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ABSTRACT

The home healthcare initiative aims to reduce healthcare cost, improve post-hospitalization healthcare quality and increase patient independency. Information technologies such as home healthcare robots are expected to play a major role in this effort. There have been some preliminary findings on the socio-technical determinants of robot adoption in home healthcare. However, there is a lack of understanding of other factors that moderate the effects of these determinants. To this end, this research aims to investigate demographic characteristics as possible moderators for robot adoption based on the UTAUT model. By analyzing the data collected from a survey, this study empirically demonstrates the moderating effects of gender, age and experiences on the adoption of home healthcare robots. In addition, the findings of this research lead to the development of a decision tree that can guide a cost- effective robot design. The paper concludes with the theoretical and practical implications of this research.

Keywords

Home healthcare, robots, demographic characteristics, UTAUT model.

INTRODUCTION

Addressing the healthcare cost burden is a major policy priority in the US. Healthcare accounts for a remarkably large slice of the U.S. economic pie; each year health-related spending grows, outpacing spending on other goods and services. The share of the economy devoted to healthcare accounted for 17.9 % in 2010, the highest among the world's industrialized nations (Squires, 2012). A rise in the instances of chronic disease and administrative costs are the major driving factors for cost growth in the US. Among the recent nation's efforts to control cost growth is the desire to refocus healthcare delivery systems to be patient-centric. A part of this effort is to transfer healthcare from hospitals and nursing facilities to the patient's home (National academies of science, 2010). Considered one of the most effective initiatives, the move toward home healthcare has been undertaken broadly by the healthcare industry in the US, not only to control healthcare spending through reducing readmission costs and transportation costs, but also to improve post-hospitalization healthcare quality and increase patient independence (Ellenbecker, Samia, Cushman and Alster., 2008).

Today, it is almost unimaginable to consider this initiative without current information technology. Home healthcare robots (HHRs) are one of emerging technologies that hold the potential to make clinical information available at the right place and at the right time, thereby reducing human error and increasing safety and quality. In the last few years, HHRs have started helping medical professionals provide home health care and services to their patients in a variety of forms such as monitoring personal health and safety and assisting in psychological well-being. HHRs play a key role in the success of the home healthcare initiative and the reduction of overall healthcare cost. HHRs aim to help individuals to improve function and live with greater independence, promote the client's optimal level of well-being, and assist the patient in remaining at home, avoiding hospitalization, or admission to long-term care institutions (Ellenbecker et al, 2008).

Despite the promise of HHRs as key facilitators for home healthcare success and reducers for overall healthcare costs, research has repetitively shown that more than 40% of information technology (IT) developments in various sectors including the health sector have failed or been abandoned (Heeks, 2002). One of the major factors leading to failure is the inadequate understanding of the socio-technical aspects of IT, particularly the understanding of how people and organizations adopt information technology (Berg, Aarts and Van Der Lei, 2013). In addition to this is a lack of understanding of the moderating impact of different demographic factors such as age, gender, and experiences on the adoption of IT. In the context of HHRs, understanding how demographics play a role in adoption is key to identifying robot success as patients play increasing roles in managing their own health in this smart robotic environment. In particular, such understanding is important for the effective implementation of smart robotic technology in patients' homes as different users with different demographic profiles are likely to perceive HHRs technology differently. At present, this issue remains unaddressed in the HHRs' adoption literature. Therefore, this research aims to fill this knowledge gap by answering the following research question: What are the moderating factors for the adoption of HHRs? We answer this research question by adapting the UTAUT model to HHRs. In addition, this research builds on and extends previous studies that have identified the determinants of adoption of HHRs.

The research makes several contributions to the literature. First, to the best of our knowledge, this is the first quantitative study that provides empirical evidence for moderating factors in the adoption of HHRs; second, it provides an understanding of how gender, age, and experiences impact the adoption of HHRs, which can be used by robot designers to better support users' needs and expectations for cost-effective robot design; and third, it enhances the theoretical foundation of HHRs research by validating UTAUT's propositions on moderators in the home healthcare domain.

The remainder of this paper is organized as follows: the next section provides an overview of home healthcare and HHR technology. The third section introduces the research model and hypotheses. Section four describes the research methodology. The fifth section reports the results followed by discussion and conclusion in sections six and seven.

