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Abstract: Home healthcare initiatives are aimed to reduce readmission costs, transportation costs, and hospital medical errors, and to improve post hospitalization healthcare quality, and enhance patient home independency. Today, it is almost unimaginable to consider this initiative without information technology. Home healthcare robots are one type of the emerging technologies that hold promise for making clinical information available at the right place and right time. Several robots have been developed to facilitate home healthcare such as remote presence robots (e.g., RP2) and Paro. Most previous research focus on technical and implementation issues of home healthcare robots, there is a need to understand the factors that influence their adoption. This research aims to fill this knowledge gap by applying the UTAUT model. The model was tested using survey questionnaire. The empirical results confirm that performance expectancy, social influence, and facilitating condition directly affect usage intention of home healthcare robots, while effort expectancy indirectly affects usage intention through performance expectancy. Several practical and theoretical implications are also discussed.

INTRODUCTION

One of the most notable and well-established streams of research in Information Systems (IS) over the past four decades has been focused on how and why people adopt information technology. The need to investigate the factors influencing successful adoption arises, in part, due to the complex interplay between people and technology. Technology adoption research, therefore, seeks to clarify the factors that contribute to the success and failure of information systems and technologies (Wills, El-Gayar & Bennett, 2008).

Recently, healthcare has been transferred from hospitals and nursing facilities to the patient home, which leads to what is commonly known as home healthcare. This initiative has been undertaken broadly by healthcare industry in the U.S. to reduce readmission costs and transportation costs, and to improve pos-hospitalization healthcare quality and finally increase patient independency (The Joint Commission, 2011). Moreover, the rapid increase of the older adult population, which is expected to reach 21 percent in the U.S. by 2030 will create new challenges for our society. The growing population of those with disabilities will also create the need for more nursing and home-care services from the healthcare industry (U. S. Census Bureau, 2005).

Today, it is almost unimaginable to consider this home healthcare initiative without information technology. Clinical decision support systems, mobile health systems (mHealth), sensor based monitoring systems (SMS) and longitudinal electronic medical records (EMR's) promise to make clinical information available at the right place and right time, thereby reducing error and increasing safety and quality.

One of these promising technologies is home healthcare robots, which is the focus of this study. It is critical that we understand the factors that influence their adoption. Home healthcare robots that are perceived negatively by stakeholders are no longer applicable like any product or service, customers must be satisfied or they will look elsewhere to fulfill jobs they are interested in completing. Most previous research focused on technical, implementation and algorithmatic design issues (Advait & Kemp, 2010; Choi, Anderson, Glass, & Kemp, 2008; King, Tiffany, Jain & Charles, 2012; Fan, Chen, Fan, Glass & Kemp, 2010). Limited research has focused on user perceptions, needs and requirements of such technology. Thus, this research fills this knowledge gap by leveraging the UTAUT model.

The research makes several contributions to the literature. First, it enables robot designers and service providers to understand what influence stakeholders' decision to adopt home healthcare robots; second, it enriches the literature on technology adoption by extending the related theories to the home healthcare robots domain; third, it enhances the theoretical foundation of home healthcare robots research by innovatively applying technology acceptance models to explain the adoption of this technology.

The remainder of this paper is organized as follows: the next section reviews the related literature. The third section introduces the research model and hypotheses. Section four describes the research method. The fifth reports the analysis of the results and followed by discussion and conclusion in section six, and section seven, respectively.

LITERATURE REVIEW

Home Healthcare Initiative

In this first decade of the 21st century, great attention is being devoted to U.S. society's needs for access to health care and health care delivery. To date, there has been increasingly focus on the transition of care into the home. Health care is coming home. Health care is increasingly occurring in residential settings rather than in professional medical settings (National Research Council, 2010). The Centers for Medicare and Medicaid Services (CMS) estimates that 8,090 home health care agencies in the United States provide care for more than 2.4 million elderly and disabled people annually (Alaiad & Zhou, 2013). By 2020, 70 million elderly people will increasingly need to stay at home rather than in nursing home (Hughes, 2008), technology is helping 80% of seniors to live independently at home out of institutions.

This change in the locus of care needs to be seen in context. In the United States, health care devices, technologies, and care practices are rapidly moving into the home. This transition, which is likely to accelerate in the future, has raised a host of issues that have received insufficient attention in the past such as very few homes have been designed for the delivery of health care, and technologies that are designed for hospitals and clinics can be ill suited for use in the home. However, researchers indicated that many health care treatments that were once offered only in a hospital or a doctor's office can now be done in home. Home health care is usually less expensive, more convenient, and just as effective as care you get in a hospital or skilled nursing facility (National Research Council, 2011).

