Title

Using in-Home Monitoring Technology to Identify Deviations in Daily Routines Preceding Changes in Health Trajectory of Older Adults

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Publication Date
2016

UNIVERSITY OF CALIFORNIA

Los Angeles

Using in-Home Monitoring Technology to Identify Deviations in Daily Routines Preceding Changes in Health Trajectory of Older Adults

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Nursing

by

Maria Yefimova

2016

ABSTRACT OF THE DISSERTATION

Using in-Home Monitoring Technology to

Identify Deviations in Daily Routines Preceding Changes

in Health Trajectory of Older Adults

by

Maria Yefimova

Doctor of Philosophy in Nursing

University of California, Los Angeles, 2012

Professor Janet C. Mentes, Chair

The boom of in-home monitoring technology offers unprecedented information about an individual's interaction with the environment. A variety of low cost sensors can continuously and unobtrusively collect information about activities in the living space. Capturing early changes in the daily routines of vulnerable older adults residing in these "smart homes" may allow clinicians to predict and prevent negative health consequences through timely intervention. However, the current state of science is hampered by the lack of theoretically driven approaches to analyze sensor data in relation to clinically meaningful health outcomes. The aims of the study are 1) to characterize an older adult's daily routine, as captured with smart home sensors, 2) to assess if deviations from it are indicative of changes in their health trajectory, such as falls, ER visits or unplanned hospitalizations, and 3) identify between person factors that affect the characteristics of the daily routine. It used previously collected data from 10 residents of TigerPlace, a unique retirement facility that evaluates health technology affiliated with University of Missouri, Columbia. Older adults live in apartments equipped with network of motion, depth and bed sensors that unobtrusively collect information about daily activity of its resident. Thirty months of continuous sensor data were analyzed in the context of bi-annual clinical assessments and nursing notes extracted from the electronic health record. A retrospective multiple case study approach is guided by the conceptual model developed for this study that is grounded in nursing and gerontological literature. Changes in the temporality and frequency of daily activity were found for common geriatric symptoms, such as urinary symptoms and confusion. Seasonal and weekly effect was evident across participants in the duration of time spent in various areas of the apartment. Participants varied in their baseline daily routines, but for the majority of symptoms there were prodromal changes in at home activity that was detected with sensors. As the cost of technology adoption decreases, nurses can use these innovative tools to coordinate care and intervene early to prevent or mitigate the functional decline associated with vulnerable older adults.

The dissertation of Maria Yefimova is approved.

Diana Lynn Woods

Betty L. Chang

Wendie A. Robbins

Janet C. Mentes, Chair

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2016

DEDICATION

To my supporter, critic, and interdisciplinary collaborator —

my future husband, Mark Gottscho.

To my role model in innovative nursing entrepreneurship —

my mother, Julia Yefimov.

To all older adults living fervently, independently, and alone —

among them, my grandmother, Tatyana Ivanovna Rumyantseva.

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ACKNOWLEDGMENTS

This dissertation was made possible with the generous support of John A. Hartford Building Academic Geriatric Nursing Capacity Scholarship, Sigma Theta Tau International Honors Society Gamma Tau at Large Chapter Research Award, and the UCLA Graduate Research Mentorship and Dissertation Year Fellowship Awards.

Thank you to my dissertation committee members, Dr. Lynn Woods, Dr. Betty Chang and Dr. Wendie Robbins and my dissertation chair, Dr. Janet Mentes, for guidance, feedback and support in the processes of preparing the dissertation.

As an accelerated Bachelors-to-PhD student, I was apprehensive to embark on a non-traditional path of pursuing an academic career straight after completing my undergraduate nursing degree. However, at UCLA School of Nursing Center for Advancement of Gerontological Nursing Science (AGNS) I found the inspiration and support to follow my dream of improving nursing care for older adults through research. I especially and deeply thank my long-standing mentors, Dr. Woods and Dr. Mentes, as well as other AGNS faculty, Dr. Mary Cadogan and Dr. Linda Phillips. They opened a window of opportunities that was only possible at an outstanding, research-intensive institution, such as UCLA.

I also want to thank my Hartford co-mentor, Dr. Marilyn Rantz at the University of Missouri, Columbia, who shared her vision of aging-in-place with technology and allowed me to use TigerPlace data for secondary analysis. The Center for Eldercare and Rehabilitation Technology, led by Dr. Marjorie Skubic, is an example of an outstanding interdisciplinary team. Thank you to my then-student collaborators and now Drs. Tanvi Banerjee and Zahra Hajihashemi who taught me the intricacies of working with sensor data and the publishing

process in the technical field. Thank you to Akshay Jain for helping me create visualizations of the data. I hope we continue to collaborate!

Thank you to my family, friends, and colleagues who continuously supported me through these five years and made this process less lonely and isolating. Thank you for keeping me grounded and reminding to get out of my academic bubble once in a while.

Lastly, I cannot find words to express my gratitude to a particularly special person, who was there every day of this journey, from before I even considered applying to the PhD program. He listened to my theoretical ponderings at 3am, taught me how to code in MATLAB (and really, wrote most of the code himself), let me cry when my data did not make sense, recovered my files when I messed up the cloud sync, and brought me food when I was sitting in the library all day on Sundays – among so many other things. I cannot thank you enough, Mark Gottscho. Without you, this dissertation would not be.

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Yefimova, M., Woods D.L. & Rantz, M.J. Using Smart Home Technology to Monitor Routines of Older Adults. *13th National Hartford Centers for Gerontological Nursing Excellence Leadership Conference*. New Orleans, LA. November, 2013. Poster Presentation.

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INTRODUCTION TO DISSERTATION

The rapid growth of the aging population, the evolving role of nursing in healthcare, and the ubiquitous proliferation of technology pose challenges and opportunities for the future. The number of people over the age 65 will more than double, from 40.2 million in 2010 to 88.5 million by 2050 (US Census Bureau, 2010). As more adults survive into the old age, many navigate lives burdened by multiple chronic conditions and disability. Currently, more than 50% of people over the age of 65 have three or more chronic diseases (Anderson, 2010), which affects their ability to perform daily activities. Nevertheless, older adults want to maintain independence through optimal function and to "age-in-place" of their choosing (Vasunilashorn, Steinman, Liebig, & Pynoos, 2012). The need to support the growing numbers of older adults puts a strain on caregivers and long-term care services. Nurses can improve health of older adults through chronic disease management, health promotion, education, and collaboration with other disciplines.

The challenges following this demographic shift create a unique opportunity for nurses to spearhead the health system reform. Spurred by the Patient Protection and Affordable Care Act of 2010, new care delivery models emerge with the goal of containing cost and providing quality outcomes through care coordination (American Nurses Association, 2010). With older adults being the primary users of healthcare resources accounting for 60% of total US healthcare expenses (Centers for Disease Control and Prevention, 2013), the scope of practice makes nursing profession indispensable to the evolving healthcare organizations (American Nurses Association, 2012). Nurses can improve health of older adults through chronic disease management, health promotion, education, and collaboration with other disciplines.

The healthcare delivery system needs reorganizing to accommodate older adults aging with multiple chronic illnesses. Instead of the current focus in primary care that emphasizes acute illness and symptom relief, Wagner (1994) proposes shifting towards a systematic ongoing assessment of functional ability, illness course and self-management strategies. These can be used to initiate preventative interventions, education, psychological support, and follow up in those with chronic illness. Understanding the progression health and illness over time rather than focusing on episodes of care, such as hospitalizations, can inform clinicians about timely and appropriate interventions (Wyman & Henly, 2011). A continuous, rather than occasional, assessment of the individual's needs and abilities would allow nurses to more effectively support independence and preserve function of the older adults.

Rather than focusing on disease burden and disability, a more holistic approach may be more insightful in understanding complex and fluctuating needs of older adults. Performance and participation in daily activities have been major indicators of function (Palmer & Harley, 2012) Existing measures evaluate impairment by proxy of how much help is needed in performing certain everyday tasks, sometimes missing the pre-clinical stages of functional decline (Fieo, Austin, Starr, & Deary, 2011). On the other hand, the variety, level and duration of engagement in daily activities may be more sensitive markers of change. Monitoring temporal changes in the daily routines of older adults may assist in understanding the overall trajectory of their health (Zisberg, Young, Schepp, & Zysberg, 2007).

Using Technology for Health Monitoring of Older Adults

Interdisciplinary engagement with sciences outside the health field can further transform the provision of care. Recent advances in electrical and computer engineering have already revolutionized everyday life but have been slowly integrated in the healthcare industry (Groves

& Knott, 2013). Embedded systems, ranging from large computer systems to various specialized sensors and devices, can collect large amounts of information about the world. Ubiquitous computing and analysis of this "big data" have the potential to generate robust predictions based on past patterns (Swan, 2012; Vimarlund & Wass, 2014). Information and communication technology allows for global connectivity of both people and devices sharing information in the "Internet of Things" (Boyd & Crawford, 2011; Nitzsche, Thiele, Häber, & Winter, 2014). These technological capabilities can create powerful change when applied to the questions about nursing care for older adults.

Tele-health and tele-medicine have already proven effective in monitoring vital signs and basic physiological markers for certain chronic conditions, such as congestive heart failure and chronic obstructive pulmonary disease (Brettle, Brown, Hardiker, Radcliffe, & Smith, 2010; Wakefield et al., 2008). Behavior monitoring is an emerging expansion of this endeavor (Yang & Hsu, 2012). Low-cost and unobtrusive sensors can objectively collect data about person's activity throughout the day for months and years (Rantz, Skubic, & Miller, 2009; Yang & Hsu, 2012). For people with multiple chronic conditions where symptoms are not clear, pronounced, monitoring behavior rather than physiological markers may be more robust for detecting health changes.

Currently there are multiple attempts to breach the disciplines involved in "geron-technology" and to create effective behavior monitoring technology (Dara-Abrams, 2008). Wearable and mobile sensors proliferate the market and research arena for physical activity, but they have limitations with the older adult population (Bakkes, Morsch, Krose, & Kröse, 2011; Banaee, Ahmed, & Loutfi, 2013). Non-wearable sensors can be more effective because they are unobtrusive for long-term monitoring (Cutler, 2007; Kaye et al., 2011). "Smart homes" with networks of cheap and reliable sensors installed in various locations can monitor activity without any effort on the resident's part (Reeder, Demiris, & Thompson, 2015; Thielke et al., 2012). There is a bursting interest in the development of ambient technologies for the aging population, but in the recent years the field of geron-technology stalled in the analysis and interpretation of the evaluation phase.

Identified Gap

A number of research groups have attempted to employ environmental sensors for detecting in-home activities of older adults (Hayes et al., 2008; Kaye et al., 2011; Rantz et al., 2013). Due to large volume and complexity of sensor data, the challenge has been in extracting meaningful signals from the noise (Rashidi & Mihailidis, 2013). Much work has been done in the fields of electrical engineering and computer science to develop novel activity recognition algorithms for these types of data (Noury et al., 2011). However, many of these statistical models lack a solid theoretical foundation or clinical insight into human behavior and health. Oftentimes, it becomes an interesting computational challenge not validated with established clinical outcomes.

Moreover, while some approaches have been successful in precisely controlled laboratory settings with healthy (if old) test subjects, issues arise when these algorithms are applied to complex "real life" situations (Chan, Campo, Estève, & Fourniols, 2009; Wilson, Hargreaves, & Hauxwell-Baldwin, 2015). Implementing and evaluating technology with real subjects requires collaboration among multiple stakeholders, including researchers, clinicians, family members and older adults themselves. To move the field forward, there is a need for clinically driven and theory-supported approaches to analyzing sensor data from real older adults.

Study Overview

This dissertation attempted to fill the gap by developing and applying a conceptual model to explain the relationship between health and everyday behavior of older adults, captured with in-home sensors. The proposition that changes in stability of daily routines signal symptomatic phases in the health trajectory was explored using retrospective descriptive multiple case studies. An ongoing multi-disciplinary project at the University of Missouri, Columbia (Rantz et al., 2005, 2008, 2010, 2014) provided secondary data from an in-home monitoring system already deployed in apartments of its residents and the corresponding clinical assessments and health records. It was analyzed for patterns of changes in day-to-day activity (measured by environmental sensors) through the years of health changes (measured by clinical assessments and medical records).

The purpose of the study is to answer the research question: *What changes in the daily routines of older adults, as measured by in-home monitoring technology, precede acute changes in their health trajectory?*

Definitions

- **Health Trajectory** is the course of temporal changes in illness, wellness and functioning throughout the person's life. A cute changes in health trajectory, such as an increase in physical, cognitive or psychological symptoms or functional decline, can lead to the need for a higher level of care, such as unscheduled primary care visits, emergency care, hospitalization or transfer to skilled nursing facility.
- **Daily routine** is a consistent pattern of everyday activities that a person establishes as an adaptation to the demands of the environment. This behavioral pattern consists of a sequence with a particular order, timing and duration of activities throughout the day.

- **In-home monitoring technology** is an unobtrusive system that continuously collects information about the person's activity in their home. It consists of a network of environmental sensors that detect and record the time of motion in various parts of the apartment. In this study it is synonymous with *smart home for health tele-monitoring*.

Significance

The need for innovative approaches to understanding patterns of health trajectories has been at the forefront of the national and international research agendas. The International Federation on Aging emphasized remote health monitoring as one of the two priority research areas, "due offering high value to stakeholders and surmountable barriers to adoption" (International Federation on Aging, 2012). Domestically, the National Institute of Nursing Research Strategic Plan encourages "the development of new technologies and informatics-based solutions" and "improve assessment and management of symptoms over disease trajectories" (National Institute of Nursing Research, 2011). The Strategic Agenda of the National Institute of Aging also includes the need to "identify, analyze, and track changing patterns of disability for older adults" and encourages research on "more sensitive measures that are needed to better track these changes" (National Institute on Aging, 2007). Using low-cost in-home monitoring systems to characterize trajectories of daily routines may provide insight towards most appropriate and timely treatment strategies to prevent decline and support optimal function of older adults.

Organization of Chapters

The rest of the dissertation is presented in a three-manuscript format. The first chapter is a theoretical paper that describes the development of the conceptual framework used for the study. The second chapter is a manuscript that presents the methods and results of the inductive case studies with ten participants. The third chapter is a manuscript that describes considerations for future interdisciplinary work based on a critical review of literature and lessons learned from implementation of this study. Lastly, the conclusion summarizes the insights from this dissertation study and proposes future work for effective and practical developments in the field of gero-technology.

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CHAPTER 1

Trajectories of Daily Routines in Older Adults: A Model for Monitoring with Technology

Abstract

Background. The boom of in-home monitoring technology offers innovative ways to care for the health of the growing aging population. Yet, its technology-centric development is hampered by poorly defined theoretical foundations, leading to mixed success in clinical evaluations. **Purpose.** To develop a theoretical model that guides tele-monitoring by elucidating the relationship between health and daily activity of older adults. **Theory Development.** Compression of Mortality Theory, Chronic Illness Trajectory Framework, Ecological Model of Aging, and Social Zeitgerber Theory were evaluated through the lens of the meta-concepts of person, environment, health and nursing. Their structural and functional components and were used to synthesize a new model. **Proposed Model.** The Trajectories of Daily Routines in Older Adults model links the concepts of an older adult's health trajectory and their daily routines, as measured with in-home monitoring technology. An individual's health trajectory can be tracked with clinical measures on a macro-scale of months and years. As their health fluctuates over time, the older adult exhibits varying levels of functional adaptation to the environment. This behavior on the micro-scale of days and weeks can be seen in the consistency of the person's daily routine. Monitoring daily activity with in-home technology may identify temporal changes in health that are amendable to timely intervention. **Implications.** The proposed model is person-centric, grounded in nursing and gerontological knowledge. Its conceptual definitions would improve interdisciplinary evaluations of in-home monitoring. These technologies have the potential to enable timely and personalized healthcare delivery for older adults.

Keywords: theory development, in-home monitoring, health trajectory, daily routine

Introduction

The rapid growth of the aging population and the ubiquitous proliferation of technology generate unprecedented opportunities for innovation in healthcare. Various monitoring systems are able to remotely collect continuous information about an individual's interaction with the environment, as he or she experiences changes in health. This "big data" can be used in predictive analytics for early detection of health problems and timely intervention to prevent further complications (Bauer, Thielke, Katon, Unützer, & Areán, 2014). However, successful implementation of these interventions requires an understanding of fluctuating needs of the older adults and linking technology-based indicators to clinically meaningful outcomes.