BACKGROUND

Home Healthcare

There has been an increased focus on the transition of healthcare into the home. The rapid increase of the older adult population, which is expected to reach 21 percent in the U.S. by 2030, the growing population of those with disabilities (ACS, 2013) and the unequal ratio between medical staff and patients will create the need for more nursing and home-care services from the healthcare industry (AHIP center for policy and research, 2010).

Home healthcare can be defined as a system of care provided by skilled practitioners to patients in their homes under the direction of a physician (Ellenbecker et al., 2008). Home healthcare services include nursing care, physical, occupational, and speech-language therapy, and medical social services. In addition to its main vision to reduce healthcare costs through reducing readmission costs and transportation costs, it aims also to improve post-hospitalization healthcare quality and increase patient independency (Ellenbecker et al., 2008).

Healthcare delivery systems are rapidly changing, and individuals are assuming an increasing role in the management of their own health. In this environment, individuals are expected to perform a range of healthcare tasks and interact with a vast array of medical devices and technologies in residential settings (LaPlante, Hendershot, and Moss , 2013). Home healthcare therefore requires the use of IT, both by caregivers and by care recipients.

Much of the medical equipment and technology now used in homes were designed by device manufacturers to be used only in clinical settings by trained healthcare caregivers (U.S. food & drug administration, 2010). As a result its migration to the home poses many challenges to both caregivers and care recipients (Rialle, Duchene, Noury, Bajolle, and Demongeot, 2002) because such equipment was not generally designed with the limitations of patients in mind and home environment differs in significant ways from the controlled environment of the hospital or clinic (Anthony and Milone-Nuzzo, 2005) as shown in Table 1. These developments also pose a challenge to the medical technology industry, which must take into account socio-technical, contextual, moderating and other human factors when designing medical technology for use in the home (Aarts and Gorman, 2007). This paper focuses on moderators' impact on HHRs adoption, which thus far has been unaddressed in the HHRs literature.

➢ Nurses work alone at home with support resources available from a central office while they collaborate with physicians, doctors and other professionals in the hospital settings.
➢ The nurse-physician work relationship involves less direct physician contact at home settings than that in the hospital settings.
➢ The physician relies to a greater degree on the nurse to make assessments and communicate findings in the home settings in comparing with the hospital settings.
➢ Home healthcare nurses spend more time on paperwork than hospital nurses and more time dealing with reimbursement issues.

➢	In the home settings, there is high degree of patient autonomy comparing with that in the hospital settings.
➢	In the home settings, limited oversight of informal caregivers by professional clinicians.

Table 1. A Comparison between Home Healthcare and Hospital Care Settings

Home Healthcare Robots: Tasks and Roles

Robots have several domain applications: manufacturing, military, agriculture, exploration and recently medical and healthcare applications. NASA defines Robots as machines that can be used to do the jobs performed by humans. When these jobs are related to home healthcare, they are termed home healthcare robots (HHRs). HHRs are being used for a wide range of jobs in home healthcare as summarized in Table 2.

➢	Monitoring personal health and safety such blood pressure, blood sugar, body temperature, and injuries, and detecting people lying on the floor.
➢	Providing medication management and scheduling such as medicine preparation and reminders to take medicine.
➢	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 enabling submission for the medical data into a centralized medical IT system over wireless network (WLAN) so that doctor can access and check the data remotely.
➢	Helping in cognitive and occupational therapy such as Paro (Wada, Shibata, Musha, and Kimura, 2013) which is used for psychological well-being .
➢	Helping in nursing tasks such as bed RIBA (Mukai, Hirano and Nakashima, 2010), which helps lift patients in and out of the bed.

Table 2. HHRs Tasks and Roles

Recently, several HHRs have been developed such as Tele robot (Michaud, Boissy and Labonte, 2007), Robo robot (Smarr, Fausset, and Roger, 2010), Skillegent robot, Pearl and Wakamuru (Smarr et al., 2010). Given the diverse applications of HHRs, we only focus on two HHRs in this paper: remote presence robots (RP) (In touch health, 2013) and Paro robots (Wada et al., 2013). Professionals (e.g. physicians) at one location are able to take care of remote patients at different locations (e.g. home) by using RP robots, which provide direct access to the patient in emergency cases, especially in rural areas, and provides diagnostic capabilities through the use of a camera, sensors, remote control, speaker, light, ultra sound and EMR access (Figure 1).