Home health care is a system of care provided by skilled practitioners to patients in their homes under the direction of a physician. Home health care services include nursing care; physical, occupational, and speech-language therapy; and medical social services. The main goals of home health care services are to help individuals to improve function and live with greater independence; to promote the client's optimal level of well-being; and to assist the patient to remain at home, avoiding hospitalization or admission to long-term care institutions. Common diagnoses among home health care patients include circulatory disease (31 percent of patients), heart disease (16 percent), injury and poisoning (15.9 percent), musculoskeletal and connective tissue disease (14.1 percent), and respiratory disease (11.6 percent) (Hughes, 2008).

In summary, a number of factors are driving the migration of health care practice from professional facilities to the home and, as a result, significantly increasing the numbers of people who must receive health care in the home (National Research Council, 2011):

- The costs of providing health care at formal medical facilities are increasing. Advanced medical technologies and procedures, as well as the training of medical professionals to employ them, can be very expensive.
- Hospitals are discharging patients, including premature infants, sooner into home care, sometimes with complex care regimens.
- The U.S. population is aging, and consequently the demand is growing for various health services (particularly related to conditions associated with aging). At the same time, people are focusing increasingly on overall wellness and quality of life, even into advanced age.
- The prevalence of chronic conditions across the entire age spectrum is growing (particularly conditions related to obesity, such as diabetes), and growing along with it is the demand for health care. More people are living longer with increasingly complex medical and social needs.
- Larger numbers of veterans are surviving military conflicts and returning home to live with disabilities.
- People who may have had a rapidly fatal illness years ago, such as a heart attack or AIDS, are instead now living with longer chronic illnesses, such as congestive heart failure or HIV.
- Some types of health care professionals are in short supply, which shifts the burden of some types of care onto lay caregivers to fill the gap.
- Consumers want to be independent in their health management and are seeking more home-based services.
- Innovations in information technology, along with consumer demands for more health care quality and personal independence, are shifting the focus from health care providers, procedures, and prescriptions onto consumers and how they can manage care at home.

Home Healthcare Robots

Robots can be defined as machines that can be used to do jobs, according to NASA. Some robots can do work by themselves. Others must always have a person telling them what to do. When these jobs are related to home healthcare, then it is called home healthcare robot. Robots are being used for a wide range of jobs in home healthcare. Table 1 provides a summary of these jobs.

➢ Monitoring personal health and safety such as monitoring blood pressure, blood sugar, and body temperature, monitoring of injuries, following-up with the family, and detecting people lying on the floor and call doctor for help.
➢ Providing medication management and scheduling such as medicine preparation and reminder
➢ Helping in physical therapy such as rehabilitating from leg/hand illness through the use of a wearable leg robot for mobility enhancement.
➢ Facilitating communication with doctor/physician and enable submission for the medical data into a centralized medical IT system over wireless network (WLAN) so that doctor can access and see the data remotely.
➢ Helping in cognitive and occupational therapy (e.g. Paro improves the bad mood).
➢ Helping in nurse tasks such as keep monitoring the blood pressure and bed bath.

Table 1. Common Home Healthcare Robots Jobs and Tasks

In the last few years, home healthcare robots have started helping professionals including nurses, doctors, therapists and physicians provide home health cares and services to their patients in several forms. Our research focuses on two main popular home healthcare robots, namely; remote presence robots RP (Intouch, 2013) and Paro robots (Wada, Shibata, Musha & Kimura, 2008). Professionals (e.g. physicians) at one location are able to take care of remote patients at different locations (e.g. home) by using remote presence robot which provides direct access to the patient in emergency cases especially in rural areas and provides diagnostic capabilities through the use of camera, remote control, speaker, light, ultra sound and EMR access. For those patients who are suffering from cognitive disabilities, a paro robot (friendly looking pet robot) can be used to increase positive mood, decrease the feeling of loneliness, alleviate stress and the feeling of social connectedness. Such a robot can respond to petting by moving its tail and opening and closing its eyes. It can show emotions such as happiness, getting surprised and even anger. It can produces sound similar to a real baby seal active during the day and asleep at night. Doctors/Therapists can teach patients on how to use the Robots at home to achieve better cognitive skills instead of using traditional therapies.