Older adults have complex health needs that change throughout their life course. As people age, their risk of developing chronic conditions increases (Goodman, Posner, Huang, Parekh, & Koh, 2013). These conditions contribute to frailty, increasing the risk of functional impairment (Fried, Ferrucci, Darer, Williamson, & Anderson, 2004), requiring ongoing clinical management that shapes the person's daily life (Vogeli et al., 2007). Moreover, fluctuations in symptoms of chronic conditions can be complicated by sudden acute events (Karlamangla et al., 2007). For example, seasonal influenza may have a detrimental effect on the health of a frail older adult with a history of chronic obstructive pulmonary disease. Poor health management can trigger symptom exacerbations with concurrent development of geriatric syndromes, such as incontinence, delirium and falls (Inouye, Studenski, Tinetti, & Kuchel, 2007), that require hospitalization or care in a skilled nursing facility; transitions that complicate recovery and worsen quality of life (Boyd & Fortin, 2011). Nurses need to understand these dynamics of health and illness over time (Henly, Wyman, & Gaugler, 2011). Detecting prodromal symptoms may lead to better timed interventions to prevent decline and support older adults in their ongoing health management.

A continuous, rather than occasional, assessment of individual needs and abilities allows early detection of health changes. Performance and participation in daily activities are major indicators of function, related to the overall health trajectory (Palmer & Harley, 2012). Functional decline may influence the structure of the older adult's daily schedule, — their routine, — with respect to frequency, duration, order and timing of various activities. Engagement in some activities is necessary for physiological survival, such as eating and toileting; others are required for personal maintenance in cultural terms, such as chores and banking (Horgas, Wilms, & Baltes, 1998; Lawton, 1990).These have been clinically classified into activities of daily living (ADL) and instrumental activities of daily living (IADL). Other activities may be more self-enriching and discretionary, such as work, leisure, hobbies and socialization with others (Moss & Lawton, 1982). The variety, level and duration of engagement in these activities, reflected in daily routine, may be more sensitive markers for the pre-clinical stages of health decline (Zisberg & Young, 2007) than the often-measured level of need for assistance with ADL/IADL (Guralnik, Fried, & Salive, 1996). Monitoring temporal changes in the daily routine may assist in understanding the overall health trajectory.

The cost associated with intensive and long-term observation of daily activity can be offset with current technological capabilities. Behavior monitoring is an emerging extension of in the area of tele-health/tele-medicine (Yang & Hsu, 2012). Environmental sensors placed in the living spaces of a "smart home" can objectively collect data about a person's activity throughout the day for months and years (Peetoom, Lexis, Joore, Dirksen, & De Witte, 2014). A review of health-related smart home technologies found that the most prevalent approach is the collection and analysis of data pertaining to activity levels, motion and other ADLs (Demiris & Hensel, 2008). Monitoring behavioral markers may be more robust for detecting changes when prodromal symptoms or subclinical disability are not clear or pronounced, such as subtle changes in behavior, mood and appearance (Peirce, Hardisty, Preece, & Elwyn, 2011).

While the premise of monitoring the health of older adults through their daily behavior in the smart home is appealing, there has been limited evidence to support its widespread implementation in practice (Reeder et al., 2013). The development and evaluation of this technology requires expertise from multiple disciplines including informatics, engineering, gerontology, and health sciences such as nursing (R. Schulz et al., 2014). Many current technology-centric approaches are built on poorly defined theoretical foundations (Reeder et al., 2013), leading to systems that are not generalizable and results that are not clinically meaningful or interpretable. Hence, there is a need for a clear, person-centric theoretical framework for health monitoring of older adults in the smart home that is grounded in interdisciplinary knowledge.

The purpose of this article is to propose a theoretical model that elucidates the relationship between the daily activity of older adults and their health trajectories that can be operationalized with remote monitoring technology, such as smart homes.

Background

Technology has been used for monitoring health in various forms in the past 60–70 years. In the field of tele-medicine and tele-health, technology as simple as a phone has been used to monitor vital signs and symptoms in hard-to-reach populations (Darkins, Kendall, Edmonson, Young, & Stressel, 2015). Wearable technologies, such as mobile devices, actigraphs and accelerometers, have been used to continuously monitor various aspects of an individual's activity and health (Kang et al., 2010). They require long-term adherence to wearing and charging them, with a risk of being misplaced (Bakkes, Morsch, Krose, & Kröse, 2011). This may be a challenge for an older adult with cognitive impairments or dexterity limitations. Non-wearable sensors, such as those placed in the environment, are more unobtrusive because they do not require effort from the individual, and thus are more effective in long-term and integrated monitoring of older adult's daily life.

These considerations led to the development of "smart homes", living spaces equipped with sensors that collect data about person's interaction with the environment (Demiris, Thompson, Reeder, Wilamowska, & Zaslavsky, 2013;). A variety of low-cost devices are commercially available to measure multiple facets of a person's behavior, such as acoustic, pressure, ultrasound and infrared sensors (Rashidi & Mihailidis, 2013). These sensors can detect and record the time, amount and quality of movement, pressure or temperature, as the person interacts with their living environment in their daily life. For example, a pressure bed sensor may track long-term changes in the amount and quality of sleep as the person experiences the onset of mild cognitive decline (Suzuki, Murase, Tanaka, & Okazawa, 2007). A motion sensor in the bathroom may provide insight about the presence of symptoms of urinary tract infection, such as increased urination (Rantz et al., 2011). This long-term and unobtrusive monitoring of behavior in the smart home may have more ecological validity than infrequent in-person examinations at the clinic (Lyons et al., 2015), assuming that sensor data can be linked to clinically significant changes in the person's health trajectory.

The challenge in remote health monitoring is identifying clinically meaningful signals from the smart home data. Environmental sensors generate large amounts of data about older adult's interaction with the environment. It is then analyzed to detect any changes or anomalies.

If an anomalous event is found, often when the signal in the sensor data stream reaches a certain threshold, an alert is generated to inform the healthcare provider (Figure 1). This information can initiate an intervention to prevent further deterioration in health. To make this system effective and timely, the analysis has to be robust for prompt detection of changes in sensor data that are related to prodromal symptoms or subclinical disability (Peirce et al., 2011).

Engineering and computer science groups have led the majority of efforts in building predictive models that analyze smart home sensor data based on machine learning (Roggen et al., 2013). These algorithms are mathematical models that “mine” the data for patterns based on underlying statistical relationships. They often require input about known rules or associations in the data, such as at what thresholds would the sensor signal be considered as a clinically significant change (Pavel, Jimison, Korhonen, Gordon, & Saranummi, 2015). However, these thresholds have not been well articulated in clinical literature due to previously limited measurement tools (Elwyn et al., 2012). Moreover, population or group-based thresholds may not be useful when tracking within-person changes over time, so it is important to establish individual “baselines”.

A way to mitigate these limitations is to be guided by pre-existing theoretical assumptions about human behavior. A strong theoretical foundation for statistical model building has the potential to derive clinically meaningful insight from the data and produce generalizable models (Collins, 2006). A theory identifies a set of important measurable concepts, specifies propositions that link these concepts, and provides an explanation for these relationships (Meleis, 2011, p.35). Concepts moderating the relationship between behavior on the *micro*-time scale and overall health trajectory of the older adult may explain expected day-to-day variability in the data. Filtering changes in activity due to extraneous factors on the *macro*-time scale of months or years, such as weather, can help detect clinically meaningful patterns.

A recent review of health smart homes found that few studies were based on a theoretical framework or a conceptual model (Reeder et al., 2013), although theories have been developed to understand the use of technology by older adults. The Technology Acceptance Model (Venkatesh, V., & Davis, 2000) incorporates perception and attitudes to predict behavioral intent to use technology. When applied specifically to remote monitoring of older adults' daily activities, adoption is moderated by the interplay of the need for safety versus independence (Mahoney, 2011). Another model proposes that non-specific gero-technology can be used a *compensatory mechanism* in person-environment interaction to assist aging-in-place (Mahmood, Yamamoto, Lee, & Steggell, 2008). Reeder, Demiris, & Thompson (2015) applied the epidemiologic triad of host-agent-environment to explain how smart home technology should be used to create *task advantages* and reduce barriers to the performance of tasks required for independent living. While a number of theories emphasize the importance of person-environment interaction in the use of smart home technology for older adults, none of the surveyed studies have explicitly articulated assumptions about monitored behavior.

Theory development in research on smart homes for older adults is complicated by the multi-disciplinary nature of inquiry. The frequently involved disciplines of informatics, engineering, gerontology and clinical health sciences, such as nursing, have different expectations and understanding of theoretical applicability; therefore, a useful framework needs to be clear, understandable and operationalizable. Existing theories relevant to these disciplines can serve as the building blocks, providing concepts, propositions and empirical indicators for the development of a new conceptual framework.

Prior to proposing a new model based on existing theoretical literature, it is important to identify and characterize concepts of interest. The goal is to elucidate the mechanisms for early detection of health deterioration by monitoring daily routines of the older adult living in the smart home. This can be studied through the lens of the four meta-concepts of *person, environment, health* and *nursing* (Meleis, 2011, p.94). The older individual is an instance of the *person* meta-concept, and due to the need to establish an individual baseline" calls for a person-centric theory. The *environment* includes both the physical space equipped with sensors and the social resources and a temporal component. *Time* as a distinct concept is imperative for linking macro and micro instances of *health*. Given the gerontological focus, the meta-concept of *health* encompasses the continuum between optimal function and aging-related limitations. Daily routines can be viewed as an instance of functional adaptation to these limitations on a *micro* time scale (days), while a trajectory of these instances can be traced on a *macro* time scale (months and years). Theoretically clarifying these temporal relationships provides a basis for using remote monitoring technologies, an instance of the *nursing* meta-concept, to supplement clinical decision-making and adjustments in the provision of care.

Theory Development

Four guiding theories have been selected based on their concepts and propositions as they relate to outlined meta-concepts: the Compression of Mortality Theory (Fries, 2002), the Chronic Illness Trajectory Framework (Corbin & Strauss, 1991), the Ecological Model of Aging (Nehemow & Lawton, 1973) and Social Zeitgerber Theory (Ehler, Frank & Kupfer, 1989). They are described below, beginning with a theory with a population-based intervention focus and narrowing to a theory of within-person psycho-physiological mechanisms.

Compression of Morbidity

The Compression of Morbidity (COM) hypothesis (Fries, J 1980) focusing on the public health of the growing aging population, proposes that postponing the onset of morbidity would "squeeze" the prevalence of disease into a shorter time span before death. Delaying the decline in health due to age-related conditions as long as possible would minimize the number of years the individual would spend being ill before their death, allowing them to enjoy a high quality of life and die as healthy as possible. This shift of an individual's health trajectory towards an ideal "squared" curve would reduce the population's disease burden and the associated medical care costs.

Compression of morbidity through the delay of disability can be achieved by primary, secondary and tertiary prevention strategies (Fries, 2011). While the aim of this theory is to reduce the disease burden of the aging population, COM provides the basis for incorporating technology as a secondary prevention approach for individuals. Smart homes have the potential to provide integrated, evidence-based electronic support for healthcare providers to adjust provision of services (Reeder et al., 2015). Timely customized interventions would stabilize each older individual's health trajectory, reducing disability and "squaring the curve". In extending the COM to in-home monitoring of older adults, Rantz et al. (2005) described a typical current health trend that consists of short plateaus of relatively stable function and frequent step-downs indicating progressive age-related functional decline over time. The target trend is to extend the plateaus using technology, which would culminate in a "squared" decline at the end of life.

While theoretically sound and practically applicable these models would benefit from a more descriptive conceptualization of changes in health over time.

Chronic Illness Trajectory Framework

While COM provides the general framework for technological intervention, there is a need for a more nuanced understanding of temporal health changes. These temporal changes can be elucidated by the Chronic Illness Trajectory Framework (CITF) (Corbin and Strauss, 1991). This nursing framework, based on the idea that chronic illness has a course, or a trajectory, that varies over time, is characterized by nine different *trajectory phases*: pre-trajectory, onset, crisis, acute, comeback, stable, unstable, downward, dying (Table 1). These dynamic states are defined by the magnitude, stability and direction of illness symptoms. Moreover, each phase may have sub-phases, daily or weekly periods of symptom reversal, plateau, upward movement or drop. While the overall trajectory can be fully understood only in retrospect, its projection, or the desired outcome for the course of illness, can be shaped by the *trajectory management*. The overarching aim of trajectory management is to maintain quality of life by controlling symptoms, treating side effects, handling crises, preventing and handling disability (Corbin and Strauss, 1991).

An important relationship introduced by the CITF is the reciprocal impact of the trajectory management on the biographical and everyday life of the person with chronic illness. A person's *biographical identity*, or the temporal self-perception, is shaped by the illness symptoms, interactions with healthcare providers, adherence to various treatments and lifestyle changes. Illness imposes limitations on *everyday life activities* and requires special arrangements for its management, such as taking medications, undergoing treatments, handling diet and rest.

These everyday adaptations to chronic illness trajectory management often become routinized with set times, places and interactions (Corbin and Strauss, 1991).

While this middle range theory does not have clear operational definitions (Miller, 1993), it is useful in describing the various phases of a health trajectory. It links the trajectory management to self-concept and everyday life activities (daily routines) that can be monitored in the smart home. In creating predictive models using sensor data to generate alerts for clinicians, thresholds for detecting "abnormal/symptomatic" activity may be adjusted based on what phase of the trajectory the older adult is experiencing. Moreover, a better understanding of the factors that influence the trajectory phases may enhance the timing of interventions, rendering them more effective.

Ecological Model of Aging

Factors affecting the health trajectory may be reflective in the interaction between the older adult and their surroundings. A prominent gerontological framework, the Ecological Model of Aging (EMA) (Lawton & Nahemow 1973), positions behavior and affect as outcomes of the interaction between personal competence and environmental demands. Personal competence encompasses an older individual's social, physical, psychological and intellectual abilities, while environmental "press" is the level of stimulation and challenges in the physical and social surrounding. Both lay on a continuum from weak to strong with a dynamic interaction between the two. A zone of adaptive behavior and positive affect occurs when there is a match between these forces within an optimal range. The adaptation level is "the point for any competence at which environmental press is exactly balanced such that awareness of stimuli is minimal and resulting behavior is effortless" (Lawton, 1987b). Increases in the environmental press beyond this zone will exceed the individual's coping capacity and result in maladaptive behavior and negative affect.

The strength of this model is in establishing a theoretical link between the personal and their environmental factors that affect behavior. Behavioral competence is the result of successful adaptation and balance between personal resources and environmental demands. Lawton (1983) defines behavioral competence as a multidimensional construct that includes "health, functional status, cognitive status, time use, and social behavior", which can be reflective in the daily routine. Analyzing a person's interaction with a "smart home" environment may reveal changes in personal competence and signal the need for intervention, such as reducing the environmental press. In addition, conceptualizing the environment as comprised of both space and time allows the exploration of temporal effects on the health of a person.

Social Zeitgerber Theory

Another theory that provides insight into daily routines as an adaptive interaction between the person and the environment is the Social Zeitgerber Theory (SZT) (Ehlers, Frank, & Kupfer, 1988). Originally developed to explain the etiology of depression through a unifying relationship between psychological losses and physiological changes (Ehlers, Kupfer, Frank, & Monk, 1993), the SZT proposes that the internal biological rhythms and external social cues, such as interactions with others, direct the stability of everyday activities, or *social rhythms*. Changes in social cues brought by life events, such as loss or trauma, alter the stability of behavioral and biological rhythms, triggering affective symptoms.

Sleep-wake patterns, hormone release and daily fluctuations in body temperature are examples of stable rhythms that follow the internally regulated, naturally recurring twenty-four hour cycle (Schulz & Steimer, 2009). The environment also sends signals to the body, such as light, that serves as a time cue, or zeitgerber, of the circadian rhythm (Van Someren et al., 1996). The SZT expands these zeitgerbers to include more complex signals, such as mealtimes, going outside and social interaction (Monk, Kupfer, Frank, & Ritenour, 1991). Regularity of these social rhythms is defined by the frequency and specific times of participating in specific daily activities.