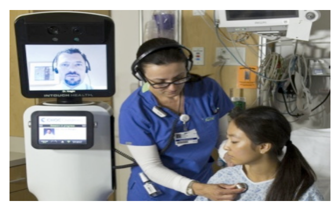

Figure 1. RP Robot

For those patients who are suffering from cognitive disabilities, the Paro robot (friendly looking pet robot) can be used to increase positive mood, decrease the feeling of loneliness, alleviate stress, and increase a feeling of social connectedness. The Paro responds to touch by moving its tail and opening and closing its eyes. It can show emotions such as happiness, surprise and even anger. It can produce a sound similar to a real baby seal that is 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 (Figure 2).

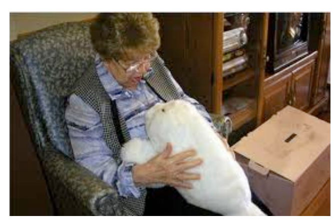

Figure 2. Paro Robot

Most previous HHRs research has focused on technology development and technical implementation with limited discussion of the impact of demographic factors on the adoption of HHRs.

RESEARCH MODEL AND HYPOTHESES

Traditionally, acceptance models have been used to help explain and predict the facilitators and barriers of adoption of new technologies. Venkatesh (2003) closely examined eight adoption theories and combined the relevant constructs from them (Fishbein et al., 1975; Davis, 1989) under one model, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, and Davis, 2003). This research adapts the UTAUT model as the theoretical foundation and focuses primarily on moderator effects on the adoption of HHRs. To this end, we develop a research model (Figure 3) and propose four research hypotheses as described next.