Technology Acceptance Theories

Technology acceptance is defined as "an individual's psychological state with regard to his or her voluntary or intended use of a particular technology" (Gattiker 1984). Technology acceptance research has been profoundly impacted by the theories of individual human and social behavior emerging from the disciplines of psychology and sociology. With its origin in the area of social learning, Social Cognitive Theory (SCT) is focused on the process of knowledge acquisition through observation (Bandura, 1986) . This theory was expanded and became known as SET, or Self-Efficacy Theory (Bandura, 1977). (Fishbein & Ajzen, 1975) publish their research on the Theory of Reasoned Action (TRA). The theoretical basis for TRA lies in the tenets of social psychology, and has been widely accepted as a foundational theory of human behavior.

Theory of Planned Behavior (TPB) emerges as an extension of TRA with perceived behavioral control from SET as an additional determinant of intention (Ajzen & Fishbein, 1980). (Thompson and Howell, 1991) published an alternative to TRA and TPB, the Model of PC Utilization (MPCU). This theory too has its roots in psychology. The Technology Acceptance (TAM) model represents the first theory developed specifically for the IS context, i.e. people in business (Davis, 1989). A few years later, (Taylor & Todd, 1995) put forth their theory, known as Combined TAM-TPB, or C – TAM – TPB. This theory of technology acceptance combined the predictive elements of TPB with the concept of perceived usefulness from TAM. TAM was further extended to TAM2, and included subjective norm as a predictor in settings where use is mandatory (Venkatesh & Morris, 2000).

The most recent model to emerge from this long line of study is known as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, David & Davis, 2003). The UTAUT has been studied in at least six organizations and found to explain roughly 70% of the variance in user intention to use information systems. The UTAUT integrates eight user acceptance models: TRA, TPB, TAM, TAM2, IDT, MM, PCI, MPCU, and finally, social cognitive theory (SCT). Each of these models has usage intention or actual usage as the dependent variable.

RESEARCH MODEL AND HYPOTHESES

The UTAUT attempts to explain usage intention, as well as subsequent usage behavior. The theory suggests that four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of usage intention and behavior. In addition, gender, age, experience, and voluntariness of use will mediate the impact of the four constructs on usage intention and usage behavior (Venkatesh, 2003). The comprehensiveness, suitability, validity, reliability and a accuracy of the model have been demonstrated in different contexts (AlAwadhi & Morris., 2008) . Thus, our research model for determinants of usage intention is shown in figure 1.