Developed to explain the etiology of affective disorders and evaluated in older populations, SZT proposes linkages between physiological, environmental and social factors that affect the stability and consistency of behavior. It led to the development of the Social Rhythm Metric (Monk et al., 1991), a self-report metric of stability of daily behaviors derived from important characteristics such as timing, duration and order of activities, similar to the conceptualization of the daily routine. The SZT expands the concept of environment both in physical and social dimensions that affect stability of person's behavior from day to day.

Proposed Model

Theoretically linking concepts of interest into a new multi-disciplinary conceptual model can be achieved by: 1) analyzing existing theories from various disciplines that support the goal of inquiry; 2) extracting their meta-concepts and propositions, and 3) constructing a new model. The four theories guide the new model for monitoring dynamic relationships in older adult's behavior and health with in-home technology. Since they are based on the knowledge of their respective disciplines, theory synthesis on a meta-conceptual level would generate an interdisciplinary result.

Below, each theory is "standardized" in terms of the meta-concepts of *person*, *environment, time*, *health, nursing,* and an additional concept of *behavior* (Figure 2):

- *Person* is defined as a "person living with chronic condition" (CITF), an "older adult exhibiting personal competence" (EMA), and indirectly as a "[person with] physio-social rhythms" (SZT).
- *Environment* is explicitly defined in only one theory (EMA), but also applies to external zeitgerbers (SZT), spanning across physical and social domains.
- *Time* is defined on a number of different scales, ranging from years and months of disease progression (COM; CITF) to days of circadian rhythms (SZT).
- *Health* is defined as the continuum spanning "morbidity and disability" (COM), "illness" (CITF), and "somatic symptoms and affective episodes" (SZT).
- *Nursing* is defined as encompassing interventions to improve health (COM, CITF), such as in-home monitoring technology.
- *Behavior* is defined as "everyday activities" (CITF), "adaptive/maladaptive behavior" (EMA), and "social rhythms" (SZT).

The synthesis of the four theories uncovers a proposition of dynamic stability as an adaptive behavioral mechanism in the older adult's interaction with environment over time. COM defines the overarching link between *health* and *time* on a macro-scale ("disability curve") and establishes the goal of *nursing* interventions ("squaring it"). CITF provides a more in-depth description of this relationship ("trajectory phasing") as well as its effect on *person* ("biographical self") and *behavior* ("everyday activities"). *Adaptive behavior* is the result of balanced *person* and *environment* interaction (EMA). *Stability* is the proposed driving force between *health* and *behavior* (circadian and social rhythms) on a micro-scale in SZT. Thus, *continuity/stability over time* is the main proposition that links health and behavior across varying time scales.

Based on these concepts and propositions, we synthesize a new model, called Trajectories of Daily Routines in Older Adults (Figure 3). It elucidates the dynamic relationship between older adult's daily activity and their health trajectory and guides tele-monitoring efforts to identify early subtle changes for timely intervention. Moreover, the model defines person and context-specific factors that may affect the stability of behavioral and health patterns. This model is grounded in nursing and aging frameworks with the focus on the person in the context of their living environment, while taking into considerations general healthcare goals.

The concept of health trajectory encompasses the course of health and illness on the macro-scale of months and years (left side of Figure 3: a function of *health* on y-axis and *time* on the x-axis). It can be tracked with clinical measures in functional, physical, cognitive and emotional domains. The trajectory can be traced through three distinct phases (subdivisions labeled as *stable*, *unstable* and *acute*). The stable phase is characterized by stability in clinical measures or no illness symptoms. The trajectory may enter an unstable phase with subtle decline in function or prodromal symptoms. The goal of monitoring is to identify this unstable phase and prompt clinical follow-up and intervention to avoid the deterioration. The acute phase may be identified by acute health events such as urgent care, ER visits or unplanned hospitalizations.

As the person's health changes during each of these phases the person exhibits varying levels of adaptation to their environment in their day-to-day function (small circles on the trajectory). This adaptation on the micro-scale of days and weeks can be seen in the consistency of the person's daily routine (big circle on the right of Figure 3). Daily routine can be defined by the order, frequency and duration of activities performed by the person in their living environment. A consistent pattern of daily activity with some natural variability can serve as a person's baseline adaptation level and allows to track changes. These could happen within the environment (a novel situation), or within person (a health decline).

Personal competence (top square on the right) is driven by within-person factors that include demographic characteristics and health status. Demographic characteristics, such as age, gender, educational attainment and past occupations and preferences, are intrinsic to the person and static on the macro-scale. The health status is more dynamic as it may fluctuate from day to day, depending on the person's physical, cognitive, emotional and functional reserve. Personal competence is either balanced or challenged by the environmental press (bottom square on the right), generated by the physical space and the social resources. Physical space encompasses both the room layout and the furniture, which is unchanging day to day. Social resources include people, such as caregivers and visitors, who can facilitate or stimulate the person's interaction with the environment. These social cues often vary based on the day's schedule and can have weekly or seasonal patterns. Hence, multiple within-person and contextual effects, some of which are time-varying, need to be accounted for when monitoring the variability of behavior.

The long-term trajectory of daily routines in an older adult can be assessed in a smart home. A continuous monitoring of person-environment interaction can link changes in micro-scale behaviors to a macro-scale health events. The smart home can be tuned for an individual's baseline activity patterns in a particular living environment, which allows to control for personal and contextual factors. This improves the identification of meaningful changes in the timing, frequency, duration and order of daily routine activities as they related to health outcomes. For example, an older adult with subclinical cognitive decline may stop leaving the apartment (decrease in frequency) or a person experiencing prodromal depressive symptoms may spend more time in bed (increase in duration). This operationalization of routine features using smart homes allows to build predictive behavioral models for health trajectory management.

Implications

The proposed model is person-centric and grounded in nursing and gerontological knowledge domains. In linking the model to research methodology it is important to distinguish between a population-based prediction and person-based prediction. Healthcare is now shifting more toward personalized and individualized delivery mechanism, by taking into consideration personal needs and preferences. Previously, within the empirical reductionist paradigm research focused on conceptual relationships and their differences between individuals (Fang & Casadevall, 2011). However, it has limited application to understanding dynamic processes that occur within the individual. A paradigm that emerged in developmental psychology, the holistic-interactionist paradigm regards the individual as an active agent in the dynamic person-environment system whose function is organized and integrated on multiple levels (Magnusson & Stattin, 2007). Thus, a variable-oriented approach to testing relationships between concepts may neglect its complexity and nonlinearity (Bergman & Andersson, 2010). Alternatively, in person-oriented approach, the person is the focal point of research, with emphasis on typical patterns, their development and connections across domains.

Conclusion

Trajectories of Daily Routines in Older Adults is a theoretical model developed to guide application of technological interventions to monitor day-to-day activity in relation to long-term health outcomes. It facilitates the exploration of dynamic temporal processes within the individual that allow for more personalized and timely healthcare delivery. The model emphasizes the link between health and behavior on multiple temporal scales that has been often overlooked in nursing research. It bridges theories related to population-level interventions to "compress morbidity" to individual-specific bio-psycho-social mechanisms and clarifies how health-monitoring technologies can be applied and why it can be useful.

TABLES

Chapter 1 - *Table 1*

Phases in Chronic Illness Trajectory Framework and Their Management Schemas

Phase	Definition	Management Scheme
Pre-trajectory	Lifestyle/risk factors for illness, asymptomatic	Prevent the onset
Onset	First symptom occurrence, diagnostic period	Form an appropriate scheme
Crisis	Life-threatening situation requiring emergency care	Remove life threat
Acute	Active symptoms that require hospitalization	Bring symptoms under control
Stable	Symptoms controlled by regimen	Maintain stability
Unstable	Symptoms not controlled, but not requiring hospitalization	Return to stability
Downward	Progressive deterioration, increase symptoms and disability	Adapt to increasing disability
Comeback	Gradual return to acceptable level of functioning imposed by illness	Maintain upward projection with trajectory scheme
Dying	Immediate weeks, days, hours preceding death	Achieve closure and peaceful death

Note. Adapted from “A nursing model for chronic illness management based upon the trajectory framework” by J.M. Corbin and A. Strauss, 1991, *Research and Theory for Nursing Practice*, *5*(3), p. 155–174.

FIGURES

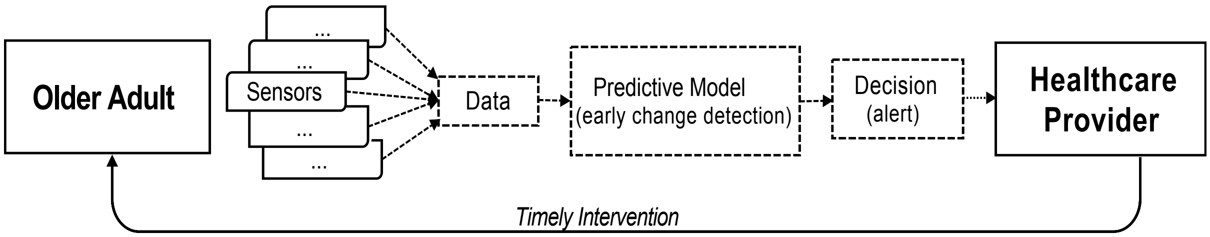

Figure 1. General process of remote health monitoring.

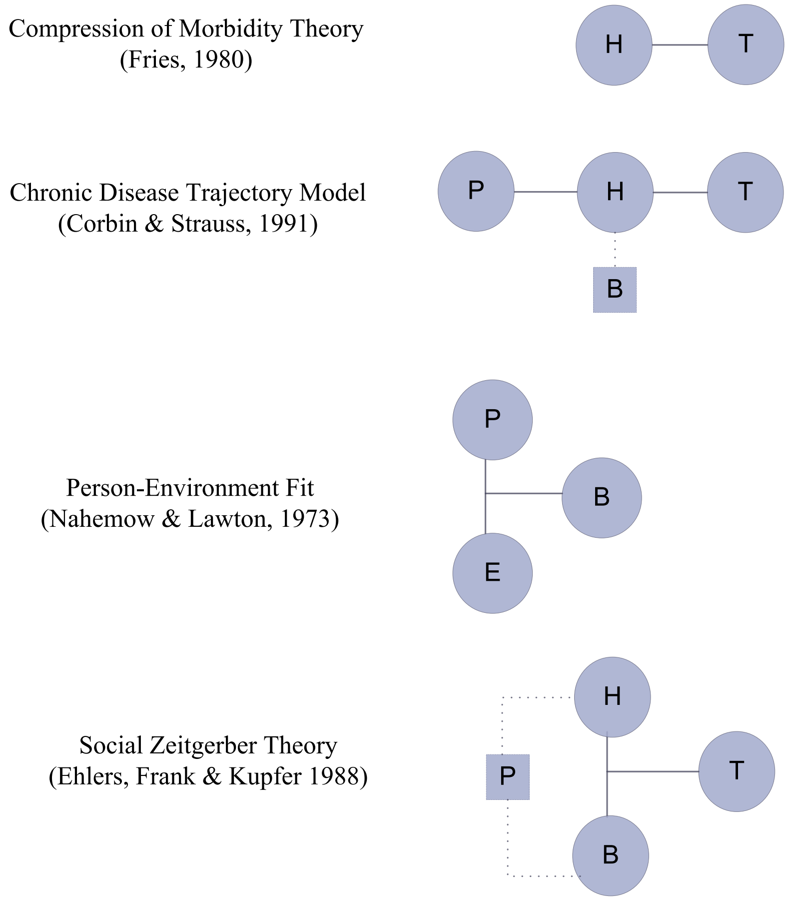

Figure 2. Relationships between meta-concepts from the four guiding theories.
(P – person; H – health, T – time, B – behavior)

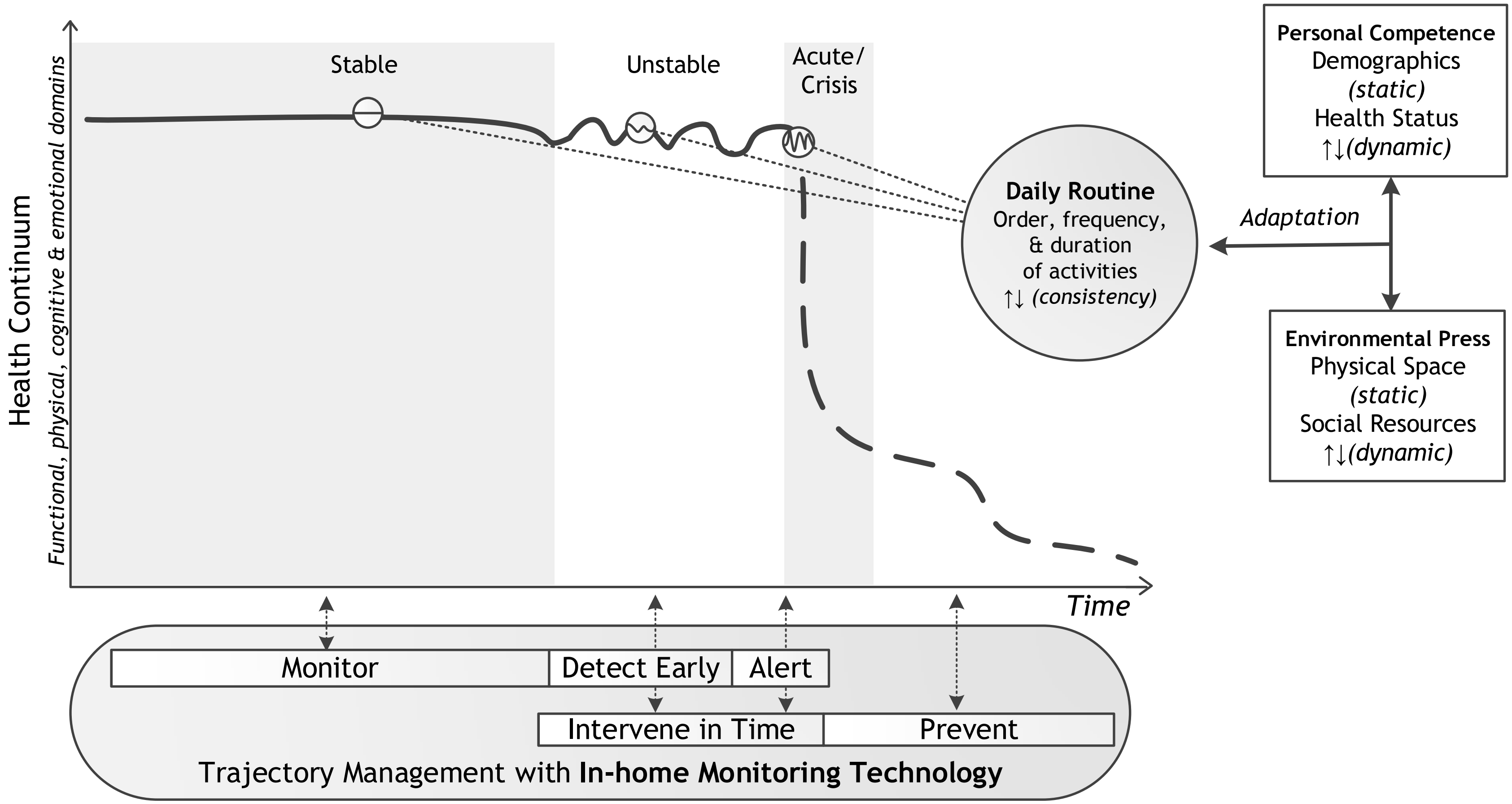

Figure 3. Trajectories of Older Adult's Daily Routines.

The proposed conceptual model clarifies relationships between factors affecting daily routine of older adults in the context of the health trajectory to guide the use the in-home monitoring technology.