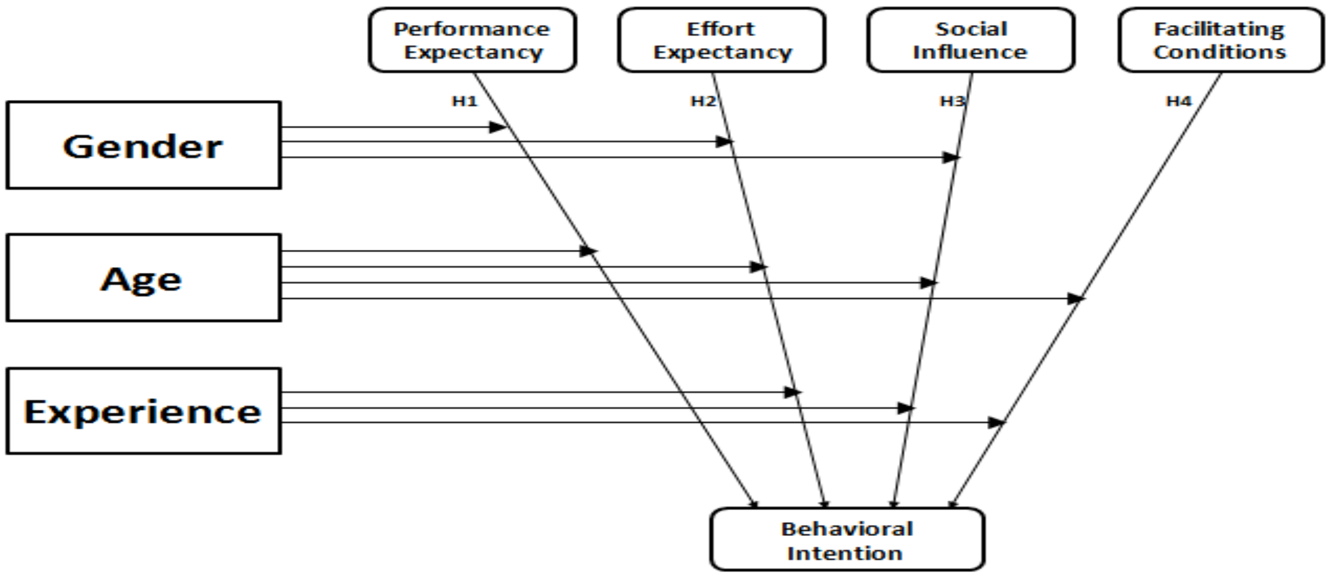

Figure 3. Research Model

Performance expectancy is defined as the "degree to which an individual believes that using the HHRs will help him/her to attain gains in job performance" (Venkatesh et al., 2003). This construct has been modified to fit according to gains in standard of living/quality of life due to the use of HHRs. Performance expectancy is not only found to be the strongest determinant of intention but also moderated by age and gender (Anderson and Schwager, 2004; Alshehri, Drew, Alhussain, and Alghamdi, 2012). Research on gender differences indicates that men tend to be highly task-oriented and therefore performance expectancies, which focus on task accomplishment, are likely to be especially salient in men (Bem, 1981). Moreover, gender roles have a strong psychological basis and are relatively enduring, yet open to change over time. Similarly, research on task-related attitudes suggests that younger men place more importance on extrinsic rewards (Venkatesh et al., 2003). In addition, the importance of task-related factors may change significantly (e.g. become supplanted by family responsibilities) for women between the time that they enter the labor force and the time they reach childrearing years. Thus, we propose the following hypothesis about HHRs:

***H1**: The influence of performance expectancy on behavioral intention to adopt HHRs will be moderated by gender and age, such that the effect will be stronger for men and particularly for younger men.*

Effort expectancy is described as the "degree of the ease of use of the HHRs" (Venkatesh et al., 2003). Age and gender are found to moderate the relationship between effort expectancy and behavioral intention (Anderson et al., 2004). Gender differences could be driven by cognitions related to gender roles that are enforced from birth according to gender schema theory (Bem, 1981). Effort expectancy for adopting HHRs is more salient for women than for men. Increased age is associated with difficulty in processing complex tasks and allocating attention to information on tasks, therefore effort expectancy would be stronger determinant for older workers which may be generalized to HHRs. Thus, we predict the following:

***H2**: The influence of effort expectancy on behavioral intention to adopt HHRs will be moderated by gender and age, such that the effect will be stronger for women, particularly older women.*

Social influence refers to the "degree to which an individual perceives that people s/he considers important believe that the individual should also use the HHRs" (Venkatesh et al., 2003). Due to social perception of HHRs – from the number of people using them to their reputation, an individual can be significantly influenced in his/her decision to use them. Women are predicted to place more importance on social influence than men due to psychological differences (i.e. sensitivity, emotional, and subjectivity) (Miller, 1976). In addition, as a person grows with age, social influence will be more salient as social factors become increasingly pertinent. However, as experience grows (and hence more awareness and objectivity), the importance placed on social influence decreases (Lubrin, Lawrence, and Zmijewska, 2005). Therefore, we propose the following hypothesis:

H3*: The influence of social influence on behavioral intention to adopt HHRs will be moderated by gender, age, and experience, such that the effect will be stronger for women, particularly for older women and for those in the early stages of their experience.*

Facilitating conditions deals with the “degree to which an individual believes that an organizational and technical infrastructure exists to support use of the HHRs” (Venkatesh et al., 2003). It has been augmented to reflect a more individual basis where cost of using the HHRs, and compatibility with lifestyle/surroundings and aesthetics are considered. Nevertheless, facilitating conditions have been found to have an effect on the usage intention of the technology (Alshehri et al., 2012). With growing experience, its effect is stronger due to people’s increased ability to sustain use of the technology. Age is additionally a moderator in this case, as older individuals tend to require more support in dealing with the HHRs. Thus, we propose the following hypothesis:

H4*: The influence of facilitating conditions on behavioral intention to adopt HHRs will be moderated by age and experience, such that the effect will be stronger for older individuals, particularly those with increasing experience.*

METHODOLOGY

Participants

The participants were randomly selected from a list of 150 home healthcare agencies located in over 50 cities in the East Coast of the U.S. These agencies are classified into non-medical and medical homecare categories. They offer nursing care, physical, occupational, speech, and respiratory therapy, social services, hospice care, medication administration and help in health promotion exercises. Each of these agencies contains members from both patients and medical professionals, such as doctors, physicians, nurses, social workers, therapists, pharmacists, and dentists. The unit of analysis for this research is the individual and the participation is voluntary.

