

Mobilizing Older Adults: Harnessing the Potential of Smart Home Technologies

Contribution of the IMIA Working Group on Smart Homes and Ambient Assisted Living

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Summary

Objectives: This paper highlights the potential of smart home applications to not only assess mobility determinants for older adults in the home environment but also provide the opportunity for tailored interventions.

Methods: We present a theoretical framework for assessing mobility parameters and utilizing this information to enable behavior change based on the Health Belief Model. We discuss examples that showcase the potential of smart home systems to not only measure but also improve mobility for community dwelling older adults.

Results: Mobility is a complex construct that cannot be addressed with a single monitoring approach or a single intervention. Instead, tailored interventions that address specific needs and behaviors of individuals and take into consideration preferences of older adults and potentially their social network are needed to effectively enforce positive behavior change. Smart home systems have the ability to capture details of one's daily living that could otherwise not be easily obtained; however, such data repositories alone are not sufficient to improve clinical outcomes if appropriate mechanisms for data mining and analysis, as well as tailored response systems are not in place.

Conclusions: Unleashing the potential of smart home applications to measure and improve mobility has the potential of transforming elder care and providing potentially cost-effective tools to support independence for older adults. A technologically driven smart home application can maximize its clinical relevance by pursuing interactive features that can lead to behavior change.

Keywords

Aging, mobility, remote sensing technology, self-efficacy

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Introduction

Health care systems worldwide are facing significant challenges as the aging population increases coupled with a shrinking health care workforce. It is imperative to explore innovative approaches to managing wellness of older adults, not only to prevent adverse health events but to also proactively maintain and maximize mobility and independence. Wellness programs aimed at improving physical activity and mobility of older adults have been shown to protect against falls and functional decline, maintain or improve cognitive function and increase socialization [1-3]. However, these efforts have not translated into effective health care promotion; in the US less than a quarter of older adults reported participating in regular physical activity [4]. In order to maintain independence and prevent physical decline and disease, we need systems to accurately assess mobility over time and facilitate tailored interventions for behavior change. Given constraints on resources, implementing systems that rely on additional health care providers to observe and collect information about older adults' mobility and well-being is not feasible. In this paper we explore the potential of smart home applications to facilitate data collection and analysis to support the assessment of mobility and the design of tailored

interventions. Smart homes are broadly defined as systems integrated into the residential infrastructure supporting passive monitoring of residents with the ultimate goal of improving their quality of life [5].

Given that mobility is a complex construct, efforts to design and implement smart home applications need to have a sound theoretical basis. One such comprehensive conceptual framework of mobility is defined by Webber, Porter and Menec [6] which considers multiple determinants influencing mobility for those living independently. Grounded in the life-space literature [7, 8] and the mobility continuum [9], the framework includes concentric areas of expanding locations with increasing requirements for independent mobility (see Figure 1). Each life-space order is displayed as a cross section made up of determinants that influence mobility. As life-space expands, there are a greater number of factors that potentially affect mobility (which is reflected in total cross-sectional area of each zone).

The key determinants of mobility in this framework include cognitive, psychosocial, physical, environmental, and financial factors:

Cognitive determinants include a broad range of factors such as mental status and memory. *Psychosocial* determinants include factors like self-efficacy, social interactions and depres

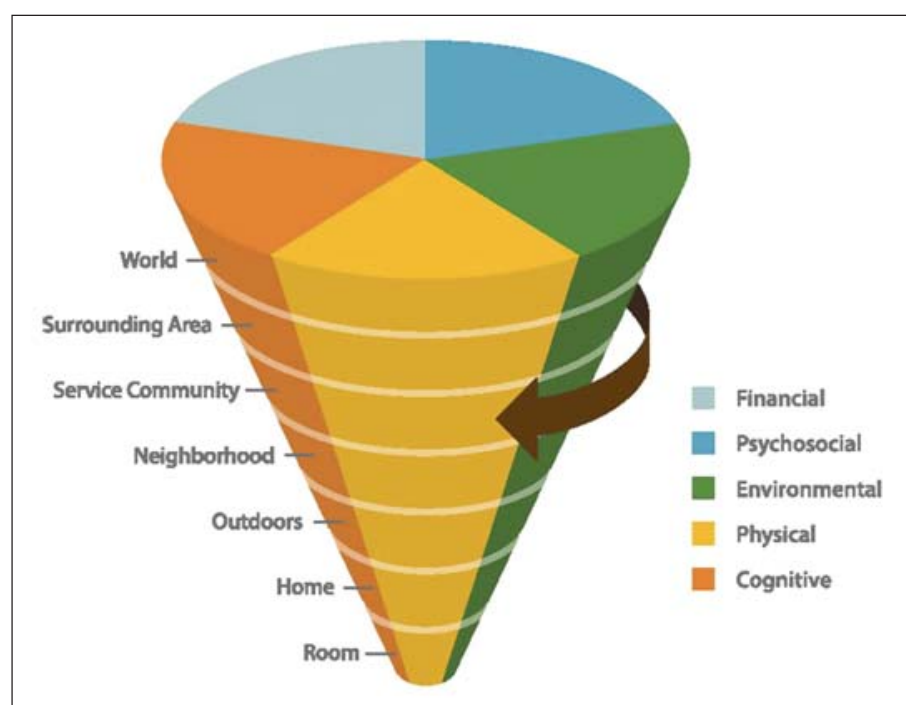


Fig. 1 Conical model of the theoretical framework for mobility in older adults adapted from Webber, Porter and Menec VH [6] [used with permission]