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CHAPTER 2

A Case Study of In-Home Monitoring Technology Reveals Health-Related Changes in Daily Routines of Older Adults

Abstract

The emergence of in-home monitoring technology offers an unprecedented opportunity to learn about how individuals interact with their personal environment and how such behavior changes with their health. One of the most promising applications of such technology is to predict changes in health for the vulnerable population of older adults, enabling proactive care. The purpose of this study was to identify the features of daily routines that are sensitive to changes in health over time. It was performed using a theory guided, retrospective analysis of secondary data from the TigerPlace in a multiple case study (N=10) over a 2-year period. Features of the daily routine were calculated from data collected in the real apartments equipped with a wireless network of motion, depth and hydraulic bed sensors. Health phases were demarcated with reported symptoms and acute events recorded in the electronic health records. Constant comparative technique and pattern matching of visualizations were used to characterize individual baseline and between-person factors that affect daily routine, and to identify features with deviations that match health changes. We identified temporal effects on baseline daily routines, such as day of the week and seasonality, on variability and trend of the time series. Idiosyncratic changes in multiple features of the daily routine marked non-specific symptoms, providing insight for future automated predictive models. As the cost of technology adoption decreases, nurses can use these innovative tools to coordinate care and intervene early to prevent or mitigate the functional decline associated with vulnerable older adults.

Keywords: smart home, tele-monitoring, health trajectory, daily routine, older adults

Introduction

There is a need for innovation in care of the growing aging population to support their health and quality of daily life within the constraints of the current healthcare delivery system. Older adults are at high risk of multiple co-occurring chronic conditions, frailty and geriatric syndromes (Fried, Ferrucci, Darer, Williamson, & Anderson, 2004), contributing to high use of healthcare resources (Fried et al., 2004). Periodic symptom exacerbations may require transfers to higher levels of care, such as a hospital or a skilled nursing facility (Boyd & Fortin, 2011). Fluctuations in symptom severity and impairment can be complicated by additional acute events (Karlamangla et al., 2007). Assessing the individual over time helps establish a baseline to track changes in their health (Glasziou, Irwig, & Mant, 2005), yet it is often limited by infrequent and oftentimes delayed visits to the health provider's office. Technology allows us to take long-term health monitoring into the person's home using low-cost sensing devices (Aguilar, Campbell, Fiester, Simpson, & Hertel, 2014; Morris, Intille, & Beaudin, 2005).

In-home monitoring technology can provide more details about how the older individual deals with their health in the context of everyday life. Their activity and interaction with various objects in the home can be captured by small, unobtrusive devices placed in the living environment (Lee & Dey, 2010). In-home sensors can supply continuous, objective, and detailed information about behavior may signal changes in health (Morris et al., 2005); this assertion is supported by a growing body of literature on clinically meaningful sensor-generated insights (Gokalp & Clarke, 2013; Peetoom, Lexis, Joore, Dirksen, & De Witte, 2014). For example, in one study the traditional physical assessments by a nurse failed to detect any change in health status prior to a cardiac event, but sensor data revealed an increase in bed restlessness captured by a bed sensor (Rantz et al., 2010). Another study found a relationship between a decrease in time spent out of apartment, as recorded by sensors, and increase in depressive symptoms (Thielke et al., 2014). Similarly, an increase frequency of nighttime bathroom visits was found to be associated with a diagnosis of urinary tract infection (Rantz et al., 2011). These studies show the potential of linking behaviors captured with sensors to health outcomes, yet there is a gap in understanding this new type of information.

The major hurdle in a wider spread use of smart home technology is the difficulty in data analysis. Sensors can collect unprecedented amounts of information, but much of it has had limited clinical interpretation. The majority of effort has been led by engineering and computer science groups with an intense focus on the application of machine learning algorithms to sensor data (Rashidi & Mihailidis, 2013). These algorithms are mathematical models that "mine" the data for patterns based on underlying statistical relationships (Roggen et al., 2013). They require input about known rules or relationships in the data, which can be gained from clinical insight, pre-existing knowledge or theoretical assumptions about human behavior. However, in many of the studies from the technical fields, descriptions of assumptions about human behavior are cursory, obfuscated or lacking altogether due to limited clinical collaboration.

This study aims to fill the gap by applying a theoretically-driven approach to generating clinically meaningful indicators from sensor data. It proposes conceptualizing activity measured by in-home sensors as *daily routines*, with changes in stability reflective of an individual's *health trajectory*. Our secondary analysis was based on data from TigerPlace (Rantz, Aud, et al., 2008), a unique retirement facility that incorporates technology in coordinating care of its residents. The purpose was to answer the research question: *What changes in the daily routine of the older adult, as measured with in-home sensors, precede acute changes in their health trajectory?*

Background

Repeated observations of individual's *health trajectory* can trace a course of recovery or deterioration, successful management of chronic disease or further impairment (Clipp, Pavalko, & Elder, 1992). While there is rich qualitative literature on personal trajectories of health and illness, objective, quantifiable measures have been a challenge. Insight from quantitative longitudinal studies are limited by crude categorical measures of health and functional impairment (Fieo, Austin, Starr, & Deary, 2011; Lowry, Vallejo, & Studenski, 2012), that are too distant in time to capture day-to-day variability (Buurman, van Munster, Korevaar, de Haan, & de Rooij, 2011) and diversity in patterns of transitions between health states among older adults (Chang, Lu, Lan, & Wu, 2013). Moreover, for people with multiple chronic conditions where symptoms are not clear and pronounced, the variety, level and duration of engagement in daily activities may be more sensitive markers in the pre-clinical stages of health decline (Higgins, Janelle, & Manini, 2014). Transitions between health and illness can be reflected in changes in activity patterns of older adults.

These patterns of *daily routines* are comprised of activities repeated at a specific time, in a specific location, alone or with others (Kielhofner, 2008). Consistent routines in older adults have been linked to well-being (Bouisson & Swendsen, 2003), sleep quality (Zisberg, Gur-Yaish, & Shochat, 2010), emotional stability and self-esteem (Baltes, Wahl, & Schmid-Furstoss, 1990). However, measurement issues limit a deeper understanding of changes in routines related to health. Commonly used time budget diaries or retrospective interviews, such as the Social Rhythm Metric (SRM) (Monk, Flaherty, Frank, Hoskinson, & Kupfer, 1990) and the Scale of Older Adults Routines (SOAR) (Zisberg, Young, & Schepp, 2009), are prone to recall bias, especially in older adults with memory impairments, and pose burden and cost if used to monitoring daily routines for months or years.

With in-home sensor monitoring, it is possible to unobtrusively gather continuous fine-grained information about patterns of daily activity (Lee & Dey, 2015), but it is critical to account for baseline variability in behavior to make insights about health. Daily routines are more consistent in the stable home environment (Clark, 2000; Golant, 2003), yet the effect of the physical living space in research is often neglected (Gitlin, 2003). Biological and social clocks also shape behavior. An internal circadian clock shapes the daily rhythms of sleep-wake states, cognitive performance, and digestion (Brown et al., 2008). A stable pattern of rest and activity is expected in a healthy individual in the recurrent 24-hour period. Another temporal cue that regulates activity is the culturally defined entity of a week. Studies have shown that day of the week has an effect on the amount of food intake (de Castro, 2002), sedentary behavior (Conroy, Maher, Elavsky, Hyde, & Doerksen, 2013) and out-of-home activity (Kaspar, Oswald, Wahl, Voss, & Wettstein, 2015). This variability in activity on different weekdays is expected and cannot be dismissed. These fluctuations are part of "normal" behavioral patterns and disregarding them may yield widely inaccurate inferences about health.

We developed a conceptual model that is grounded in gerontological and nursing theories for this study in order to provide a systematic framework for analyzing sensor-derived activity patterns in the context of older adult's health trajectory, while accounting for known constraints (Yefimova, 2016). A *daily routine* is defined as a consistent behavioral pattern with a particular order, timing and duration of activities throughout the day, that a person establishes in response to their environment. Both static and time-dependent *personal* and *environmental factors* affect its baseline variability. Deviations from daily routine may occur either due to the environment (a novel situation), or when transitioning between health states. *Health trajectory* on the macro-scale of months and years can be divided into phases: stable (no reported symptoms), unstable (illness symptoms present) and acute (such as hospitalization or fall). As health fluctuates during each phase, the individual exhibits varying levels of adaptation to their environment *reflective in the consistency (variability) of their daily routine* on the micro-scale of days and weeks. These theoretical concepts were included in our study's analysis and interpretation.

Research Aims

1. To characterize an older adult's daily routine as captured with an in-home monitoring technology.
    a. Proposition: For an individual there will be a day-to-day consistency (low variability) in the order, timing and duration of the recorded motion in the different parts of the apartment.
    b. Proposition: Each individual will have a unique pattern of activity (daily routine) that based on his or her health and the living environment at that that particular time.
2. To compare between-person factors that affect stability of the daily routine.
    a. Proposition: People with more functional impairment will have more stable daily routines (less variability).
3. To assess if deviations from the daily routine can be indicative of acute changes in health trajectory of the individual.
    a. Proposition: Changes in the daily routine will be observed during the period of self-reported symptoms, changes in the clinical measures of function, mood or physical performance, or prior to an increase in the level of care.

Methods

Retrospective, inductive multiple case study design was used to characterize the temporal relationship between daily routines and health trajectories of older adults in the context of the proposed conceptual model. The study was a secondary analysis of previously collected data at TigerPlace (Rantz, Aud, et al., 2008). It is one of the few places nation-wide where sensor data is continuously collected in a real living environment for multiple years, and is supplemented by ecologically valid clinical information about the older individual and their environment.

Setting and Participants

Participants were selected from TigerPlace, a unique retirement community where multidisciplinary group from Schools of Nursing, Engineering, Computer Science and Health Informatics at University of Missouri, Columbia work to develop technology to support aging (Rantz, Porter, et al., 2008). TigerPlace is licensed with nursing home standards but operates on multiple levels of care to allow residents to live there until their death. Its residents are representative of Caucasian older adults in assisted living facilities nationwide in age, gender and number of chronic conditions (Demiris, Skubic, & Rantz, 2006; Rantz et al., 2013). All residents have provided informed consent for ongoing data collection until they withdraw from the study, move away or die. The University of Missouri, Columbia Institutional Review Board (IRB) has approved all TigerPlace projects that involve evaluating in-home monitoring technology; additional IRB clearance was obtained from UCLA.

Inclusion criteria: 1) information from residents who have been living in TigerPlace apartments for at least 6 months to include two clinical assessments, at admission and every 6 months, until July 1, 2015, and 2) health records indicating at least one *acute event*, defined as death, transfer to higher level of care, hospitalization, emergency room/urgent care visit, or unplanned surgery 1) information from residents living alone, because currently the system is unreliable in differentiating between individuals living together. Exclusion criteria: 1) a part of the sensor system in the apartment is not functioning properly as reported by research staff.

Instruments

Participant's de-identified electronic health record (EHR) information was used to contextualize health trajectory, and personal and environmental factors. It included administrative records of routine care and bi-annual clinical assessments. Documentation included the Minimum Data Set (MDS) 2.0 and Home Health Certification and Plan of Care Form (HCFA-485), federally mandated assessments with demographics, diagnoses, functional limitations, continence status, pain, Medication list, and Aging-in-Pace care plan with information on resident's environmental needs and resources. EHR also had dated *clinical notes* by staff regarding resident's medical and care plan changes, scheduled surgeries, visits from home health services, skilled nursing, social work, and any acute injuries, such as falls or emergency room visits. Clinical assessments were conducted every six months or at change of resident's health during in-person interviews. Trained research staff used valid and reliable instruments commonly used in the older adult population: Mini-Mental State Examination for cognitive function (Folstein, Folstein, & McHugh, 1975), Geriatric Depression Scale for mood disturbances (Yesavage et al., 1983), basic and Instrumental Activities of Daily Living for functional limitations (Katz, Ford, Moskowitz, Jackson, & Jaffe, 1963; Lawton & Brody, 1969), and Short Form-12 (SF-12) for self-reported quality of life related to mental and physical health (Jakobsson, 2006).

A sensor network in each apartment collected information about in-home activity that was used to operationalize the daily routine. The living space was fitted with 10-15 motion sensors, a Microsoft Kinect sensor in the living room, and bed sensor (Figure 4). Wireless motion sensors were placed on the walls or over the doorways of bedrooms, bathrooms, shower, walk-in closets, laundry, kitchen, living room and the outside patio. Another one was positioned over the front door to monitor entrance/exit activity. When a person moved in the sensor's cone-shaped field of view (45 ° horizontally, 15 ° vertically) within a 20-ft range, it sent a signal every 7 seconds (Wang, Skubic, & Zhu, 2009). A wired Microsoft Kinect for Xbox sensor was placed above the front door to monitor the living room, dining area and parts of the kitchen. It has an infrared camera with rate of 30 frames per second (field of view with 57 ° horizontally, 43 ° vertically; extended range of 19.7 ft.). A simple algorithm captured the beginning and end time of any motion detected by Kinect and stored in a text file by resident ID and date. A hydraulic bed sensor, developed at the University of Missouri, Columbia (Heise, Rosales, Sheahen, Su, & Skubic, 2013) was placed under the mattress where the resident primarily slept. The bed sensor sent signals when pressure on the bed changed. As the person moved through the apartment, sequences of sensor IDs and corresponding times were logged by small computer in a cupboard on top the fridge, and then transmitted via Internet to the university server.

Analysis

Coding clinical data. Bi-annual assessments of wellness (SF-12), function (ADL/IADL), mood (GDS), cognition (MMSE), MDS 2.0 and HCFA were summarized for changes over time. MDS 2.0 and HCFA documentation was coded on the level and rate of change of difficulties over time in ambulation, pain, cognition, and mood. Clinical notes were reviewed for need of outside assistance or care (scheduled vs. non-routine), presence and type of reported symptom, or acute events, such as falls, unscheduled hospitalizations or ER visits. A day was coded as "symptomatic" if any symptom was reported or non-routine care was provided, or as "acute" if an acute event occurred. A random subsample of clinical notes (N=60) was tested with an independent advance practice registered nurse for inter-rater reliability (95% agreement) and decision agreement on the code categories. Symptomatic and acute days were visualized using Google Charts Calendar application programming interface. Health trajectory phases were defined as “unstable” if a week contained at least one symptomatic day and “acute” if it contained at least one acute event.

Pre-processing sensor data. Daily routine was operationalized as a *set of features: duration, frequency and intensity* of activity in different areas of the apartment over a 24-hour period. These four functionally different areas were covered by multiple sensors (Figure 1): *rest* (bedroom motion and bed sensors), *personal care* (bathroom, shower, closet, and laundry motion sensors), *common* (living room, kitchen, front door motion, and Kinect sensors), *outside* (a sequence of front door or patio sensors, followed by no activity for more than 30 min, then activity in the common area). A *secondary* area (non-*rest* bedroom/bathroom motion sensors) was added for two-bedroom apartments. The assumption is that *motion* in different rooms is proxy for *activities* that comprise a daily routine such as sleeping/napping/resting, personal hygiene, toileting, dressing, medications/health management, leisure/hobbies, housework/chores, eating, and socialization. This approach also reduced noise and improved reliability of sensor data. Pre-processing was performed in a commercial software package, MATLAB and Statistics Toolbox (Student Release 2013a; The MathWorks, Inc, 2013). Days in which routine features were than three standard deviations above or below the mean for that home were excluded from the analysis, consistent with previous work (Hayes et al., 2008). This filtering process allowed identifying days when there was no motion in the apartment either because the resident was gone for the majority of the day or there was sensor failure.

Triangulation. Since no normative data exists, visual inspection and constant comparative method (LeCompte & Sechensul, 1999) were used to categorize patterns in stability and change. Visual inspection is one of the most common approaches to exploratory data analysis, defined as the process of reaching a judgment about reliable and consistent effect or change over time by visually examining graphed data (Kadzin, 1982). Qualitative techniques of note taking on decisions about patterns of change were used to enhance the rigor of visual inspection.

To characterize an individual's daily routine (aim 1) we used qualitative constant comparison techniques for pattern matching of *time maps* during stable health trajectory phases. Time maps are graphs developed by the author to show the sequence and time spent in different areas of the apartment throughout a 24-hour period. Descriptive statistics of personal and environmental characteristics were used to examine factors affecting stability of the daily routines across individuals for aim 2. Time series and statistical control charts (Tennant, Mohammed, Coleman, & Martin, 2007) were used to identify routine features are sensitive to changes in health for aim 3. For individual, daily values of feature by area (duration, frequency, intensity x rest, personal care, common, outside, secondary) were plotted in Microsoft Excel. Exponential smoothing (ES) for mean values was used with $\alpha = 0.3$ ($0 < \alpha < 1$, smaller values weigh the effects of more distant past on present activity) (Elbert & Burkom, 2009). It was chosen to account for gradual changes (cumulative disease burden or general aging over time), rather than abrupt effects. Control limits were within two sigma of the average standard deviation of raw data in a calendar year to account for seasonal variability. Trends and outliers were examined in the context of the specific health trajectory phase (e.g. kinds of symptoms, degree of change in clinical measures).