Data Collection

A survey method was used to collect data for this study. A multiple-item method was used to construct the survey instrument based on the literature (Venkatesh et al., 2003). An online survey was posted to the online communities of home healthcare agencies and forwarded to their mailing list. Paper-based copies of the survey were also distributed physically to the target population. The study received IRB approval in accordance with all applicable regulations. The research instruments were refined through pilot studies. The pilot studies provided preliminary evidence that the scales were valid and reliable. One major feedback from the pilot study was that there was a need for different versions of the survey based on audience type (patients vs. medical professionals).

Each survey consisted of four main parts: background information, robot opinion, robot familiarity and a robot preference checklist. The first part provides background information about HHRs, and elicits demographic information such as gender, age, and education. The second part aims to understand the participants’ opinions about HHRs. The third and fourth parts collect information about the participants’ experiences with robot technology and their preferred tasks and applications of HHRs.

RESULTS

A total of 166 responses were received, 108 of which were complete and valid, and were thus included in our analysis. Table 3 reports the demographic statistics of the participants.

	Variable	**Frequency**	**Percentage**
Gender	Male	68	63%
	Female	40	37%
Age	18 - 33	84	77.7%
	34 - 49	12	11.15%
	50 +	12	11.15%

Education Level	High school degree or equivalent	11	10.1%
	Some college but no degree	19	17.5%
	Associate degree	11	10.1%
	Bachelor degree	24	22.2%
	Graduate degree	43	39.8%
Stakeholder Category	Patients	69	63.8%
	Professionals	39	36.2%

Table 3. Statistics of Demographic Profile

As shown in Table 3, 63% of the participants are male, 77.7% are young, ranging between 18-33 years old, 11.15% are 34-49 years old and 11.15% are above 50 years old. About two-fifths of the participants (39.8%) have a graduate degree, 22.2% have a bachelor degree, and the remaining have a college or high school degree. The statistics also show that all the participants use the Internet and computer several times a day.

The survey results also show that participants have experiences with different kinds of robots. For instance, 36.4% of the participants have used entertainment/toy robots, 8.5 % have used remote doctors, and 13.1 % have used manufacturing robots. In addition, more than half of the participants have heard about or seen some kind of robot, for instance, 49.4 % have heard about or seen a home healthcare robot, 51.6 % have heard about or seen remote doctor robots, and 55.6% and 80% have heard about or seen surgical robot and military robots, respectively. These findings suggest that: 1) robots are no longer strangers to home healthcare professionals and patients; and 2) study participants have some level of experience or knowledge about robot technologies, justifying their fit for the purpose of the study.

The survey items along with statistical results are shown in Table 4, outlining how the items fit into the categorization of the UTAUT model. Means, standard deviations, and variations for the items are also reported. The following items have the highest mean values: PE2, EE4, SI3, and FC4.

To investigate moderators' effect on the adoption of HHRs, we follow an approach proposed by Lubrin E. et al. (Lubrin et al, 2005) where participants are partitioned based on gender along 3 age distributions. Further, they are sub-classified into experienced and minimal experienced users. In this research, the first and fourth part of the survey provides us with the necessary information about gender, age and experiences. Table 5 cross-tabulates the direct determinants of intention to adopt HHRs with respect to gender, age and experiences.

Performance Expectancy		**Mean (SD, V)**
PE1	I would find home healthcare robots useful in my job (my home).	5.14 (1.54, 2.36)
PE2	Using home healthcare robots would enable me to accomplish tasks (get treatments) more quickly.	5.18 (1.38, 1.90)
PE3	Using home healthcare robots would increase my productivity (my effectiveness).	4.79 (1.54, 2.38)
PE4	Using home healthcare robots would increase my chances of getting a raise (better)	4.44 (1.57, 2.47)
Effort Expectancy		**Mean (SD, V)**
EE1	My interaction with home healthcare robots would be clear and understandable.	4.91 (1.19, 1.43)
EE2	It would be easy for me to become skillful at using home healthcare robots.	5.49 (1.09, 1.21)
EE3	I would find home healthcare robots easy to use.	5.32 (1.06, 1.12)
EE4	Learning how to use home healthcare robots would be easy for me.	5.56 (1.06, 1.13)
Social Influence		**Mean (SD, V)**
SI1	People who influence my behavior thought that I should use home healthcare robots for better job (better health).	3.81 (1.53, 2.33)
SI2	People who are important to me thought that I should use home healthcare robots for better job (better health).	3.82 (1.52, 2.32)