sion. *Physical* determinants include gait characteristics such as balance and speed, and history of falls. *Environmental* determinants include both aids (such as walkers or canes) and barriers (such as inaccessible residential features or tripping hazards) that can be found in the immediate or extended environment in which older adults find themselves. *Financial* factors interact with other key determinants to affect overall mobility status. For example, it is documented that older adults with lower income are at higher risk for mobility disability [10].

As noted from the multiple key determinants, this framework holds that while physical activity is a necessary component, it alone does not determine an individual's mobility. Mobility may be enhanced proactively as one studies the potential progression of key determinants, for example by increasing stamina or addressing issues of social isolation, etc. Examining key determinants of progression over time enables the design of personalized messages for sustainable behavior change. In order

to maintain control and independence, older adults adapt to environmental demands or constraints. Thus, the mobility framework acknowledges that deficits affecting mobility at a particular life-space may be compensated for by altering other determinants at that level. This is also outlined by the competence-press model [11], which suggests that people will adapt within a range of environmental demands or constraints in an effort to maintain control and independence.

Technology and Mobility

A barrier to the assessment of mobility in community dwelling older adults includes the fact that such assessment often takes place in a clinical setting where performance may not reflect real world conditions [12]. To date, existing methodologies lack the holistic and multidimensional assessment that includes diverse sources (i.e., self-report, informant report and objective

assessment) and cover a breadth of underlying components of mobility (such as physical, functional, cognitive, environmental and social parameters). Ubiquitous home based sensing technology holds the promise of introducing cost-effective non-obtrusive monitoring and assessment of mobility. Furthermore, such ongoing monitoring has the potential to identify problems while they are still small, providing an opportunity to intervene and alleviate problems before they become catastrophic. Several efforts have already been in place to examine the role of technology in assessing parameters of mobility and more specifically activities of daily living. Different technologies have been utilized to demonstrate this potential role, for example, the Center for Future Health at the University of Rochester, New York in the US, has provided a demonstration of a smart home as a highly controlled environment including infrared sensors, biosensors, and video cameras [13]. One of the earlier initiatives in this area is the Aware Home at the Georgia Institute of Technology which explores various ubiquitous computing technologies that sense and identify potential crises, assist an older adult's memory and cognitive performance and allow tracking of behavioral trends [14]. In Europe the ENABLE project demonstrated the potential of temperature monitors, locators for lost objects and automatic bedroom lighting to support people with early dementia in their daily living [15]. The PROSAFE project studied the use of infrared motion sensors to support automatic recognition of resident activity and possible falls [16]. These are only few of a growing number of smart homes worldwide that explore overall activity levels in one's residence and daily routines in order to identify emergencies or in many cases proactively address changes to prevent adverse events. Thus, such passive monitoring applications have focused on assessing mobility changes (whether assessing one or more under-

lying parameters of mobility) but not always utilizing this information to promote behavior change and facilitate communication with health care providers to design specific interventions and promote independence of older adults. Technology advances enable monitoring not only within the home setting but also outside the residence tracking individuals as they move around in the community and beyond (e.g., using GPS devices).

Smart home applications can be designed to not only assess mobility determinants in the home environment but also provide the opportunity for tailored interventions informed by the ongoing mobility assessment. Such personalized interventions can target older adults aiming at maximizing their mobility level and engaging multiple stakeholders (such as family members, clinicians or others) based on individual needs and preferences.

Tailored Proactive Mobility Management facilitated by Smart Homes

In order to be most useful, trends and patterns in sensor-based mobility data should be evaluated using algorithmic and threshold approaches which would be applied at the individual or community level. On the individual level, positive reinforcement can be provided via messages or prompts to promote and sustain positive behavior change such as progress towards meeting national recommendations for physical activity. This may allow individuals to be actively involved in their own health promotion activities by addressing the need to change health behaviors and providing a simple means of monitoring the effects of changes on overall activity and health. Further, smart home technology can enable older adults to compare themselves to age-similar peers for motivation as well as

provide a means to engage their family and clinicians in these activities. At the community level, this metric will also make it easier to characterize wellness for specific demographics and that would help to study changes in behavior as a variety of geriatric conditions arise.