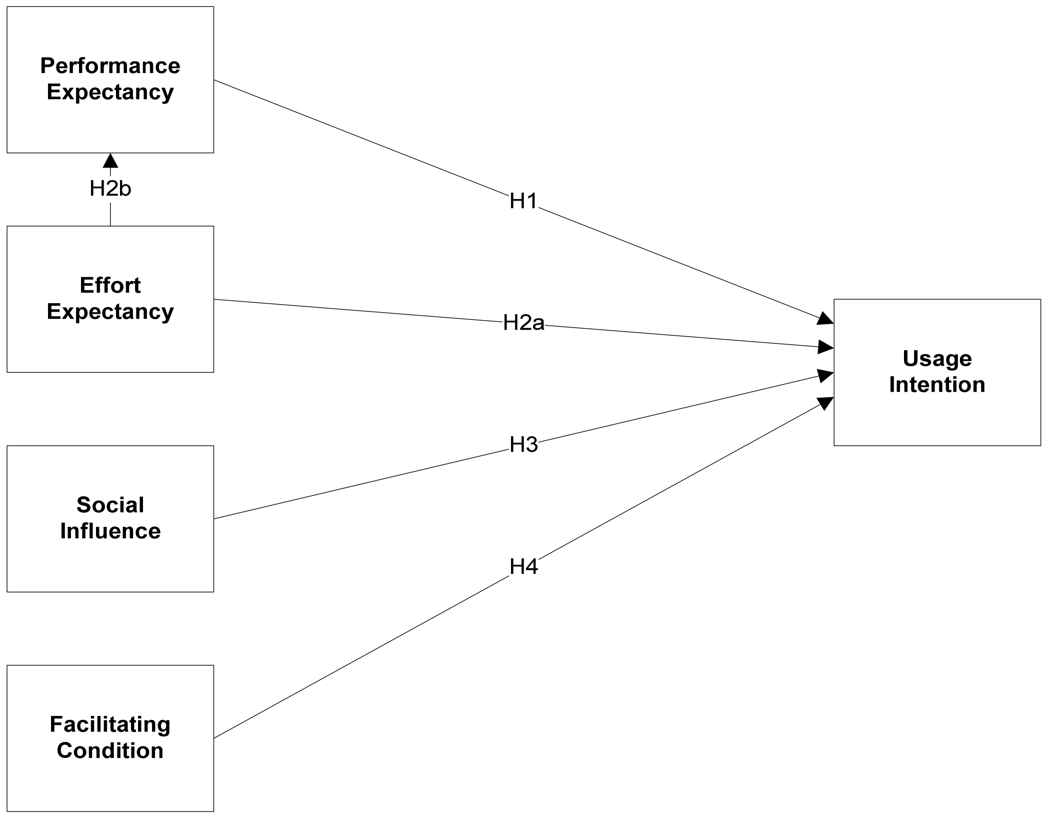

Figure 1. The Research Model

Usage intention is the dependent variable, which relates to the way(s) stakeholders intend to use home healthcare robots. Usage intention is a predictor of actual use, which is in turn influenced by performance expectancy, effort expectancy, social influence, and facilitating condition.

Performance Expectancy

Performance expectancy can be defined as the extent to which stakeholder believes that using home healthcare robots will help him/her improve job performance. The following five constructs, taken from the eight models, capture the concept of performance expectancy: perceived usefulness (TAM/TAM2 and C-TAMTAB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectations (SCT) (Venkatesh, 2003). In addition, it has been demonstrated that performance expectancy is the strongest predictor of usage intention of IT (Venkatesh, 2003). Adapting performance expectancy to home healthcare robots suggests that stakeholders think home healthcare robots are beneficial in that they can help them get better/ a raise, improve overall productivity and perform tasks/ treatments quickly and flexibly , or access services effectively. There is also extensive empirical evidence that supports the significant effect of performance expectancy on usage intention (Alshehri & Drew, 2012; Wills, El-Gayar, & Bennett, 2008). Thus, we put forward the following hypothesis:

***H1**: Performance expectancy has a positive effect on stakeholders' usage intention of home healthcare robots.*

Effort Expectancy

Effort expectancy is defined as the degree of ease stakeholder feels with respect to the use of home healthcare robots (Venkatesh, 2003). The three constructs that relate to effort expectancy are perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT) (Venkatesh, 2003). We believe that stakeholders adoption of home healthcare robots depends on whether home healthcare robots are easy to use. There is also extensive empirical evidence that supports the significant effect of effort expectancy on usage intention directly (Kijsanayotina, Pannarunothaib & Speediec, 2009) or indirectly through the performance expectancy (Chaua, & Hu, 2002).Thus, we posit the following hypothesis:

***H2a**: Effort expectancy has a positive effect on stakeholders' usage intention of home healthcare robots.*
***H2b**: Effort expectancy has a positive effect on stakeholders' performance expectancy of home healthcare robots.*

Social Influence

Social influence is defined as the extent to which stakeholder perceives that significant others believe he or she should use home healthcare robots (Venkatesh, 2003). Three constructs capture the concept of social influence, namely, subjective norm (TRA, TAM2, TPB and C-TAM-TPB), social factors (MPCU), and image (IDT) (Venkatesh, 2003). Prior studies suggest that social influence is significant in shaping an individual's intention to use new technology (Taylor, 1995; Thompson, Higgins & Howell, 1991). We believe that other people such as friends, relative and peers in the society may influence the stakeholder' decision to use home healthcare robots. Therefore, we propose the following hypothesis:

***H3**: Social influence has a positive effect on stakeholders' usage intention of home healthcare robots.*

Facilitating conditions

Facilitating condition can be defined as the degree to which stakeholder believes that an organizational and technical infrastructure exists to support use of home healthcare robots. This definition captures concepts embodied by three different constructs: perceived behavioral control, facilitating conditions, and compatibility. Each of these constructs was operationalized to include aspects of the technological and/or organizational environment that are designed to remove barriers to use (Venkatesh, 2003). (Thompson, Higgins, & Howell, 1991) stated that providing support for PC users may be one type of facilitating condition that influences system utilization. By training users and assisting them when they encounter difficulties, some of the potential barriers to use can be alleviated or eliminated. There is also extensive empirical evidence that supports the significant effect of facilitating condition on usage intention (Zhou, 2012). Thus, we expect that stakeholders' perceived facilitating resources, including technical, organizational, time and money, will influence their intention to use the applications of home healthcare robots.

***H4**: Facilitating conditions have a positive effect on stakeholders' usage intention of home healthcare robots.*

METHOD DESIGN

Data Collection

A questionnaire is employed in this study to collect empirical data. The questionnaire instrument is one of the most common tools of technology adoption as it uses a set of specific questions to cover the study topic and to target a large number of participants in a practical and efficient way. The proposed model includes five constructs and each construct is measured with multiple items. All construct items were adapted from Venkatesh (2003). The questionnaire instrument collects additional information such as gender, education, age and robot knowledge. All questionnaire items were measured using a 7-point Likert scale, ranging from "strongly disagree" to "strongly agree".