SI3	People whose opinions that I value prefer that I should use home healthcare robots for better job (better health).	4.51 (1.44, 2.07)
Facilitating Condition		**Mean (SD, V)**
FC1	I will have the technological resources necessary to use home healthcare robots (e.g. Internet connection)	5.66 (1.28, 1.63)
FC2	I will have the knowledge necessary to use home healthcare robots (e.g. IT background).	5.44 (1.25, 1.58)
FC3	Home healthcare robots will be compatible with other technologies I use.	4.08 (1.72, 2.96)
FC4	A specific person (or group) should be available when I have difficulties using robot.	5.71 (1.22, 1.48)

Table 4. Descriptive Statistics of the Survey Items

Performance Expectancy- Mean (SD, V)					
Male			**Female**		
20-35	36-50	51-65	20-35	36-50	51-65
5.70 (1.27, 1.60)	5.54(0.40, 0.16)	4.99(0.32, 0.11)	4.55(1.46, 2.13)	4.78(1.70, 2.90)	4.57(0.77, 0.60)

(a) Performance Expectancy

Effort Expectancy- Mean (SD, V)					
Male			**Female**		
20-35	36-50	51-65	20-35	36-50	51-65
5.29(0.94, 0.89)	4.83 (0.78, 0.61)	4.33 (1.75, 3.05)	5.26 (1.10, 1.22)	5.28(0.86, 0.74)	**5.46(0.71, 0.51)**

(b) Effort expectancy

Social Influence- Mean (SD, V)						
	Male			**Female**		
Age	20-35	36-50	51-65	20-35	36-50	51-65
Min Exp*	4.18 (1.20, 1.44)	4.83 (0.33, 0.11)	3.92(1.71, 2.92)	4.80 (1.45, 2.09)	3.75(1.26, 1.58)	**4.84(1.54,1.20)**
Exp**	4.50(1.81, 3.30)	4.83(1.64, 2.72)	-	3.24(2.22, 4.91)	3.61 (1.54, 2.37)	3.73(1.01, 1.02)

(c) Social Influence

Social Influence- Mean (SD, V)						
	Male			**Female**		
Age	20-35	36-50	51-65	20-35	36-50	51-65
Min Exp	5.14(0.78, 0.61)	4.56(0.75, 0.56)	5.50(0.41, 0.17)	5.45(0.78, 0.62)	4.75(0.49, 0.25)	6.50 (0, 0)
Exp	5.81(0.37, 0.14)	6.12(0.18, 0.03)	**6.23(0.19, 0.04)**	4.50(1.64, 2.68)	4.66 (1.38, 1.89)	**6.75(0.75, 0.56)**

(d) Facilitating conditions

*Minimal experienced users ** Experienced users

Table 5. Cross-Tabulate Determinants with Respect to Gender, Age, and Experience

Table 5 (a) shows that performance expectancy scored higher for men, particularly younger men (mean = 5.7). In addition, the results, table 5 (b), show that effort expectancy is generally rated higher by women, particularly older women (mean = 5.46). Table 5 (c) shows that the effect of social influence is generally stronger (mean = 4.84) with older women and those with minimal experience. Similarly, the facilitating condition scored higher for older individuals, particularly those with increasing experience as shown in Table 5 (d) (mean = 6.23 and 6.75). All the research hypotheses have been supported.

Based on the above findings, we developed a decision tree for selecting design criteria for cost-effective HHRs implementation (Figure 4). The decision nodes in the tree are demographic factors, and the leaf nodes are the final decisions, representing the most preferable design criteria to focus on for that group of users. For instance, if the target is a younger male, then performance expectancy would be the most preferred cost-effective design criterion.