Once sensor data are collected, they need to become informative to different stakeholders (e.g. older adults and health care providers). For health care providers, change beyond a certain threshold can prompt an alert indicating that immediate action may be required for a proactive response rather than reactively once an adverse event has occurred.

There are several frameworks that attempt to explain and predict health behaviors. One of the oldest and frequently used models is the *Health Belief Model (HBM)*, which can support the design of tailored proactive mobility management systems. The HBM was first developed in response to the failure of a free tuberculosis screening initiative; central to the model are the attitudes and beliefs of individuals [17]. It has since been adopted to explore and support management of numerous chronic diseases, and it is also used in the prevention of health risk behaviors. The underlying premise of HBM is threefold: people take health-related actions if they (1) believe that a negative condition can be avoided, (2) have positive expectations that by taking a recommended action, a negative condition can be avoided, and (3) believe that the recommended action can be pursued successfully. According to HBM, four constructs represent the perceived threat and net benefits: perceived *susceptibility*, perceived *severity*, perceived *benefits*, and perceived *barriers*. *These concepts are integrated into what is often referred to as „readiness to act.“* A recent addition to the HBM is the concept of *self-efficacy*, or one's confidence in the ability to successfully perform an action. This concept was included to

enable HBM to better address challenges of changing habitual unhealthy behaviors, such as being sedentary, overeating or smoking [18].

In Table 1, we highlight how a smart home system with interactive features can function as a catalyst, leading to behavior change which is based on the collection, organization, and display of information in a user friendly format to make it available to stakeholders. The table is modified from [18]. One advantage to our approach is the availability of personalized data to facilitate the development of cues and prompts based on user preferences. Older adults are called upon to play an active role in health-related decision making often without appropriate tools to facilitate access to information, synthesis of information from multiple longitudinal sources. The provision of a tailored proactive mobility management interface will allow for efficient visualization of data to facilitate health promotion activities and health related decision making by older adults.

Such a system can perform continuous mobility assessment and extract models and metrics for providing feedback using the health belief model. Applying these scientific advances to the challenge of mobility for older adults, allows the synthesis and visualization of information generated from the sensing system to support decision making for older adults and health care providers using context driven messaging that includes cues, prompts and alerts. It thus would deploy a sensor based system that is founded on a novel integration of two frameworks, one clinical one that defines the multiple dimensions of mobility and one that helps us understand the role of information to facilitate health behavior change.

To demonstrate the potential of smart home application to not only measure mobility but also encourage behavior change, we provide an example case founded in our own work. Rita is an 82 year old widow living alone

Table 1 The Health Belief Model (HBM)

Concept	Definition	Application
Perceived Susceptibility	One's opinion of chances of getting/avoiding or controlling a condition	Provide accurate information to demonstrate „areas of susceptibility“ (e.g., low activity levels, overall sedentary lifestyle, reduced gait speed)
Perceived Severity	One's opinion of how serious a condition and its consequences are	Specify consequences of the risk and the condition (provide platform to explain the meaning of the data)
Perceived Benefits	One's belief in the efficacy of the advised action to reduce risk or seriousness of impact	Involve stakeholders (older adults, healthcare providers) to determine action to take; how, where, when; clarify the positive effects to be expected
Perceived Barriers	One's opinion of the tangible and psychological costs of the advised action	Reduce barriers through reassurance and feedback on potential changes in the data sets as result of behavior changes
Cues to Action	Strategies to activate „readiness“	Provide personalized context driven messaging with reminders to motivate action
Self-Efficacy	Confidence in one's ability to take action	Engage older adults and health care providers to create guidance in performing action

in an independent retirement community. She has two daughters who live approximately two hours away. Rita is overweight and has been diagnosed with several chronic conditions (Type II diabetes, hypertension, osteoarthritis). While she is independent in activities of daily living, she needs some assistance with shopping. She no longer drives but relies on public transportation. Her apartment has been wired with various sensors to detect overall activity levels; specifically, a bed sensor to detect restlessness at night and sleep interruptions, a combination of door sensors, stove and motion sensors to detect meal preparation, bathroom visits and time spent in different areas of the apartment. The system has been collecting data about Rita's mobility in her apartment over the last two months. Summary reports of overall mobility levels are shared with Rita and her two daughters. In the last two weeks Rita has been less active and monitoring data indicate that she spends more time in bed or on the sofa, engaging less in meal preparation and receiving no visitors. This change in overall activity levels and social interactions has triggered a prompt that is displayed on

a tablet computer that Rita can operate using the touch screen. The prompt is encouraging Rita to become more active and identifies several opportunities within her community that she can take advantage of, based on prior preferences for types of social activities and recreation. These prompts are tailored to Rita's preferred style for communication and motivation. In the initial assessment using personality inventory features, it was established that Rita lacks intrinsic motivation and prefers frequent supportive reinforcement. Furthermore, the system generates a few specific questions pertaining to Rita's diabetes and blood pressure management as well as screening for depression. Rita has identified in the system settings her preference to have her community health nurse and her daughters be notified when sensors indicate a deviation from her regular activity levels. Rita responds to the questions and screens negative for depression; the system generates a short summary for all stakeholders based on their role in her care encouraging them to work with her to pursue cues for action and achieve self-efficacy.