The sample for this study consists of potential stakeholders of home healthcare robots: patients and professionals. The professionals include nurses, doctors, physicians, technicians and therapists, please see Table 1. Two online versions of the questionnaire were developed relevant to the target stakeholders (one for patients and the other for professionals). Each questionnaire has four main parts: introduction to home healthcare robots, demographic information, robot opinion questions and robot knowledge level. The patient questionnaire items are listed in Appendix A. The questionnaires were distributed to the participants randomly selected from a mid-sized university on the east coast and online healthcare communities. A total of 90 questionnaires were returned, and 64 (71.1%) were considered complete and valid.

Data Analysis

Partial least squares (PLS) was selected for data analysis in this study applying smartPLS software. A number of recent technology acceptance studies have utilized PLS, such as (Wills, El-Gayar & Bennett, 2008; Kijsanayotina, Pannarunothaib & Speediec, 2009). To evaluate the measurement model, PLS estimates the internal consistency for each block of indicators. PLS then evaluates the degree to which a variable measures what it was intended to measure. This evaluation is comprised of convergent and discriminate validity. Following Gefen and Straub (2005), convergent validity of the variables is evaluated by examining the *t*-values of the outer model loadings. Discriminate validity is evaluated by examining item loadings to variable correlations and by examining the ratio of the square root of the AVE of each variable to the correlations of this construct to all other variables. For the structural model, path coefficients are interpreted as regression coefficients with the t statistic calculated using bootstrapping, a nonparametric technique for estimating the precision of the PLS estimates. To determine how well the model fits the hypothesized relationship PLS calculates an R^2 for each dependent construct in the model. Similar to regression analysis, R^2 represents the proportion of variance in the endogenous constructs which can be explained by the antecedents.

RESULTS

Sample Profile

Table 2 provides a general demographic overview of the stakeholder subjects who participated in this study in terms of gender, age, education level, and stakeholders category.

Variable		Frequency	Percent
Gender	Male	42	65.6
	Female	22	34.4
Age	18 - 33	51	79.68
	34 - 49	9	14
	50 +	4	6.25
Education Level	High school degree or equivalent (e.g., GED)	8	12.5
	Some college but no degree	4	6.25
	Associate degree	7	10.93
	Bachelor degree	15	23.8
	Graduate degree	30	46.8
Stakeholder category	Patients	43	67.18
	Professionals (doctor, physician, nurse, technician and managerial)	21	32.81

Table 2: Sample Characteristics

As shown in Table 2, the majority of the participants is male (65.6%), 18-33 old (79.68%) and have a graduate degree (46.8%). About 67.18% of the participants are patients and 32.81% are professionals. All the participants use the Internet and computer several times a day. Table 3 summarizes the participants' knowledge levels on robots. It is shown that most participants have heard about robots, but few have actual experience of using them.

	Not sure what it is	Never heard about	Have only heard about or seen this robot	Have used or operated it only occasionally	Have used or operated it frequently
Home healthcare robot (e.g. Paro)	19.4%	29%	**50%**	1.6%	
Surgical Robot (e.g. daVinci surgical system).	19.4%	21%	**51.6%**	8.1%	
Robot lawn mower	16.1%	32.3%	**46.8%**	4.8%	
Space exploration robot (e.g. Mars Rover)	9.7%	12.9%	**71%**	4.8%	
Manufacturing robot (e.g. robotic arm in factory)	4.8%	16.1%	**71%**	3.2%	4.8%
Entertainment/toy robot (e.g. Aibo, Furby)	8.1%	17.7%	**40.3%**	30.6%	3.2%
Unmanned Aerial Vehicle (UAV)	9.7%	24.2%	**62.9%**	3.2%	
Military Robot (e.g. search and rescue)	6.5%	12.9%	**79%**	1.6%	
Robot security guard	12.9%	40.3%	**45.2%**	1.6%	
Domestic/Home robot (e.g. Roomba)	9.7%	30.6%	**54.8%**	3.2%	1.6%
Personal Robot 2 (PR2)	22.6%	37.1%	**35.5%**	1.6%	
Autonomous Car	14.5%	14.5%	**66.1%**	1.6%	1.6%
Research robot (e.g. at university or company)	17.7%	24.2%	**54.8%**	3.2%	
Remote presence robot (e.g. remote doctor)	9.7%	25.8%	**58.1%**	6.5%	

Table 3: Level of Robot Knowledge

Measurement Model Validation

Table 4 summarizes the results for the items comprising the model. The results show acceptable convergent validity to all the constructs except facilitating condition. All item loadings are significant. Except for facilitating condition, all AVEs are above 0.5, all CRs are above 0.7 and all alpha values are larger than 0.7, showing good reliability. Therefore, the results support the convergent validity of all the scales except facilitating condition but we will keep it for the purpose of this study since its values close to the minimum (Gefen & Straub, 2005).