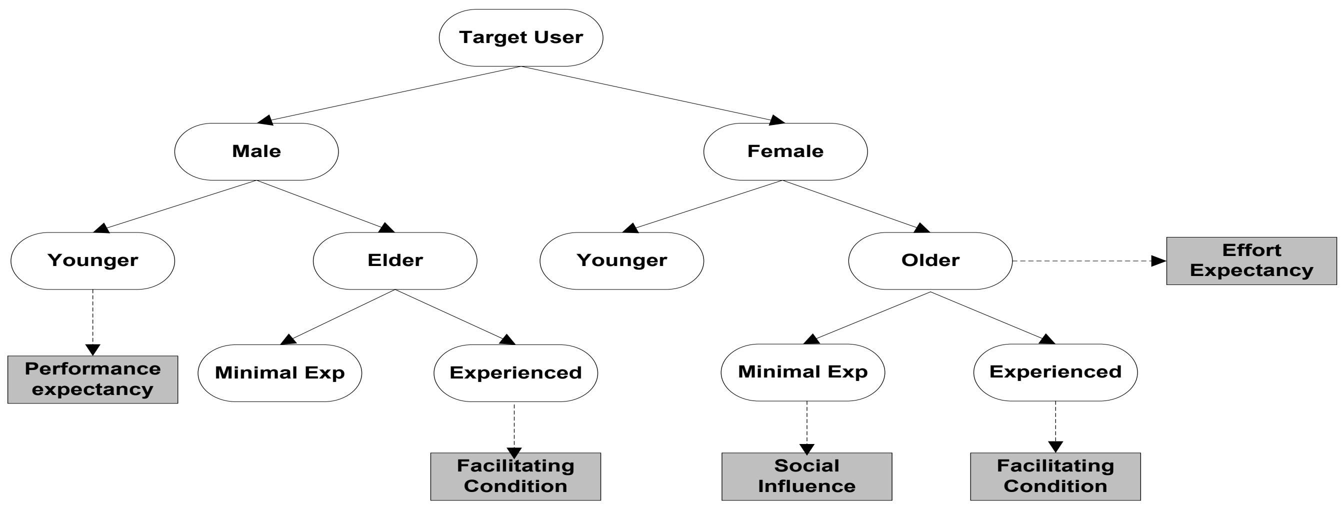

Figure 4. Decision Tree for Selection of Cost-Effective Design Criteria

DISCUSSION

For the 21st century, robots hold tremendous potential as smart and connected health IT by way of supporting or replacing manual, time-consuming, and potentially error-prone health care or maintenance tasks performed by human agents. However, when it comes to leveraging smart and connected health IT at home in our society, the success will largely depend on using the right strategies for the effective and efficient adoption of these systems. These strategies must be planned and tailored for all stages of adoption including the design and development of robots to training, education, and marketing by considering the particular contextual determinants. Only by doing so, we can assure that a healthy and thriving healthcare robots industry will serve its consumers in a sustained manner and increase the population's well-being and health. The results of this research should inform all of the stakeholders interested in learning more about the contextual moderating determinants for HHRs adoption. These stakeholders include individuals, patients, caregivers, robot vendors, healthcare providers, and local and federal governments.

This research contributes to the evidence base about the moderating effects of gender, age, and experience on the adoption of HHRs. The empirical findings provide preliminary support for all the research hypotheses and confirm the validity of the propositions about moderators of the original UTAUT model in the domain of HHRs. These findings illustrate that differences exist between males and females, older and younger individuals, and experienced and minimally experienced users in their HHRs adoption. Understanding and investigating the effects of demographic factors, therefore, directly influences individuals' decision to accept or reject the technology, which is crucial for robot success.

The findings suggest that the influence of performance expectancy on behavioral intention is stronger for younger men. The usage intention of HHRs varies with gender and age. For instance, men – especially young men – tend to be more receptive to new robot technology. Moreover, if the targets are younger men, then service providers, robot designers and manufacturers should focus on improving various perspectives of performance expectancy. For instance, given the task orientation of such users, robot designers should focus on developing task oriented robots that improve effectiveness and outcomes for efficient healthcare management.

As expected, the effect of effort expectancy is moderated by gender and age, showing a stronger effect on older women. This is consistent with previous studies (Anderson et al., 2003; Venkatesh et al., 2012). The two moderators are interrelated as differences in age are associated with psychological and societal differences. Robot designers and manufacturers should focus on developing robots that are easy to use, and that minimize mental efforts when their targets are mostly the elderly, particularly elderly women.