Results

Out of 55 potential TigerPlace residents we narrowed our sample to 10 participants whose data we examined for at least six months and on average two calendar years. The major exclusion criteria were for the apartment to have all three types of sensor (motion, bed and Kinect) functional during the study time (excluded N=20), and for the participant to experience at least one acute health event (N= 9). The other limiting criterion was for participant to be living alone, since it excluded not only couples (five couples, N=10) but also residents with pets (N=6). 76% of the total time period had corresponding sensor data, with an average of 576 days (range 70-947 days) per person. Participants had at least two and on average 4.8 clinical assessments, while the number of EHR notes ranged from 80 to 3670 per person due to diversity of conditions and health needs.

Participant Characteristics

Table 1 presents a summary for each participant's personal characteristics, environmental supports. Our sample was reflective of the frail older adults with multiple health needs. All were Caucasian, and 50% were female. Mean age at the beginning of the follow up was 89.3 (range 84-97) years. Participants on average had ten health conditions (range 3-17), based on active diagnoses reported in the MDS 2.0 or HCFA 485. Most common conditions were related to cardiovascular (90% of the sample) and musculoskeletal (60%) systems, depression (60%) and memory loss/dementia (50%). Polypharmacy was also prevalent, with an average of 17 medications actively taken by the person during follow up (range 0-29). This diversity was mirrored in individual health trajectories.

Bi-annual assessments also reflected the effects of these concerns, but the relation was complex and non-linear. The chosen research instruments (MMSE, GDS, ADL/IADL, SF-12) occasionally missed changes due to the timing and frequency of administration. For example, participant 7 complained of subjective memory loss, while his MMSE remained 30 out of 30 on six occasions. In another example, participant 5 who moved to a nursing home for memory care, had MMSE score decrease from 20 to 5 (10-20 moderate, < 10 severe dementia (Perneczky et al., 2006)). Yet, his ADL score decreased only 2 points from a baseline of 19 out of 20. While participant was mostly independent in self-care, EHR notes reflected an increased need for supervision due to wandering. Moreover, in many cases multiple health events occurred in the six months between assessments. We decided not to base our understanding of health trajectories on these scores as done in the literature, even though research tools may be considered more valid and reliable sources of information than administrative medical records.

Table 2 presents characteristics of participants' health trajectories extracted from clinical data. Of note, three people that died (one with TigerPlace hospice, and two in a hospital) and one moved to a locked memory care unit. These situations represented major health transitions; others were less drastic. Most frequent symptoms recorded in the EHR notes were related to skin conditions, urinary problems, weakness, pain, depressed mood, anxiety, and confusion. We summarized four of the most prevalent concerns (pain, cognition, mood, and continence) for each individual based on the severity and frequency of occurrence to demonstrate variability of health in our sample.

Aim 1: To characterize an older adult's daily routine as captured with an in-home monitoring technology.

For each participant in stable phase of health trajectory, we compared visualizations of sensor data for similarities and differences from day to day. Figure 5 shows a calendar week of data for participant 7 in stable health phase. Figure 5-A presents 24-hour activity patterns that are fairly stable from day-to-day. Participant's morning routine is evident from the transition from *rest* to *personal care* area consistently around 07:00. Moreover, he leaves the apartment for an hour-long dinner around 17:00 every day except Wednesday. Figure 5-B is the same data as a stacked bar graph of total time spent in each area by day. It shows similar consistency in participant's daily routine, especially *rest* area. But we can also more easily quantify differences, such as lengthier time spent *outside* on Sunday (resident attends church) and slightly longer duration of activity in *personal care* on Monday and Friday (he receives assistance with showering on those days). This variability in activity is normal for the resident. The "baseline" routine characteristics can shed light on possible deviations during the unstable or acute trajectory phases.

Aim 2: To compare between-person factors that affect stability of the daily routine.

We found that physical and social resources at TigerPlace had a large impact on activity and health of the residents. The physical living spaces varied in layout configurations with one or two bedrooms, one or two bathrooms, and full walk-in kitchen or kitchenette. Seven were one-bedroom and one-bathroom apartments with four functional areas; three were two bedroom apartments with a secondary area (den or guest room). Use of environmental supports and resources also differed by individual. Four were independent in ambulation, and one used a wheelchair. Meanwhile, others switched from using cane to a walker (N=1) or from walker to a wheelchair (N=1) by the end of the follow up period. Independence in ADLs also varied. One participant did not receive any assistance from staff; four participants had weekly scheduled visits, such as skilled nursing coordination or housekeeping/laundry. Five participants received daily assistance, with scheduled medication reminders (sometimes up to 3 times a day) as the most common reason. These environmental factors were important to consider with sensor data, as high number of visitors can cause noise and problems with location inference.

We looked at both average and standard deviation of time spent in various areas (duration) and number of visits to areas (frequency). Figure 6 shows different patterns of daily routine features by participant ID. Most of them spent 84-96% of their time inside the apartment. Two participants who had a secondary area used it very infrequently, evident both in frequency and duration of time spent there. Interestingly, four participants spent little time in rest area, evident by average duration in rest less than an expected 7-8 hours one would spend on sleep. Three of those participants eventually died. Another one (ID 5) experienced dramatic cognitive decline and moved to a memory care facility. Standard deviation also showed inconsistence between days in the amount of time spent. Others were more consistent (had lower standard deviation). Interestingly, the standard deviation of visits to outside was consistently low among most participants. From the EHR record we know that TigerPlace resident would leave their apartment for two meals in the common area on a predetermined facility schedule; the third meal (usually lunch) they had at home. We can see both environmental and personal factora affecting individual daily routines.

Aim 3: To assess if deviations from the daily routine can be indicative of acute changes in health trajectory of the individual.

We found a number of observable and potentially interpretable relations between features of daily routine extracted from sensor data and individuals' patterns of health and illness recorded in the EHR. Table 3 presents lists characteristics for each participant in the scope of their individual time in the study. Sensors generated data for 76% of the total follow up time, yet missing or erroneous data was not random. Participant 9 had sensor malfunction 62% of the time. Participant 5 with the highest proportion of filtered data had dramatic cognitive decline and 36% was excluded because resident wandered out of the apartment often. Hence, lack of available data for analysis may be significant in its own right. Health trajectory phases were calculated as weeks with reported symptoms and adverse events. Over the average follow up time of 1.8 years, individuals experienced 47 acute events either related to falls or requiring urgent care. Number of acute events was unsurprisingly positively correlated with percent of time in unstable health phase, $r(9)=0.667$, $p < 0.049$, except for one individual. Resident 2 was legally blind and had 16 falls in three years. Interestingly, they tended to occur in clusters: once she fell, she would report pain, and fall again in a span of 2-3 days. This raised a question of what events can be predicted and potentially prevented.

We explored these temporal relationships of acute events and symptoms recorded in the EHR by visualizing them in calendar form. We found that nine out of ten participants reported symptoms a week before an acute event, and it happened in 28 out of 47 cases (mostly falls). Participants reported pain (N=5), urinary and bowel changes (N=3), dizziness (N=2), cough/SOB (N=2), skin problems (N=2), confusion (N=2), headaches (N=1), and trouble sleeping (N=1). While some of these symptoms may not be associated with overt changes in behavior, others have the potential to be captured through in-home monitoring with sensors. Below, an in-depth case study illustrates our approach to the data triangulation, and then we present cross-case comparisons.

Case Study. Figure 7 illustrates triangulation of clinical and sensor data of participant 2 for one year 2014. On top, a 12-month calendar with highlighted unstable and acute weeks. based on dates of falls and symptoms from the EHR notes, helps visualize temporal patterns. A cluster of events in March-April stands out. On March 24, participant had diarrhea, and fell in the bathroom while trying to clean it. Next Wednesday she reported weakness and asked to use a wheelchair for out-of-apartment activities. On April 11, participant again reported nausea and episodes of loose stool. The next morning, she fell walking from bathroom to bed. She continued to have diarrhea the next week, but it was controlled with Imodium. Moreover, participant had history of recurrent UTIs and reported urinary symptoms almost monthly from August to December. During the week of November 17 she had another fall, three days before she reported pain on urination.

In Figure 7, below the calendar subplot there are five time-series plots of daily routine features for the same time period. X-axis is scaled by week to match the calendar and to show dispersion of raw data points (weekly variability). Not surprisingly, that week had a higher average *frequency* of activity in the *personal care* are, with recorded 35 visits/day jumping from 23 in the week before. The outlier day with 76 visits was when the fall occurred. On the other hand, average *duration,* or time spent in the personal care area per day actually decreases from the previous week's high of 134 min/day to 77 min/day, possibly because the participant decreased overall activity after the fall. The question remains if the second fall could have been prevented when the participant was reporting weakness the week before.

Another interesting insight can be gleaned from looking at dispersion of observations in each week. In weeks of August-September and November-December when participant experienced UTI symptoms, the *frequency* of visits to *personal care* area were similar day to day (low variability). Meanwhile, in May and July, the *duration* of activity in *rest* and *outside* areas varied highly within each week, as evident by observations outside the control limits. One explanation may be that the *increasing routinization* of activity (decreased variability) when experiencing changes in health may provide a feeling of safety and confidence (Avni-Babad, 2011), while stable health may provide opportunities to be more spontaneous.

Cross-case comparison. We visually identified a number of trends in the daily routine features as they related to various reported symptoms. Table 4 presents a summary of our findings. We had the strongest support for the increased *frequency* in *personal care* area and reported urinary symptoms (urgency, pain on urination, and nocturia) for three people (participants with ID 6, 2, 10 from Table 1). Increased *duration* of time in *rest* area was present in when participants reported low mood (ID 9), lethargy and weakness (ID 6). However, in many instances we were unable to identify parallels, not just between individuals with the same condition but within individual who experienced multiple instances of the same symptom. For example, as participant 4 experienced more confusion related to cognitive decline, he had an increase in *frequency* of both *common* and *personal care* area visits in one month which did not hold true for the next month. This could be explained by many factors, such as increased involvement from staff.

Discussion

This paper presents a new approach to conceptualizing the older adult's "baseline" activity recorded with sensor systems as *daily routines*, or stable behavioral patterns structured in respect to time and space in the home. The results are presented in-depth exploratory case studies of real-world data from individuals that have been monitored with sensor networks. They are contrasted on factors that contribute to the normally expected variability in daily routine, such as demographic characteristics, prior functional status and level of assistance.

The observed patterns of activity in the apartments were consistent with previous findings of time use studies of older adults, where older adults receiving in-home supports spent 85% of their time at home (Moss & Lawton, 1982). However, we expanded on characterizing time spent in other in-home spaces, such as bathrooms (personal care) and living rooms (common area). Unsurprisingly, people vary markedly in their patterns of use, and it may be related to their functional status.

Understanding feature variability (high or low) is also important to predict when variability exceeds "normal" levels in the acute phase. We postulate that there is normal within-person variability in daily patterns of activity. Normal variability in activity is reflective of the routine. Trends should be accounted for when comparing features in the stable phase of the health trajectory to those in the acute phase. A downward linear trend that is reflective of a slow and progressive age-related functional decline (rather than acute onset changes in health). Upward trends may be noted if the person is engaging in health-promoting behaviors, but they are hypothesized to be rare due to frailty and age of the participants.

We found that reported symptom are consistent with geriatric syndromes often present in frail older adults with complex health needs (Inouye, Studenski, Tinetti, & Kuchel, 2007). Moreover, our experiences demonstrate the importance of considering not only healthcare utilization outcomes, such as hospitalizations and ER visits, but also intermediary contextual clinical factors, such as symptoms preceding the event. Some outcomes were more probable given a pattern of previous events in an individual.

Multiple case studies are sometimes considered less rigorous because of the concern about generalizing to a larger population. However, they are well suited for exploratory and theory-confirming studies with results that may later be tested in larger sample. Moreover, case study methodology fits within the person-centered research approach to understanding within person patterns. When exploring previously unknown patterns it is important to clarifying assumptions and decisions about the data. Each case is treated as a separate experiment (Nugent, 2009), and its results are generalizable to theoretical propositions and not to populations.

The biggest challenge has been identifying a "baseline" or the stable period when the person is not exhibiting any symptoms. For our study we used clinical notes from the EHR to identify the stable phase of health trajectory, and it is a major limitation. Clinical notes were kept by staff for administrative records and varied in quality and completion. TigerPlace EHR is not integrated with primary care provider or hospital records, so we might have missed critical information about participant's symptoms or care received elsewhere. Moreover, the older adult may have been managing symptoms on their own before reporting them to TigerPlace staff, hence our delineations between stable and unstable phases that were based on clinical notes may not have been exact. Another problem is that sensors work intermittently and there are gaps when one of the three sensors does not work. Reasons for sensor failure in a realistic environment may be power outages due to weather and network downtime. They have to be accounted for in the long run. We need all three types of sensors to make sure our calculation of routine is reliable.

The strength of this study is that it proposes a theoretically-based process for analyzing smart home data as well as clinically meaningful empirical indicators of routines to characterize an individual's health. The proposed approach may be generalizable to other similar in-home monitoring systems to create robust statistical algorithms that would analyze sensor data. Future work should focus on pooling of data and subjects for a larger observational study to solidify the evidence for in-home monitoring technology into wider use for chronic disease management in the aging population.

Conclusion

A variety of low cost sensors can collect information about various activities in the living space for long periods of time. Capturing and analyzing changes in the daily routines of vulnerable older adults living in these “smart homes” may allow clinicians to identify changes in health and functional status and predict negative health consequences. By understanding older adult’s daily routine in the home, healthcare providers can identify deviations early and adjust services to avoid health decline. It may drive future research on preventative interventions and further promote the use of these in-home monitoring technologies to support the quality of life and independence of the growing aging population.

TABLES

Chapter 2 - Table 1

Pertinent characteristics of participants and their living environments

	Personal Competence				Environmental Press		
ID	Age	Gender	Health conditions	Medications	Apartment configuration	Mobility device	Outside assistance
1	88	Male	3	13	2-1	None	None
2	87	Female	6	17	2-1	Walker, wheelchair	Weekly
3	84	Female	12	20	1-1	Cane	Weekly
4	90	Male	12	27	1-1	Cane, walker	Daily
5	88	Male	7	10	1-1	None	Weekly
6	97	Male	15	22	1-1	Walker	Daily
7	84	Male	17	29	1-1	None	Daily
8	95	Female	3	0	2-2	Walker	Weekly
9	85	Female	12	22	1-1	Wheelchair	Daily
10	92	Female	16	12	1-1	None	Daily

Note: All participants were Caucasian. In Personal Competence diagnoses are the sum of all active diagnoses reported in the MDS 3.0; medications are the number of medications taken for the duration of follow up. In Environmental Press, apartment configuration is reported as number of bedrooms-number of bathrooms; outside assistance is defined as frequency of schedule staff visits.

Chapter 2 - Table 2

Characteristics of Participants' Health Trajectories

	Any reported concerns with				Clinical assessment scores (*baseline, highest change)*				
ID	Pain	Cognition	Mood	Continence	N	MMSE	GDS	ADL	Note
1	Moderate	None	None	None	6	30	2, 4	20, 19	
2	Major	None	Some	Frequent UTIs	7	30, 27	3, 7	20, 18	
3	Major	None	Medication adjustment	Frequent UTIs	4	29, 27	1, 2	20	Died in hospital
4	Medication adjustment	Major decline	Some	Increase	5	27, 9	1, 5	19, 6	Died with hospice
5	Medication adjustment	Major decline	Some	Incontinent	6	20, 5	8, 1	19, 17	Moved to NH
6	Some	None	Medication adjustment	Difficulty	6	28	0, 3	15, 17	
7	Some	Some	Medication adjustment	None	6	30	3, 0	18, 20	
8	None	Some	None	None	4	20, 15	5, 2	19	Died in hospital
9	Some	None	Some	Foley Catheter	2	30	4, 6	8	
10	None	Some	None	None	2	30, 25	3, 1	19	

Note: Reported concerns were coded by level of occurrence of signs or symptoms recorded in the EHR notes, either self-reported or observed by staff. N = number of clinical assessments available per individual. MMSE score less than 24 indicates dementia. GDS-15 score greater than 5 indicates depression. ADL scores range 0-20, lower scores increased disability.