	Individual Item	Item Loading	AVE	Composite Reliability CR	Cronbachs Alpha
Performance Expectancy	PE1	0.9054	0.8112	0.945	0.9225
	PE2	0.8687			
	PE3	0.9312			
	PE4	0.8962			
Effort Expectancy	EE1	0.8423	0.7329	0.9163	0.8809
	EE2	0.9185			
	EE3	0.8653			
	EE4	0.7935			
Social Influence	SI1	0.8891	0.6639	0.886	0.829
	SI2	0.908			
	SI3	0.7874			
	SI4	0.6485			
Facilitating Condition	FC1	0.2152	0.3757	0.5666	0.5464
	FC2	0.3832			
	FC3	0.9665			
Usage Intention	UI1	0.9439	0.8771	0.9554	0.93
	UI2	0.9354			
	UI3	0.9302			

Table 4: Item Loadings, AVE, Composite Reliabilities (CR) and Alpha

Discriminate validity is confirmed if the square root of AVE are significantly higher than correlations between constructs in the corresponding rows and columns. As shown in Table 5 the instrument demonstrates adequate discriminate validity as the AVE (bold) are greater with respect to the corresponding correlation values in the adjoining columns and rows.

	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Condition	Usage Intention
Performance Expectancy	**0.9006**				
Effort Expectancy	0.4968	**0.8560**			
Social Influence	0.6059	0.4493	**0.8148**		
Facilitating Condition	0.3431	0.2984	0.4521	**0.6129**	
Usage Intention	0.6313	0.6645	0.6163	0.3119	**0.9365**

Table 5: AVE Scores and Correlation of Latent Variables.

Testing the Structural Model

Figure 2 depicts the structural model showing path coefficients and R^2. The R^2 value for the usage intention indicates that the model explained 50.8% of the variance. R^2 for performance expectancy indicates that effort expectancy explained 44.2% of the variance. The bootstrap method was used in smartPLS to assess the statistical significance of the path coefficients.