One of the key factors for smart home solutions is that their implementation is scalable, ranging from the personal tool for individual users to a community-based application that could in the future assess mobility at a population level. Such an approach would allow for customized community-based interventions with clear societal implications. The information provided from the sensors could allow facility administrators and public health providers to detect trends in overall community well-being and identify and implement systematic quality and safety improvement interventions. On the community level, aggregate data can also be used by public health or facility administrators to benchmark mobility between various institutions or communities and has potential to be used as a population-level metric of health. Facilitating such an aggregation of smart home data is the goal of the SILvR Network Initiative, a coalition sponsored by the Foundation for the National Institutes of Health, Intel Corporation, the National Science Foundation, and the Robert Wood Johnson Foundation. This initiative seeks to create a national research environment in the US that will serve as a testbed for independent living technologies. More specifically, this would provide the foundation for a massive scale-up of smart home initiatives, with the hopeful goal of reaching the „10,000 testbed“ a body of research to explore aging processes and uncover the technologies that best ensure independent living and healthy aging [19].

To establish ground truth between the conceptual framework and technology facilitated assessment, we need to assess mobility determinants both by validated self-report measures and smart home technology features. Prior to introducing the smart home features, it is important to perform an environmental scan of the residential infrastructure as part of the baseline assessment to identify potential environmental determinants of mobility (such as stairs,

tripping hazards). Table 2 provides examples of both self-reported measures and smart home technology features to assess mobility determinants. While the smart home features allow in most cases for an ongoing uninterrupted assessment, the self-reported measures require selecting the appropriate frequency and conditions for assessment (e.g., paper and pencil, online) which has clear implications for older adults and potential visual, functional, cognitive or other health limitations. However in some cases (e.g. financial determinants) there are currently no clear technology facilitated proxy measures available.

Conclusion

The outlined model has the potential of transforming elder care and providing potentially cost-effective tools to support independence for older adults. The proposed approach can be potentially adopted in diverse settings of elder care introducing improved services for multiple stakeholders (older adults, their families, communities at large and health care providers). This paper outlines how a technologically driven smart home application can maximize its clinical relevance by pursuing interactive features that can lead to behavior change. The Health Belief Model is one of several possible theoretical foundations that can guide the design of interventions to promote mobility and overall positive health behaviors. Smart home systems have introduced the ability to generate an extensive body of data; while the new data can capture details of one's daily living that could otherwise not be easily obtained, such data repositories are not sufficient to improve clinical outcomes if the appropriate mechanisms for data mining and analysis and tailored response are not in place. Mobility is a key component of wellness for older adults and as a complex construct cannot be addressed with a single moni-

Table 2 Assessing mobility determinants

Mobility	Self-Report Instrument Examples	Smart Home Technologies Examples
Physical	<i>Life-space Questionnaire (LSQ)</i> : A 9 item instrument that assesses mobility and space occupied during the previous 4 weeks and assistance needed to move in that space [20-23]. <i>EPFSE Physical Function Measure (EPFM)</i> : The instrument asks 3 sets of questions (15 items total) to assess physical functioning. [24].	Home motion sensors to indicate activity levels, bathroom visits during night GPS and actigraphy watch to track activities within and outside the home Bed pressure pad to indicate time in bed Gait monitor to assess gait speed
Psychosocial	Geriatric Depression Scale- Short Form (GDS-SF): A 15 question survey that can be used to assess the level of depression in the subject being questioned [25, 26].	Stove sensors to assess meal preparation activities Motion sensors to determine activity in the home, time outside the residence, number of visitors, length of visits Pressure pad to assess time in bed or sitting
Cognitive	Mini-Mental State Examination: 30 item questionnaire used to assess cognition [27].	GPS sensors for wandering outside the home
Environmental	Reported use of assistive devices (e.g., cane, walker)	RFID tags to assess use of assistive devices
Financial	Perceived Income Adequacy: 3 item questionnaire pertaining to potential worry about having enough income in the future, trouble making ends meet, and enough income for little extras [28].	Not applicable

toring approach or a single intervention. Instead, tailored interventions that address specific needs and behaviors of individuals and take into consideration preferences of older adults and potentially their social network are needed to effectively enforce positive behavior change. Smart home applications have the potential to serve as the nexus to maximize mobility by serving a multitude of stakeholders and supporting scalability of intervention approaches.

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