journal of Medical Informatics*, *132*, 103984. doi:10.1016/j.ijmedinf.2019.103984 PMID:31605884

Trope, Y., Liberman, N., & Wakslak, C. (2007). Construal levels and psychological distance: Effects on representation, prediction, evaluation, and behavior. *Journal of Consumer Psychology*, *17*(2), 83–95. doi:10.1016/S1057-7408(07)70013-X PMID:21822366

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, *36*(1), 157–178. doi:10.2307/41410412

Wang, L., Wu, T., Guo, X., Zhang, X., Yan, L., & Wang, W. (2018). Exploring mHealth monitoring service acceptance from a service characteristics perspective. *Electronic Commerce Research and Applications*, *30*, 159–168. doi:10.1016/j.elerap.2018.06.003

Wang, S. L., & Lin, H. I. (2019). Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system. *Behaviour & Information Technology*, *38*(9), 974–985. doi:10.1080/0144929X.2019.1626486

Xue, L., Yen, C. C., Chang, L., Chan, H. C., Tai, B. C., Tan, S. B., Duh, H. B. L., & Choolani, M. (2012). An exploratory study of ageing women's perception on access to health informatics via a mobile phone-based intervention. *International Journal of Medical Informatics*, *81*(9), 637–648. doi:10.1016/j.ijmedinf.2012.04.008 PMID:22658778

Yang, S., Lu, Y., & Chau, P. Y. K. (2013). Why do consumers adopt online channel? An empirical investigation of two channel extension mechanisms. *Decision Support Systems*, *54*(2), 858–869. doi:10.1016/j.dss.2012.09.011

Ye, Q., Deng, Z., Chen, Y., Liao, J., Li, G., & Lu, Y. (2019). How resource scarcity and accessibility affect patients' usage of mobile health in China: Resource competition perspective. *JMIR mHealth and uHealth*, *7*(8), e13491. doi:10.2196/13491 PMID:31400104

Yoo, J., Choi, S., Hwang, Y., & Yi, M. Y. (2021). The Role of User Resistance and Social Inñuences on the Adoption of Smartphone: Moderating Effect of Age. *Journal of Organizational and End User Computing*, *33*(2), 36–58. doi:10.4018/JOEUC.20210301.oa3

Zhang, L., Bi, Y., Zhang, B., & Chen, L. (2015). The elderly decision making: The current situations and challenges of the field. *Acta Psychologica Sinica*, *23*(5), 858–870.

Zhang, X., Liu, S., Wang, L., Zhang, Y., & Wang, J. (2020). Mobile health service adoption in China: Integration of theory of planned behavior, protection motivation theory and personal health differences. *Online Information Review*, *44*(1), 1–23. doi:10.1108/OIR-11-2016-0339

Zhang, Y., Liu, C., Luo, S., Xie, Y., Liu, F., Li, X., & Zhou, Z. (2019). Factors influencing patients' intentions to use diabetes management spps based on an extended unified theory of acceptance and use of technology model: Web-based survey. *Journal of Medical Internet Research*, *21*(8), e15023. doi:10.2196/15023 PMID:31411146

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, *43*, 342–350. doi:10.1016/j.ijinfomgt.2017.08.006

Zhou, L., Bao, J., Watzlaf, V., & Parmanto, B. (2019). Barriers to and Facilitators of the Use of Mobile Health Apps From a Security Perspective: Mixed-Methods Study. *JMIR mHealth and uHealth*, *7*(4), e11223. doi:10.2196/11223 PMID:30990458

Zhu, Z., & Liu, Y. (2016). A study of youth groups' behavioral intention to transfer usage from traditional medical channel to mobile health. *Chinese Journal of Management*, *13*(11), 1728–1736.

Zhu, Z., Liu, Y., Che, X., & Chen, X. (2018). Moderating factors influencing adoption of a mobile chronic disease management systems in China. *Informatics for Health & Social Care*, *43*(1), 22–41. doi:10.1080/17538157.2016.1255631 PMID:28068149

Zhangxiang Zhu is a lecturer in the Tourism College at Hunan Normal University, Changsha, China. He received his Ph.D. from the Central South University, China. His research interests include mobile health, smart tourism, and public opinion on the Internet. He has published in important academic journals, including Asia Pacific Journal of Marketing and Logistics, Computers in Human Behavior, Informatics for Health and Social Care, Chinese Journal of Management, Journal of Systems & Management, among others.

Yongmei Liu is a Professor of Business School at Central South University, Changsha, China. She received her Ph.D. from the Chiba Institute of Technology, Japan. Her current research focuses on supply chain management, management information systems, and team decision theory and method. She has published in leading Chinese and international academic journals, including Journal of Business Ethics, Behavior Research Methods, Computers in Human Behavior, Internet Research, Journal of the Association for Information Science and Technology, among others.

Xianye Cao is a lecturer in the School of Management at Hunan University of Technology and Business, Changsha, China. She received her Ph.D. from the Central South University, China. Her research interests include online health. She has published in important academic journals, including Computers in Human Behavior, and Business Review.

Wei Dong is a Ph.D. candidate at the Business School at Central South University, Changsha, China. Her current research interests include online health community and mobile health.