Chapter 2 - Table 3

Individual Health Trajectory Phases

ID	Time in study *weeks*	Sensor data % of time in study	Filtered out % of sensor data	Aggregates of Health Trajectory Phases: Stable % of time in study	Unstable	Acute	Falls	Urgent Care
1	130	74	26.4	87	9	4	5	1
2	156	84	8.2	76	15	9	16	0
3	103	98	1.8	71	22	7	5	5
4	107	85	12.1	59	34	7	4	4
5	88	64	36.4	81	18	1	0	1
6	158	86	14.5	52	44	4	6	0
7	148	76	23.8	81	18	1	1	1
8	74	91	6.5	91	8	1	0	1
9	26	38	0.0	77	19	4	2	0
10	36	60	10.5	92	6	2	1	0

Note: Sensor data is the proportion of total time in the study for which we had sensor data. Aggregate of the *stable* phase is defined as the proportion of weeks with no reported symptoms or acute events from the total time in the study. *Unstable* is the proportion of weeks with at least one reported symptom from total follow up time. *Acute* is the proportion of weeks with at least one fall or urgent care event. Urgent Care include emergency room visits and unscheduled hospitalizations. Multiple acute events may happen in one week.

Chapter 2 - Table 4

Relationship between daily routine feature trends and clinical context

Feature of Daily Routine	Trend	Type of reported symptom (Participant ID)	Type of acute event (Participant ID)
Duration of Activity			
Rest	+	Malaise, fatigue, lethargy (6)	
	-	Respiratory symptoms (1)	
Personal Care	+	Urinary frequency, diarrhea (2)	Cluster of falls (2)
	-	Pain (ID 2)	
Common	+		
	-	Pain (6), low mood (3)	
Outside	+	Wandering (4)	
	-	Mood (2)	Fall (6)
Frequency of Activity			
Rest	+		
	-		
Personal Care	+	Urinary frequency (2, 6, 10)	
	-	Pain (3)	ER visit (5)
Common	+	Wandering (4)	
	-	Low mood (3)	
Outside	+		
	-		Fall (7)
Possible Visitors	+	Memory complaints (8), pain (5)	
Overall Pattern		Confusion, wandering (5)	

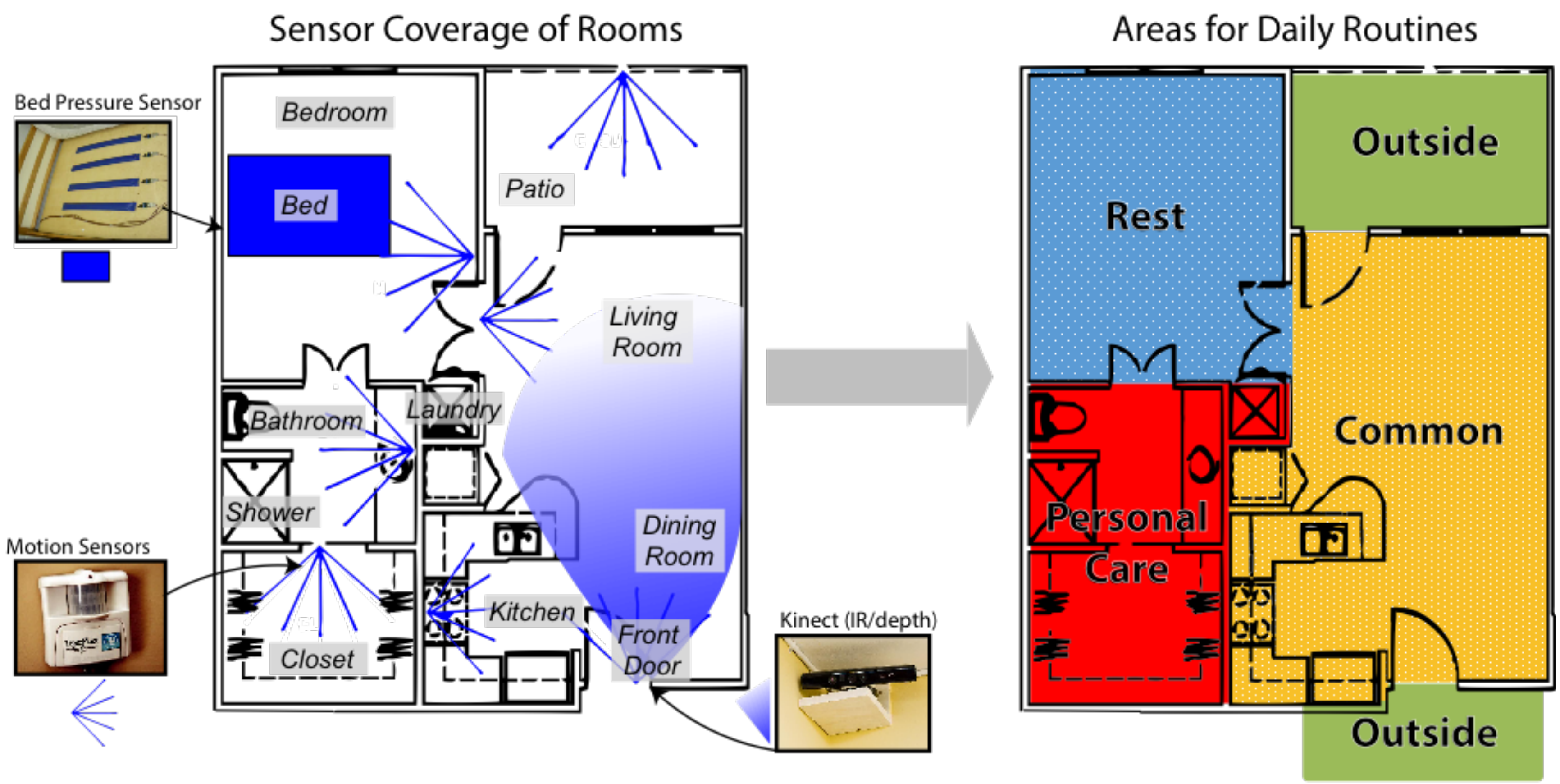

Figure 4. Sensor network for a typical one-bedroom apartment and the corresponding areas for daily routines. Data from multiple sensors were aggregated to improve reliability of inference about participant's position. A *secondary* area was added for two-bedroom apartments

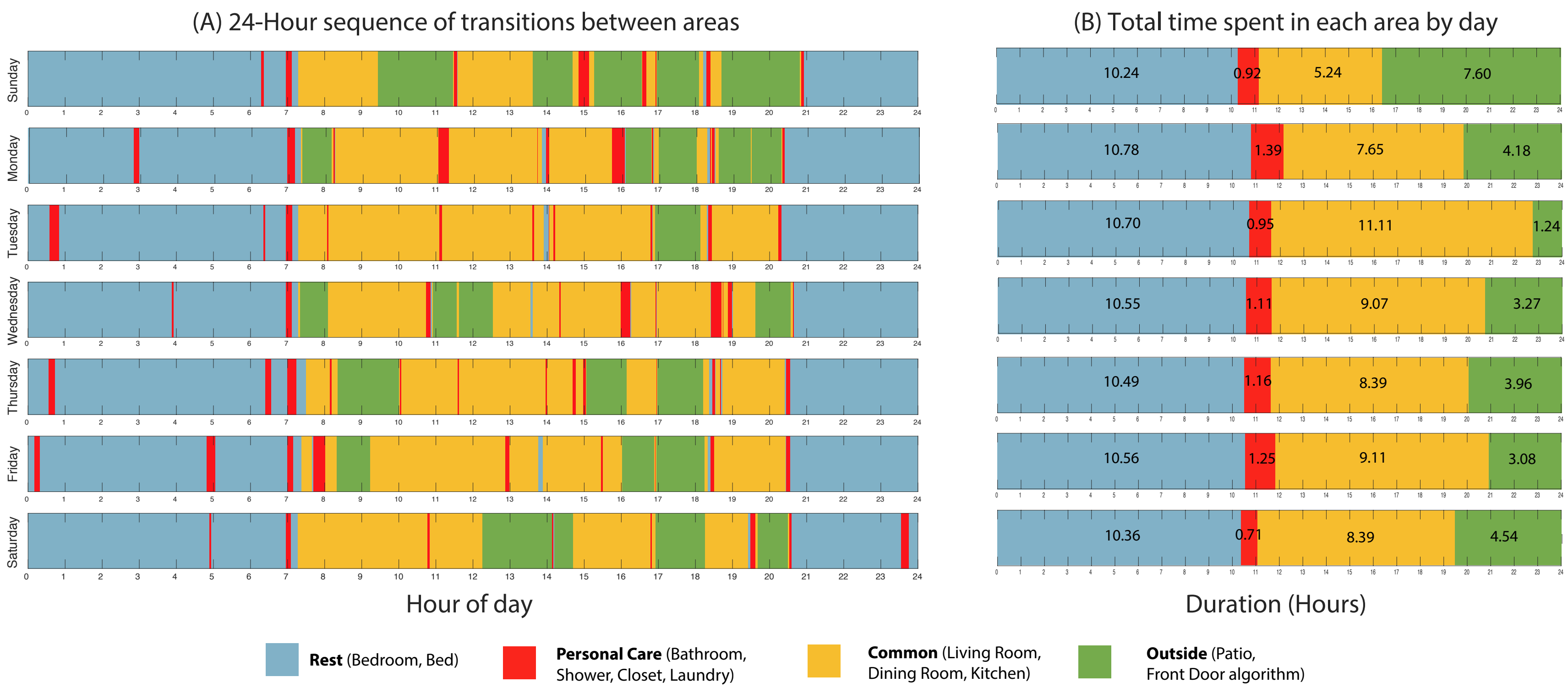

Figure 5. Identifying a personal baseline using time maps and aggregate features of the daily routine.
Seven days of sensor data for Participant 6, a 98-year-old male in stable health living in a 1-bedroom apartment. (A) Each bar is a sequence shows the temporal ordering of transitions between areas throughout the 24-hour period. (B) Each stacked bar shows total time spent in each area per 24-hour period with considerate variability in time spent outside by day of the week. Subject has assistance with showering on Monday and Friday, and visits church on Sunday.

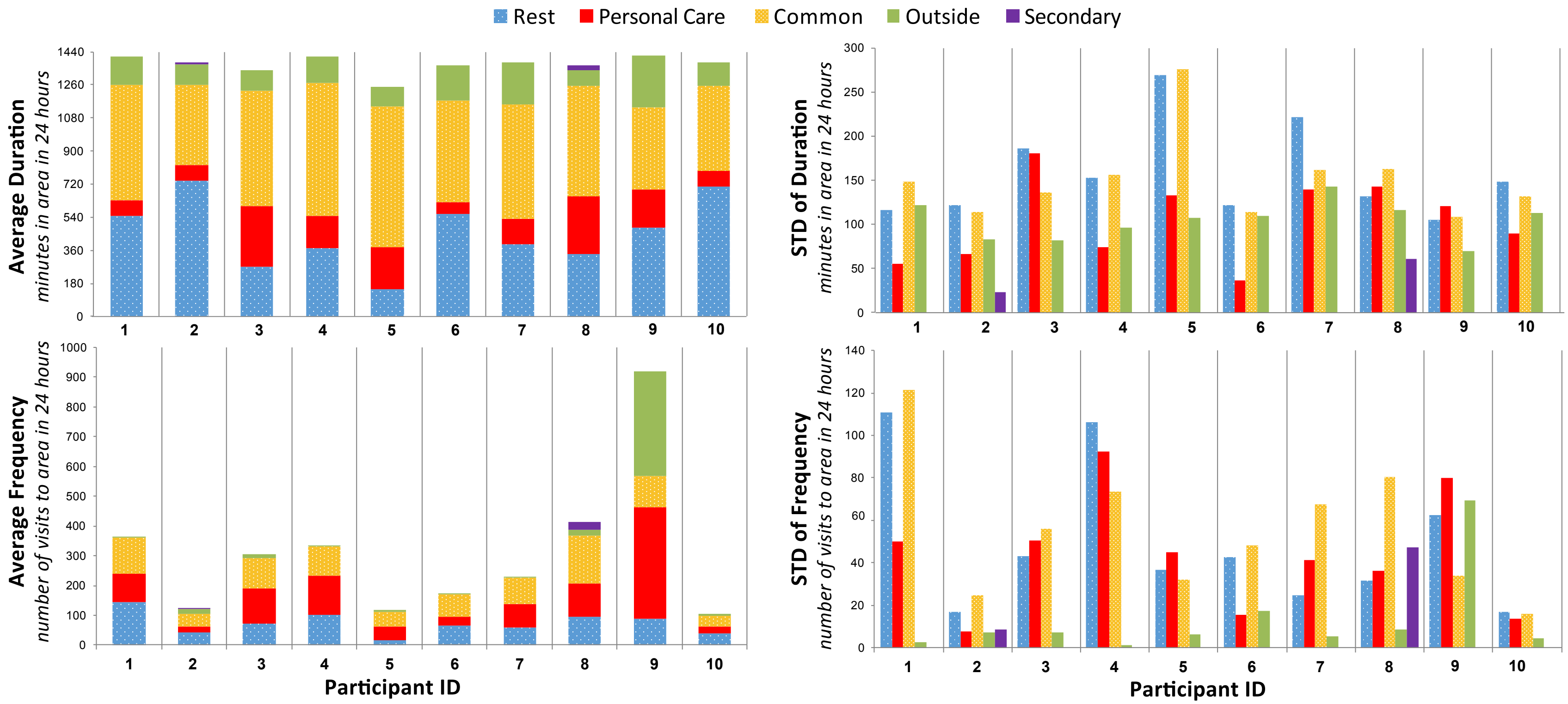

Figure 6. Features of the daily routine for each participant shown both as the average and standard deviation of duration and frequency of motion detected in various areas of the apartment, aggregated by 24 hours.

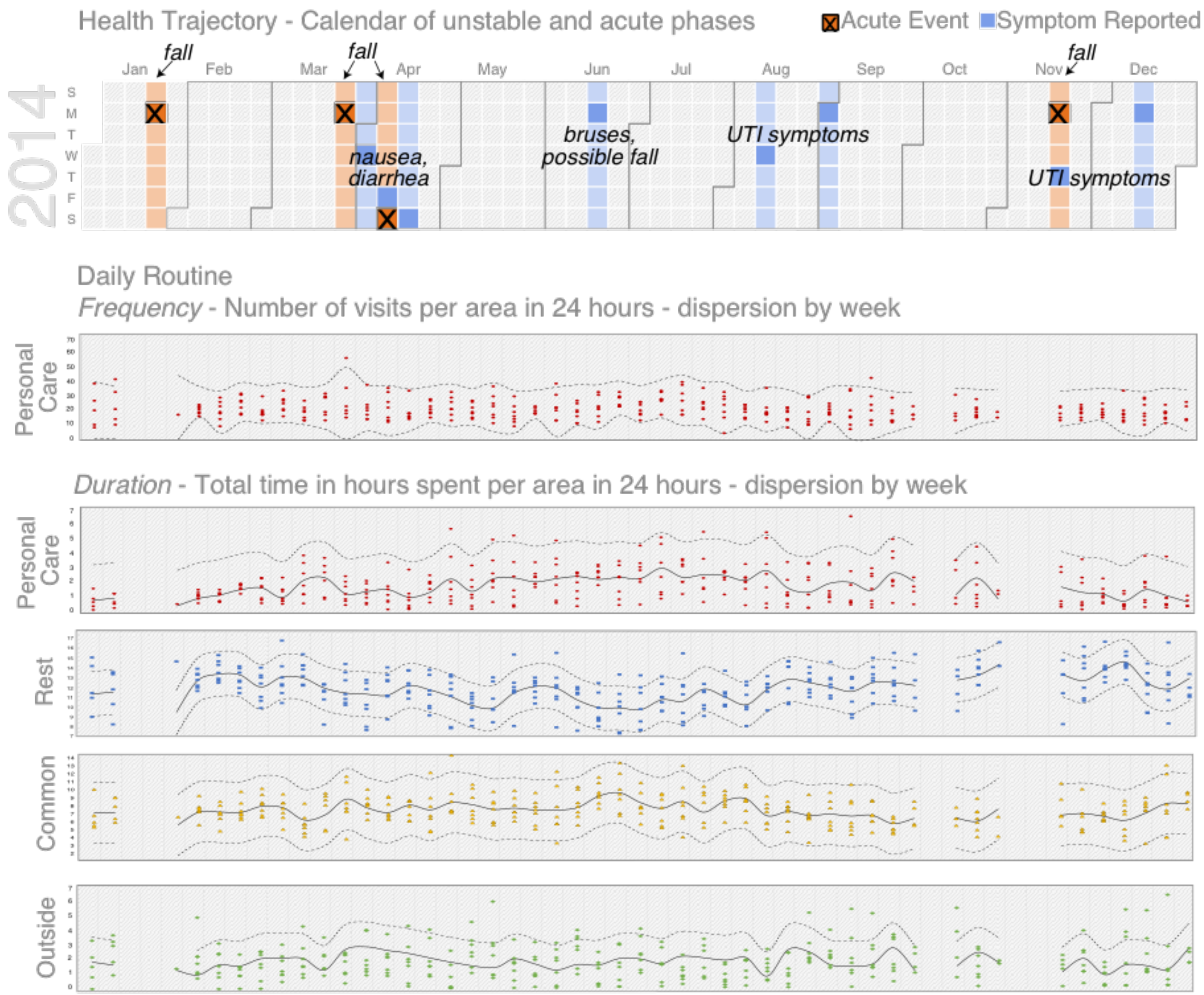

Figure 7. An example of triangulation and visual analysis of clinical and sensor data.
Top sub-figure is a 12-month calendar with acute events and symptoms recorded in 2014 for participant ID 2. Below are five sub-figures with plots of time series for features of the daily routine during the same time period. Dotted are the control limits set to two sigma of the yearly average standard deviation of feature. Sensor data was missing for some weeks due to unreliable infrastructure or apartment vacancy.