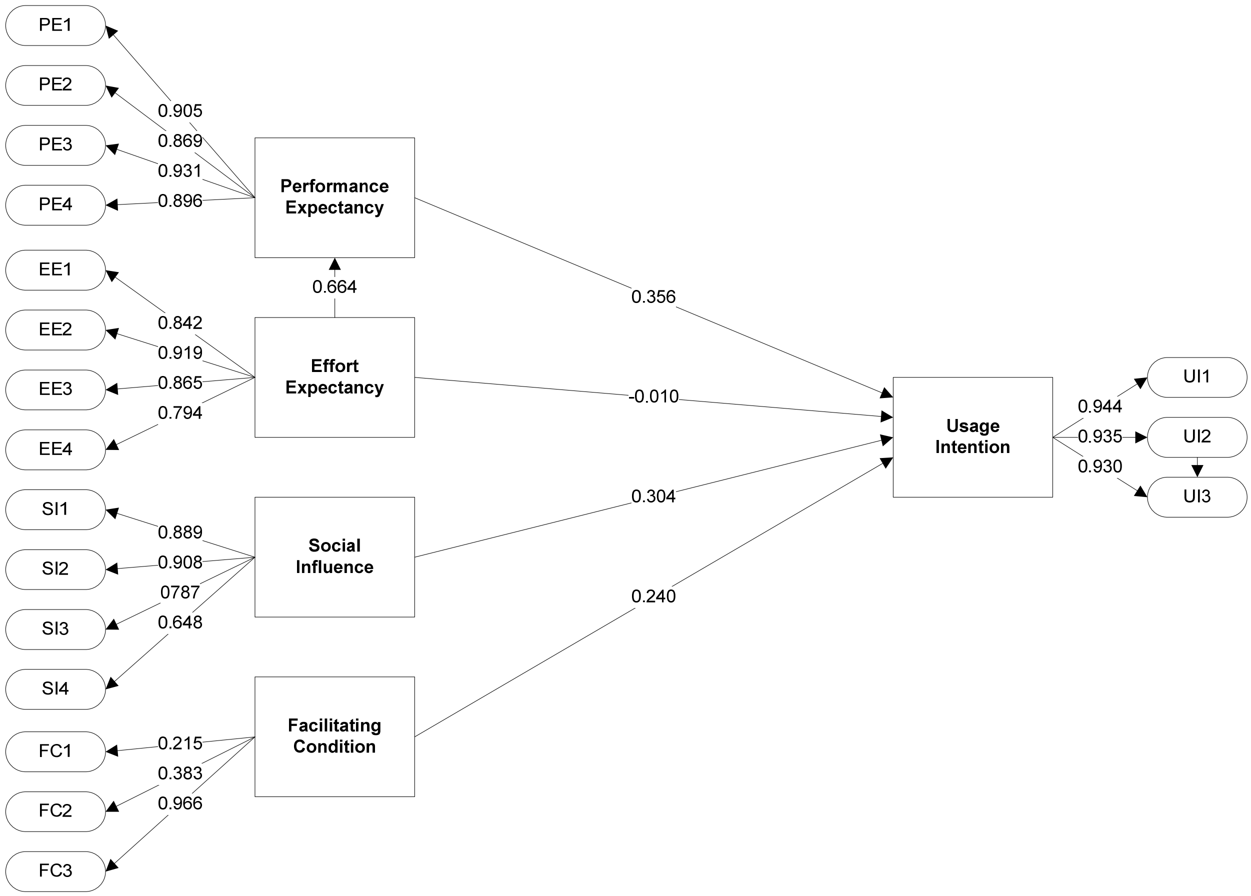

Figure 2. Model Testing Results

As shown in Table 6, performance expectancy (PE) positively predicted usage intention (0.3564, $p < 0.001$); therefore, H1 was supported. Second, social influence (SI) significantly predicted usage intention (0.3036, $p < 0.001$); therefore, H3 was supported. Third, facilitating condition positively predicted usage intention (0.2397, $p < 0.05$); therefore, H4 was supported. In summary, four hypotheses representing the relationship between performance expectancy, effort expectancy (indirectly), social influence, facilitating condition, and usage intention were supported in this study. However, the proposed direct effect of effort expectancy on usage intention was not supported. In other words, effort expectancy was not found to have a direct impact on usage intention of home healthcare robots, but have an indirect effect through performance expectancy (.6645, $p< 0.001$).

Hypothesis	Standardized path coeffecient	T Statistics	
Performance Expectancy -> Usage Intention	0.3564	3.8967	Supported
Effort Expectancy -> Usage Intention	-0.0098	0.1003	Not Supported
Effort Expectancy -> Performance Expectancy	0.6645	9.226	Supported
Social Influence -> Usage Intention	0.3036	3.4791	Supported
Facilitating Condition -> Usage Intention	0.2397	2.1507	Supported

Table 6: Structural Model Results

DISCUSSION

This study sought to identify factors that predict the stakeholders' usage intention of home healthcare robots by applying the UTAUT model. The results show that usage intention of home healthcare robots is a function of the perception that home healthcare robots are useful (i.e., performance expectancy), that important others believed that he/she should use them (i.e., social influence) and the perception that one has the sufficient knowledge and technological resources (i.e., facilitating condition). The predictive power of these factors was substantial and accounted for more than half of the variance in the usage intention of home healthcare robots.

Among these four influencing factors, performance expectancy was by far the strongest predicting factor. This result is consistent with that of a number of prior studies (Kijsanayotina, Pannarunothaib & Speediec, 2009; Venkatesh, 2003). Performance expectancy is likely to exert a great influence than effort expectancy and social influence on a stakeholders' usage intention of home healthcare robots. Stakeholders apparently tend to be pragmatic in their technology acceptance decisions, focusing on usefulness in technology assessment. That is, a stakeholder is likely to adopt the technology when it is considered to be useful to his or her practice. For professionals, the technology may help to increase their job productivity, gets a raise and finish tasks quickly. For patients, the technology may enable them to get treatment more quickly, get better soon and improve daily life effectiveness.

Effort expectancy seems to have no direct effect on usage intention of home healthcare robots. This is consistent with the results of some prior studies (Zhou, 2012, Chau & Hu, 2002). One explanation is that our sample is composed of a large percentage of knowledgeable stakeholders with the robot technologies, as showed in Table 1. They have relatively high self-efficacy and working with home healthcare robots poses no difficulty to them. The professionals have relatively high general competence and mental/cognitive capacity and thus may comprehend the use of the technology quickly; that is, become familiar with its operations without going through the intense training. Furthermore, professionals in many cases have relatively strong staff support for operating medical equipment and related technologies. Together, these factors might have contributed to less weight on effort expectancy. However, effort expectancy indirectly affects usage intention through performance expectancy. Thus, performance expectancy mediates the effect of effort expectancy on usage intention.