Regarding social influence, its effect is moderated by gender, age and experience and is stronger for older women with minimal experiences. In instances where targets are elderly women, service providers should focus not only on reducing effort expectancy but also on leveraging social influence in motivating the HHRs adoption. Given that most elderly people have minimal experiences in robot technology (Wada et al., 2013), findings suggest that they may take into consideration other peer opinions and experiences. It is likely that elderly people will perceive the technology as credible and safe when they see influential people in their lives interacting with the technology. Service providers should focus on those early adopters of the technology and motivate them to invite their peers. Further, media advertisements and social computing could be useful tools to increase learning and awareness of the technology.

Consistent with our predication, facilitating condition influence is moderated by age and experience and is stronger for older individuals with increasing experiences. Older individuals need additional support in terms of technology, resources and knowledge. This is further underscored in the context of complex IT use given the increasing cognitive and physical limitations associated with age (Smarr et al., 2010). Our finding confirms observations from organizational psychologists who have noted that older workers attach more importance to receiving help and assistance on the task (LaPlante et al., 2013). Service providers, vendors and governments should focus on educating and training older individuals with minimal experiences on self healthcare management and its importance through some training sessions and programs. Compatibility with the existing infrastructure in robot design should facilitate its adoption.

Based on the developed decision tree in Figure 4, we conducted a new round of literature searches and summarized the core design measures for each design criteria (Sommerville, 2010; Olsen and Goodrich 2003). The primary goal of these measures is to help robot designers and manufacturers evaluate the quality of robot design for cost-effective development and successful application. The design measures for performance expectancy may include time to accomplish the task, number of tasks per time unit, and perceived relative advantage in comparison to previous cases. For the effort expectancy, the design measures may include learning time, number of input, and the complexity of interactions. Those measures for the social influence may include number of relatives and number of peers and finally for facilitating condition may include resources availability, and degree of compatibility with existing infrastructure.

The research has several theoretical and practical implications. Theoretically, the research confirms the validity of UTAUT's propositions about the moderators on the domain of HHRs. The research enriches the home healthcare theory base by investigating different moderators' impact on the adoption of HHRs. To the best of our knowledge, this research is considered the first quantitative research investigating moderators' impact on the adoption of HHRs. We also provided empirical evidence about the variances of the effect on the adoption of HHRs between different genders, age ranges and experiences which influence the HHRs design and development.

In practice, the research has several implications particularly for service providers, robot designers and manufacturers. Understanding the type of target user is very important for robot success since different users with different demographic profiles perceive robots differently. The lack of this understanding could lead to costly development of robots that are no longer applicable. Robot designers should understand the unique characteristics of target users before designing the robot for cost-effective robot development and implementation by defining their needs, preferences and expectations of such technology. For instance, as we've shown younger people are more task-oriented while the elderly are more socially-oriented. Therefore, designers or/and providers should use a task specialized robot for younger people and focus more on training and educating the elderly so that they can fully benefit from the robot technology. Given the reduction in attention on task processing for the elderly, robot design should be easily understood and their interactions should be clear for this group of users for efficient self healthcare management. In addition, service providers should establish seminars and conferences to exchange knowledge about the technology between experienced and minimally experienced users to increase learning and awareness of the technology. Finally, the developed decision tree and the proposed design measures are very useful for cost-effective design of smart robotic technology.

The research has several limitations. The number of experienced and minimally experienced users is unbalanced. We have to be cautious when generalizing our results to other settings as other emerging home healthcare technologies. Due to the sample size, standardized methods for evaluating moderator effect did not provide sufficient answers to the research question. In future work, we plan to recruit more participants for the study, investigate additional moderators as culture, and compare the moderating effects between patients and medical professionals.

CONCLUSION

This study empirically demonstrates that gender, age, and experiences moderate the effects of determinants on the adoption of HHRs. This research suggests that demographic characteristics of target users influence the adoption of HHRs. Thus, these factors should be taken into consideration for cost-effective robot design and development. In addition, understanding the roles of moderating factors in HHRs adoption provides an alternative explanation for why some technologies succeeded while others failed. Furthermore, the decision tree model of HHRs we developed based on the findings on moderators can be used to guide cost-effective robot design. These findings are expected to contribute to both home healthcare research and the success of robot initiatives in home healthcare.

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