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CHAPTER 3

Considerations for the Effective Smart Home Health Monitoring of Older Adults

Abstract

Tele-monitoring can assist healthcare providers in delivering timely and personalized interventions for the growing number of older adults with complex health needs. Information collected with sensors placed in a smart home environment can be used to predict and prevent deteriorations in health. However, the success of these systems is often hindered by techno-centric approaches to their deployment and evaluation. The purpose of this paper is to present considerations for the long-term implementation of smart home health monitoring in a real world setting. They are based on a critical review of existing work and our experiences with secondary analysis of data from an on-going interdisciplinary project at TigerPlace. Both clinical and technical researchers should consider (i) diversity of smart home residents and their dynamic environments, (ii) practicality and reliability of the sensor infrastructure, and (iii) sources and frequency of clinical measures for meaningful predictions. Our insights strive to improve future interdisciplinary development of tele-monitoring systems. Smart home technology has the potential to streamline healthcare delivery and improve lives of older adults.

Keywords: smart home, older adults, tele-monitoring, interdisciplinary co-design

Introduction

The rapid growth of the aging population spurs the need for innovation in healthcare. The number of people over the age of 65 is projected to double from 40.2 million in 2010 to 88.5 million in 2050 (US Census Bureau, 2010). As people age, they prefer to remain independent as long as possible, while living in the place of their choosing (Birnholtz & Jones-Rounds, 2010). Yet, they also face higher risk of disability, frailty, and multiple health issues (Fried, Ferrucci, Darer, Williamson, & Anderson, 2004). More than 50% of people over the age of 65 have three or more chronic conditions (Anderson, 2010). Older adults with multiple chronic conditions may experience more adverse drug events, duplicative tests, and unnecessary hospitalizations (US Department of Health and Human Services, 2010). To remain independent, they would benefit from close monitoring of their health status.

Advances in technology are enabling innovation in healthcare delivery for this vulnerable population. A balance between the desire to age in place and management of complex health needs can be achieved with tele-monitoring (Satpathy, 2006). The goal of a tele-monitoring system is to predict changes in the person's health from information collected with remote sensing modalities. *Smart homes* are equipped with networks of sensors in the living spaces that collect and analyze data about person's interaction with the environment (Reeder et al., 2013). These unobtrusive systems do not require a conscious effort from the individual, which is more practical for long-term monitoring, compared to wearable or mobile devices (Bakkes, Morsch, Krose, & Kröse, 2011). They can capture clinically significant activities at home, such as sleep (Kealy, McDaid, Loane, Walsh, & Doyle, 2013), self-care (Lee & Dey, 2015), medication management (Lyons et al., 2015), mobility (Reeder et al., 2014), and socialization (Petersen, Austin, Kaye, Pavel, & Hayes, 2014). Often, such mundane activities form predictable patterns, and deviations from these daily routines may signal a health decline (Zisberg & Young, 2007). Analyzing how poor health affects changes in these patterns may guide predictive models for detecting early signs of illness (Rantz et al., 2013). This information would allow clinicians to intervene in time to prevent symptom exacerbations, functional decline, and adverse outcomes, such as hospitalizations and nursing home placement (Rantz et al., 2010). While having much potential, tele-monitoring using smart homes can suffer from several pitfalls when the technical implementation is not cognizant of clinical perspectives.

Successful operation of smart homes requires both technical and clinical expertise, yet interdisciplinary collaboration is a challenge. A recent systematic review found that most of research on smart homes is driven by technology developers in computer science, engineering and mathematics (Wilson, Hargreaves, & Hauxwell-Baldwin, 2015). Another review identified 56% out of 48 surveyed smart homes for older adults were in the pilot phase with small-scale laboratory testing, while 44% were mature but had limited evidence for the effectiveness of health monitoring (Liu, Stroulia, Nikolaidis, Cruz, & Rincon, 2016). However, a survey of tele-monitoring systems found that failures in translating prototypes to the real world setting were driven by inattention to clinical needs (Hardisty et al., 2011). To amend this gap, Hardisty et al. proposed that "knowing *what* look for" should drive "the *how*" (2011). The idiosyncrasies of older adults and their complex health needs should guide the design of sensor systems and data analysis. While this technology holds many promises, the field would benefit from a discussion about ways to improve its deployment and evaluation, and bridge the interdisciplinary gap.

This paper presents important lessons learned in using smart homes for health tele-monitoring. The insights are drawn from a combination of existing studies and our own research on tele-monitoring older adults for detecting changes in daily routines that could be indicative of future health changes. *The presented lessons urge both clinical and technical researchers to carefully consider (i) diversity of smart home residents and their dynamic environments, (ii) a balance between practicality and reliability of the sensor infrastructure, and (iii) sources of clinical information for meaningful insights about health.*

Our own project experience is based on retrospective secondary analysis of data from TigerPlace, a unique retirement facility in partnership with University of Missouri, Columbia (Rantz et al., 2008). It incorporates smart home tele-monitoring technology in coordinating healthcare for its residents to promote aging-in-place (Rantz, Phillips, et al., 2011). TigerPlace infrastructure for clinical and sensor data allows to answer new research questions about health of older adults, but with a few considerations in mind. We examine the strengths and limitations of a long-term system implementation in a realistic setting. The goal of this article is to provide insights to both clinical and technical researchers who aim to build successful tele-monitoring systems to improve health of older adults.

Considerations

The effectiveness of smart homes depends on their implementations within real-world constraints. Researchers need to understand whether and how their clinical and technical instruments suit the study of the target population – diverse individuals with complex health needs – by providing reliable and predictive capabilities. By studying current literature and by working with our TigerPlace data, we identified key research considerations for *(i)* characterizing older adults and their living environment, *(ii)* optimizing the sensor infrastructure in the smart home, and *(iii)* selecting clinical and health measures. For each subsection we present a brief overview of the current work, our experiences, and make recommendations.

Characterizing Older Adults and their Living Environments

The aim of tele-monitoring is to help older adults remain in a self-determined home environment by anticipating and meeting their health needs (Piau, Campo, Rumeau, Vellas, & Nourhashemi, 2014; Satpathy, 2006), so it is crucial to understand people and their living spaces. "Older adults," defined as those over 65 years old, is an umbrella term for a diverse group that spans at least a 35-year age range. The "oldest-old" (85+ years) are at the highest risk for disability and health decline (Lowsky, Olshansky, Bhattacharya, & Goldman, 2014). Yet, people in the same age group vary in their reported well-being, mobility, and self-care abilities (Lowsky et al., 2014), so it is important to consider individual needs. Moreover, their living arrangements offer different lifestyles and social supports. Older adults may prefer to stay in their private residences or reside in congregate housing (Vasunilashorn, Steinman, Liebig, & Pynoos, 2012). The physical space can range from a freestanding multi-story house to a studio apartment, with countless layouts and furniture arrangements. This variety of person-environment combinations has an important influence on the proper design, implementation, and analysis of the smart home that technical and clinical researchers alike must consider.

Current Work. As some in the research community shift their focus from development to translation of technology to the real world setting, investigators are urged to report demographics of study participants (Pol et al., 2013). A recent review found that the mean age of older adults in smart home trials was 75.4 years (Liu et al., 2016), yet the age range remains wide, comparing 60 to 96-year-olds. Often, the inclusion criteria are to be living alone, ambulatory and independent in self-care, which may exclude a large number of older adults. In 2012, only 28% of older adults in the community lived alone (Administration on Aging, 2014), and while this proportion increases with age, so does the prevalence of disability. Some studies included volunteers with no reported health conditions, while others compared subgroups based on a particular diagnosis, such as mild cognitive impairment (Hayes, Abendroth, et al., 2008) or Parkinson's disease (Cook, Schmitter-Edgecombe, & Dawadi, 2015). However, healthy older adults may not benefit from tele-monitoring, while focusing on one diagnosis may miss compounding effects of multiple co-occurring conditions that are prevalent in the aging population (Wolff, Starfield, & Anderson, 2002). Inadequate information on smart home residents limits our understanding of who could benefit from tele-monitoring technology or could result in misleading outcomes.

While reported clinical characteristics were not uniform, descriptions of the environment were even more cursory. Mostly, they simply stated the general type of housing in which the system was deployed. A majority of studies were conducted in private homes and independent retirement communities (Liu et al., 2016), but these lack a detailed description of the actual physical space. A few systems were installed in assisted living facilities (Alwan et al., 2007), yet the effects of such structured environments on the outcomes were not discussed. Sensor positions were often documented on floor plans, yet variability in the layout and use of living spaces was rarely described any further. One project asked participants to report changes in furniture arrangement weekly (Kaye et al., 2011), a prudent consideration since such alterations can dramatically affect the functionality of in-home sensors. Ignoring the dynamic living environment limits the insight on the factors affecting long-term implementation of smart homes.

Our Experience. We learned about the strengths and limitations of TigerPlace data by closely examining its residents and their environment. TigerPlace is a unique retirement facility where people can move while still independent and can remain until the end of their life (Rantz et al., 2008). Upon admission, the person gives consent to participate in evaluations of smart home technology, and is monitored until he or she withdraws, moves away or dies. This arrangement gave us an opportunity to observe the “aging-in-place” process in a smart home environment. We were interested in examining sensor data for patterns of activity in the apartment that might be linked to unexpected health events, such as falls and ER visits. Unfortunately, out of 55 residents, we could only examine ten specific individuals that produced sufficiently-reliable long-term monitoring data. A limiting factor was that the resident had to live alone, since the sensing system cannot distinguish the older adult participant from other beings in the apartment. This often lead to “garbage-in, garbage-out” sensor data that obfuscated the high-level routine activity of the participant. Hence, all couples and all residents with pets were excluded from consideration. Our resulting sample was 100% Caucasian and 50% female with a mean age of 89.3 (range 84-97) years. They were partly representative of older adults assisted living facilities (Demiris, Skubic, & Rantz, 2006) in age, but much less ethnically diverse than the general aging population (Ball, Perkins, Hollingsworth, Whittington, & King, 2009). Our sample had an average of seven recorded diagnoses and eight medications, reflective of complex health needs. Most common conditions were related to cardiovascular (90% of the sample) and musculoskeletal (60%) problems, depression (60%) and memory loss/dementia (50%). Urinary and gastrointestinal symptoms were also prevalent. Some of these conditions, such as depression and urinary infections, had observable effects on their daily activity while others did not. This raises the question about suitability of using smart homes to monitor certain conditions over others. The ten participants experienced 56 health events, including falls, unplanned hospitalizations and ER visits, some of which could have been preventable. Multiple comorbidities and adverse health events demonstrate that our sample is a prime target for tele-monitoring, yet insights from the collected data were obfuscated by multiple environmental factors.

We found that the physical and social milieu had a large impact on the activity of TigerPlace residents. The apartments differed in the number of bedrooms, bathrooms, and kitchen configurations. 70% of our sample lived in one-bedroom-one-bath units, so it was possible to create a general algorithm for activity based on the common layout. Yet, those with two bedrooms did not use the second room uniformly. One resident used it frequently for writing an autobiography; another left it for guests during holidays. For these reasons, we could not use a single classification of "normal" activity in that area. Moreover, the physical layout sometimes led to ambiguities and forced assumptions about resident behavior. For example, each apartment had two exits: one through a private outside patio, and the other into the facility corridor that lead to common spaces. An "out-of-apartment" detection algorithm relied on the assumption that the resident uses the front door rather than the patio to leave. It was true in majority of cases, since patio sensor firings were rare. On one occasion we noted aberrant clusters of patio signals during summer nights while the resident was in bed. It could have been an animal; it was impossible to verify.

Social resources at TigerPlace influenced residents' behavior as well, especially out-of-apartment activity and visitors. Some activity patterns could be predicted from the pre-determined facility schedules. For example, residents had two meals in the common dining area per day: usually breakfast and dinner. They also had access to a wellness center, pet therapy, interest group meetings and other leisure activities, but weekly activity schedules at TigerPlace were not kept on record for researchers. Moreover, visitors were a frequent occurrence. They could sometimes be deduced from aberrant sensor firings and care records, but not reliably.

Scheduled medication reminders (sometimes up to three times per day) were the most common reason for daily nursing aide visits; weekly housekeeping/laundry for some residents was also evident. We also noticed that as the older adult's health declined, they had more visitors from both TigerPlace staff and family members. However, due to limitations of the sensor system we were unable to determine the quality of these visits. The structure of the living situation, such as regular visits or scheduled events, influences the person's daily routines. Thus, to identify changes brought by poor health rather than external forces, the environment needs to be considered when monitoring older adults in realistic setting for long periods of time.

Recommendations. Based on the current work and our experiences, we urge researchers to consider the personal characteristics of older smart home residents. Older adults with multiple chronic conditions may benefit most from tele-monitoring interventions, since they are already the highest users of healthcare resources (US Department of Health and Human Services, 2010). If the goal of technology is to support older adults as they age in place, then health monitoring systems must be robust, personalized, and last for decades. Demographic and clinical information has to be periodically updated, since even healthy and independent older adults may experience illness and decline over time. Secondly, we implore researchers and clinical staff to carefully document information about the social and physical environment of the individual using multiple methods, e.g., detailed notes, diagrams, and photos. Information about the living space, such as room dimensions, layout, and furniture placement, can enable optimized sensor deployments to suit the habits of individuals. For example, the resident may have a "control center" — a preferred armchair in a central location with a telephone, TV remote, and grooming items arranged within reach — that maximizes independence and promotes socialization (Golant, 2003). They may use it more as their mobility or health decreases. But the physical space may change over time as people move their furniture and accumulate or lose personal effects, so both historical and current documentation should be kept. Lastly, the outside setting has an effect on activity, such as scheduled events, visitors, and even weather due to the geographical location. These issues can dramatically affect the smart home data collection, analysis, and even the validity of clinical conclusions based on tele-monitoring deployments.