Social influence was also found to have a significant effect on usage intention. This shows that stakeholders will conform to important peers' opinions when considering the adoption of home healthcare robots. They are likely to develop dependent evaluations and consequently may place high weight on others' opinions. The finding suggests that home healthcare agencies can encourage early adopters to invite their friends and colleagues to adopt the technology. They can use incentives such as awards and membership levels to promote these early adopters' recommendation.

Facilitating conditions, which measure whether stakeholders have resources and knowledge necessary to use home healthcare robots, have a significant effect on usage intention. Thus home healthcare agencies need to reduce the cost of using robots and equip the potential stakeholders with the knowledge necessary for leveraging such an emerging service. For instance, home healthcare agencies can use propaganda, training sessions and online help tutorial to increase stakeholder understanding of the technology. On the other side, professionals responded to this study generally seem to have the competence, learning capability, and access to the technical support, which paves the way for robot adoption.

This research has multifold theoretical and practical implications. Theoretically, the research provides a model that explains the adoption of home healthcare robots, which not only enhances the theoretical foundation for the home healthcare robot research, but also expands the applicability of technology adoption theory to the domain of home healthcare robots. Further, we provided empirical evidence for the efficacy of the constructs in home healthcare robot adoption.

In practice, the knowledge acquired from this study can potentially benefit both robot designers and the service provider. The strong influence of performance expectancy on the adoption of home healthcare robots suggests that work-related benefits of implemented robots must be perceivable, identifiable and substantial, and favorable perception of the robots' usefulness is crucial, whereas the ease of use might not be of equal importance to robot adoption. Once deciding to adopt robots technology, service providers should strongly emphasize, demonstrate and communicate the technology's usefulness for routine tasks and services. Thus, initial information sessions and training programs should focus on how the technology can improve the efficiency or effectiveness of stakeholders. An awareness of these effects on the robot adoption can help develop and accelerate the process of implementation. Social influence does affect the adoption of home healthcare robots. Therefore, it is important to identify individuals with strong personal influence (formal and informal) and work with them to become advocates for home healthcare robots' use in order to facilitate the implementation process. Adequate facilitating conditions (continuous training and technical support to users) also play an important role in home healthcare robots adoption. Fostering an environment, both from top-down and bottom-up perspectives, where use of technology is desirable, and that maintains the perception that use is a choice, could do much to facilitate the implementation process.

This research has several limitations, including small sample size, moderate AVE, CR and Alpha of the facilitating condition construct, and lack of consideration of unique characteristics of healthcare robots in introducing research constructs. In the future, more samples will be incorporated into the research such as more actual users, and domain-specific constructs such as trust will be introduced into the research model. In addition, possible mediating effects of gender, age, and culture warrantee future investigation. Exploring the differences in the adoption between professionals and patients.

CONCLUSION

This research is attempted to explain stakeholders' usage intention of adopting home healthcare robots. The research model is developed based on UTAUT. The results show that performance expectancy, social influence, and facilitating condition are directly associated with, and effort expectancy is indirectly associated with, stakeholders' usage intention of adopting home healthcare robots. These findings have implications for the design and implementation of home healthcare robots.

APPENNDIX A

The following is part of our survey questionnaires.

Questionnaire Items
1. I would find home healthcare robots useful in my home.
2. Using home healthcare robots would enable me to get treatment more quickly.
3. Using home healthcare robots would increase my effectiveness in the life.
4. Using home healthcare robots would increase my chances of getting better.
5. My interaction with home healthcare robots would be clear and understandable.
6. It would be easy for me to become skillful at using home healthcare robots.
7. I would find home healthcare robots easy to use.
8. Learning how to use home healthcare robots would be easy for me.
9. People who influence my behavior think that I should use home healthcare robots for better health.
10. People who are important to me think that I should use home healthcare robots for better health.
11. People whose opinions that I value prefer that I should use home healthcare robots for better health.
12. I will have the technological resources necessary to use home healthcare robots at my home (e.g. internet connection).
13. I will have the knowledge necessary to use home healthcare robots (e.g. IT background).
14. Home healthcare robots are compatible with other technologies I use in my house (e.g. internet).
15. A specific person (or group) should be available when I have difficulties using the robots.
16. Given the chance, I intend to use home healthcare robots in the near future.
17. Given the chance, I predict I would use home healthcare robots in the near future.
18. Given the chance, I plan to use home healthcare robots in the near future.

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