Optimizing Smart Home Sensor Infrastructure

The diversity of participants and living spaces requires flexibility and personalization in deployment of the tele-monitoring system. The smart home infrastructure generally consists of sensing devices embedded in the environment, a communication system that relays the data, and computing system that reason about it (Ni, García Hernando, & de la Cruz, 2015). Commercially available sensors vary in cost and capability. They can measure a variety of activity parameters, such as motion, occupancy, interaction with objects, pressure, temperature, water use, electrical use, humidity, odor, and light levels (Ni et al., 2015). Wired or wireless communication protocols transmit the data for analysis either locally or on a remote server. Computational algorithms to recognize human activity from sensor data vary in complexity and generalizability (Lowe & Ólaighin, 2014; Noury et al., 2011). Researchers are challenged to develop smart homes that are flexible, acceptable and sustainable in the long term, while also delivering meaningful and reliable information about its resident for further analysis.

Current Work. Projects around the world have piloted smart home infrastructure in laboratory settings (Vimarlund & Wass, 2014), but few have implemented it in the residences of older adults for long periods of time. This is problematic since a system developed in a tightly controlled environment may be based on assumptions that do not hold in highly dynamic one. Aside from TigerPlace, ongoing real-world smart homes have been deployed in Intelligent

Systems for Assessing Aging Changes (ISAAC) study at Oregon Health Sciences University (Kaye et al., 2011), CASAS Smart Homes at Washington State University (Cook, Crandall, Thomas, & Krishnan, 2013), and the Great North Haven project in Ireland (Doyle et al., 2014).

These projects tried to strike a balance between practicality and reliability of sensor network configuration. Many used simple passive infrared (PIR) motion and magnetic-switch door sensors to maintain relative parsimony. While specialized devices, such as water use sensor in the bathroom, can more precisely monitor certain activities (Lowe & Ólaighin, 2014), motion sensors provide a general indication of a person's movement in the home. Switch sensors can monitor the opening and closing of doors, kitchen cupboards, and medication cabinets, which can serve as proxy for clinically significant activities. The sensor's field of view (FOV) is a consideration in placement to avoid "dead zones" of no coverage and to reduce overlap that can create noise and ambiguity in interpretation. A large FOV may cover the whole room, while a sensor with a restricted FOV would trigger only when someone passes directly by it (Hayes, Pavel, et al., 2008), making localization possible. Overall, the number of sensors in a network depended on the layout of the residence. They ranged from twelve (Hayes, Pavel, & Kaye, 2004) to over a 100 (Doyle et al., 2014), affecting cost and complexity of the installation, maintenance and unobtrusiveness. Most sensors were small, battery powered and wireless, since aesthetic appeal plays an important role in acceptance of monitoring technology (Alexander et al., 2011). While wireless communication protocols work well in a controlled environment, unforeseen electrical interference or unscheduled power outages in the real world setting can disrupt data transmission and cause errors. Moreover, to reduce battery power consumption, PIR sensors often had a 6-10 second lag in firing (Hayes, Abendroth, et al., 2008), which in turn can lead to information loss. Noise, errors, and missing data were addressed through pre-processing, such as filtering invalid signals or excluding sensor sequences that were not physically realizable (Hayes et al., 2004; Petersen et al., 2014). However, ad-hoc reasoning behind these approaches may have major implications for the quality of the data.

The utility of sensor data is based on meaningful measures it can produce. Some researchers have created algorithms for activity recognition, using labeled data from scripted actions (Brownsell, Bradley, Cardinauxm, & Hawley, 2011; Dawadi, Cook, & Schmitter-Edgecombe, 2015). While this approach generates interpretable information, it may not be scalable to all environments and individuals. For example, if the algorithm was trained to identify “cooking” based on a sequence of activated kitchen and stovetop sensors, it will fail when the person uses a microwave. Another option was to monitor specific events, such as opening of a medication cabinet (Glascock & Kutzik, 2000), yet researchers have to be clear about their assumptions. Opening a medication cabinet does not mean that the person took the medication. Some groups derived measures that are clinically comparable, such as walking speed (Kaye et al., 2011; Stone & Skubic, 2012). While this approach is valid and reliable, it does not utilize the full extent of smart home data capabilities. Another way was to create new, previously unavailable metrics, such as frequency of room transitions (Campbell et al., 2011), but their interpretation was limited since no normative information exists. Most commonly used activity features were derived from frequency, duration and intensity of motion recorded in clinically meaningful areas, such bathroom (Rantz, Skubic, et al., 2011), bedroom (Hashizaki, Nakajima, & Kume, 2015), or when the person left the apartment (Thielke et al., 2014). In all of these situations, the reliability of smart home activity measures was driven by the quality of sensor data, which in turn depended on the system infrastructure.

Our Experience. The goal of our study was to relate poor health to changes in the *daily* *routine* of older adult, which we defined as the overall pattern of 24-hour activity in the smart home. In our secondary analysis of data, we had to be cognizant of TigerPlace sensor infrastructure that was not built for our research question. The system was constructed to be unobtrusive and low cost in order to be acceptable by residents for long-term use (Demiris, Hensel, Skubic, & Rantz, 2008). Each apartment was fitted with 10-15 wireless PIR motion sensors, a Microsoft Kinect device, and bed sensor. PIR sensors were installed by research staff on the walls or over the doorways of all major apartment spaces: bedrooms, bathrooms, shower, walk-in closets, laundry, kitchen, living room, front door, and outside patio. They were configured to have an unrestricted FOV with 20 ft. range, and a sampling rate of 7 seconds to preserve battery life. The wired Kinect for Xbox (Microsoft, Redmond WA) had an infrared depth finding sensor with a higher sampling rate of 30 frames per second. It was positioned above the front door to monitor the living room, dining area and parts of the kitchen for detection of gait speed and falls (Stone & Skubic, 2013). A special hydraulic pressure sensor (Heise, Rosales, Sheahen, Su, & Skubic, 2013) was placed under the mattress of the bed where the resident primarily slept to monitor bed restlessness. TigerPlace floor plans contained information about the apartment layout, room dimensions, and the general location of each sensor, but they were not personalized to the furniture arrangement of individual units.

The sensor network configuration affected the reliability of information that we needed to calculate our measure of interest. To identify the pattern of individual's daily routine, we had to know where the person was at all times. However, some apartment spaces with only one PIR sensor had "dead zones", while others were covered by multiple devices with overlapping FOVs (e.g. bathroom and shower). Unfortunately, we could not quantify these effects from the documented information. Since PIR sensors were configured to send a signal only every 7 seconds when they detected continuous motion in their FOV, we assumed *that the person remained in the same area as the triggered sensor until a sensor in a different area fired*. Yet, the slow sampling rate made it possible to "teleport" between areas without triggering a sensor. For example, the resident could briskly walk from the bathroom to the living room via the bedroom, and not trigger the bedroom sensor at all if she passed through in just a few seconds. The resulting sequence of sensors would lead to an incorrect conclusion about how long the person was in the bathroom. In addition, we noticed that some previously functioning sensors stopped triggering, possibly because the battery died or their FOVs was obstructed by moved furniture. However, we did not have historic information to confirm this.

We developed a post-processing algorithm to improve the reliability of our data. Each apartment was divided into four or five coarse areas covered by multiple sensors. This consolidation improved our confidence in resident's position. Figure 7-A shows a 24-hour sequence of sensor firings on the top plot and the corresponding areas on the bottom plot with little ambiguity in resident's location. For example, we were highly certain that the person was in the *common* area if both Kinect and living room PIR sensors fired at the same time. The downside was loss of granularity, such as distinguishing between activity in the bathroom and closet that were combined into a *personal care* area. Moreover, this approach did not address the difficulty in discerning when a person left the apartment, or merely passed by the front door area to sit motionlessly in the living room (e.g., to nap in a chair). We also did not resolve the ambiguity in data when multiple people triggered sensors in different areas simultaneously. Figure 7-B shows an example when around 13:30 sensors in the living room fired at the same time as bed sensor. We suspected visitors, and the accuracy of resident's location in the assigned area was not certain. However, our approach was deemed valid, since the theoretical definition of our daily routine measure was an *overall pattern*, rather than discreet events.

Recommendations. We advise researchers to consider factors that affect reliability of sensor data while containing cost and unobtrusiveness of the smart home infrastructure. Table 1 summarizes high level considerations for optimizing the system based on our experiences and review of the current work in the field. Clinical information, such as natural walking speed of 0.56 m/s (Hayes, Abendroth, et al., 2008), may be useful information when deciding on the position and sampling rate of motion sensors. Since smart homes are often costly to deploy, the field would benefit from standardized protocols for comparable data from different projects. Yet, researchers should not stay away from updating the systems, as emerging technologies become available and resolve reliability or cost issues.

To retain interoperability with new emerging devices and to promote fidelity in secondary analyses of data, we urge researchers to meticulously document information about the deployed system. It should be performed at the time of installation and updated periodically to include a detailed and personalized information about the floor plan, furniture arrangement, precise sensor placement, its specifications, location of "dead zones" and overlapped FOVs. System maintenance logs should contain time to battery replacement, scheduled power outages, or unscheduled network downtime, such as due to weather. These considerations will improve robustness of the sensor system and will guide what insights can be extracted from the data.

Selecting Clinical and Health Measures

Analyzing changes in activity captured by smart home sensors in respect to known clinical outcomes can identify proxy measures of poor health. The first step is to select a baseline*,* patterns of activity that are "normal" for the individual in a healthy state, and then identify deviations from it that may signal a symptom onset or a health decline. However, this process depends on clinical information about the older adult that is reliable, sensitive to longitudinal changes and easy to collect.

Current Work. To understand sensor data in relation to health, some groups have employed an epidemiologically grounded approach of quantifying differences between groups with known health outcomes, such as healthy older adults versus those with a diagnosis of MCI (Hayes, Abendroth, et al., 2008). However, often within-group variability muddles the confidence in calculating group-based norms for behavior. Another way is to observe an individual over time to detect deviations from their personal norm, such as tracking a person as they develop MCI (Akl, Taati, & Mihailidis, 2015). The sensitivity of this approach depends on the threshold for acceptable variability in the selected baseline, that is oftentimes a measure aggregated over a certain time period (Lee & Dey, 2015). For example, researchers flagged days with “abnormal” bathroom activity if the observed value was two standard deviations from an average of the previous 30 days (Glascock & Kutzik, 2006). These alerts are useful only if they correspond to meaningful changes in health.

The validity of sensor-driven insights depends on the sensitivity of selected clinical measures. One group asked a group of healthy participants to fill out weekly computer surveys about medication changes, falls, injuries health changes, ER visits, depression, changes to living space, vacation and visitors (Kaye et al., 2011). 83% of participants competed the report but its accuracy was not conformed. Moreover, this type of data collection may not be appropriate for someone experiencing cognitive decline or mood changes. Another way is to collect objective data through clinical assessments. Some groups assessed study participants annually, using commonly used research tools, such as Mini-Mental State Exam (MMSE) for cognitive function

(Akl, Snoek, & Mihailidis, 2014). While this information is based on valid and reliable sources, short-term fluctuations may not be captured with infrequent assessments.

Our Experiences. We found that the type, source and frequency of clinical information about the resident influenced our inferences about the corresponding sensor data. For each participant we had access assessments performed for research and information from the Electronic Health Records (EHR). The assessments were conducted every six months using valid and reliable instruments, such as MMSE (Folstein, Folstein, & McHugh, 1975), Geriatric Depression Scale (Yesavage et al., 1982), and Short Form 12 (SF-12) survey of health-related quality of life (Jakobsson, 2006). The EHR contained notes about routine care documented by clinical staff for administrative purposes. We used the notes to extract dates of any reported symptoms and acute events, such as ER visits and falls. Comparing these data sources revealed the importance of selecting appropriate time periods to understand fluctuating health needs of older adults with multiple comorbidities.

To illustrate this difference we present an example in Figure 8. An 88-year old woman with worsening eyesight and history of migraines reported symptoms of seasonal allergies prior to a cluster of falls in the early weeks of July. Next week she complained of hip pain and experienced a fourth fall that led to an ER visit on July 23, 2013 .Her bi-annual SF-12 scores of self-reported quality of life related to mental and physical health remained fairly stable over the 12 months (Fig. 1-A). However, the EHR notes presented a different clinical picture. Her reported symptoms and acute events cluster in different patterns each month (Fig 1-B), and are more in agreement with the trend (Fig. 1-C, solid line) in sensor-derived information on the daily time spent in the *personal care* areas of the apartment. We set a threshold for anomalies (dotted line) to 3 standard deviations of the exponentially weighted moving average with a smoothing factor of 0.3, based on previous literature (Jarrett & Pan, 2014). The duration of recorded activity in bathroom, shower, closet, and laundry lengthens from average of 78 min/day in April to 132 min/day in July when resident experienced multiple acute events. The daily variability (error bar) for that week also exceeded our threshold. The weekly average decreased to 97 min/day in October, when she had another fall and reported urinary frequency. November and December had lower means and variability because the resident was out of apartment for Thanksgiving and Christmas holidays. Even with seasonal effects on variability, we see that the trend in sensor-derived data was more in line with EHR notes rather than infrequent research assessments.

Our example illustrates the importance of selecting suitable source of clinical data to serve as "ground truth" in contextualizing sensor data. Bi-annual assessments provided an overall picture of health but did not tell us how the person is feeling on a particular day. Since sensor data generates continuous information, we needed more detailed information to capture day-to-day fluctuations in symptoms and function. The strength of using clinical documentation, such as EHR notes, is that it is data collected as part of regular care without extra burden on the participant or clinical staff. The resident reports symptoms as they become bothersome or when an acute event that requires care happens. However, TigerPlace EHR did not include information from the primary care provider visits, hospital discharges or scheduled surgeries, events that can significantly affect older adult's activities. Administrative documentation is often not standardized or complete, a limitation that has to be considered for research insights.

Recommendations. We recommend using longitudinal information rather than group-based comparisons to validate sensor data in the clinical context. This would reduce variability of extraneous factors, especially among highly heterogeneous older adults with complex health needs. Details about health and wellbeing can come from participant's self-report, administrative data, such as EHR, or additional clinical assessments. However, researchers need to be aware that specificity of insights is affected by frequency of observations and sensitivity to change of the data sources. Copious details about the older adult's fluctuating health needs would help to identify optimal times for for interventions.

Conclusion

We hope that our insights from secondary analysis TigerPlace data and reviewing current work in the field will be considered in future implementations of smart home health monitoring. While technology offers unprecedented capabilities, we need to know "who", "what", and "why" before the "how" to make it effective. A smart home sensor infrastructure needs to be flexible while delivering reliable data about the inhabitant of a highly dynamic environment over lengthy periods of time. More importantly, the generated information has to be useful in timely and individualized predictions about health. While researchers made strides in expanding technological capabilities of these systems, there has been a lack of collaboration with clinical experts who can interpret and assess significance of the produced data. This interdisciplinary misalignment impedes the progress in deployment and evaluation of health tele-monitoring for older adults. Researchers have to take into account characteristics of the target population and their setting, capabilities and limitations of technology, and, lastly, clinical indicators to "make sense of sensor data".

Moving forward the field of gero-technology and smart homes in particular is an interdisciplinary affair. Incorporating technology into healthcare for older adults requires strong and balanced teams. Diversity in skills and expertise can address current limitations in deployment and evaluation of sensors for meaningful clinical use. The success of these collaborations depends on common and complementary scope, goals, language, methods and approaches to generating evidence. Moreover, we need rigorous documentation and reporting on existing projects to identify barriers and enablers of success. Smartly implemented, health tele-monitoring may reduce cost and improve care for older adults to age in place safely and independently.

TABLES

Chapter 3 - Table 1

Considerations for deployment of sensor systems for long-term health monitoring

Infrastructure		Considerations
Sensor	Type	Adding different types of sensors increases specificity of activity recognition but also raises the cost and complexity of the monitoring system.
	Area coverage	Wide field of view may cause overlap in sensor response in smaller spaces, while restricted field of view may lead to dead zones in larger rooms.
	Sampling rate	Too low may miss transitions, too high may impede battery life. Age-appropriate natural walking speed and distance between field of view may guide the setting.
	Power source	Wireless sensors have battery life limitations while wired ones may not be aesthetically pleasing and costly to install.
System	Number of devices	A small number of sensors per area may not provide detailed enough information, while too many impede cost and aesthetics/acceptability of the system.
	Placement	Optimal and detailed coverage will be guided by sensor characteristics and dynamic physical environment.
	Maintenance	An ongoing log of time to battery replacement, power outages, software updates, and changes in the physical environment will aid system reliability.

FIGURES

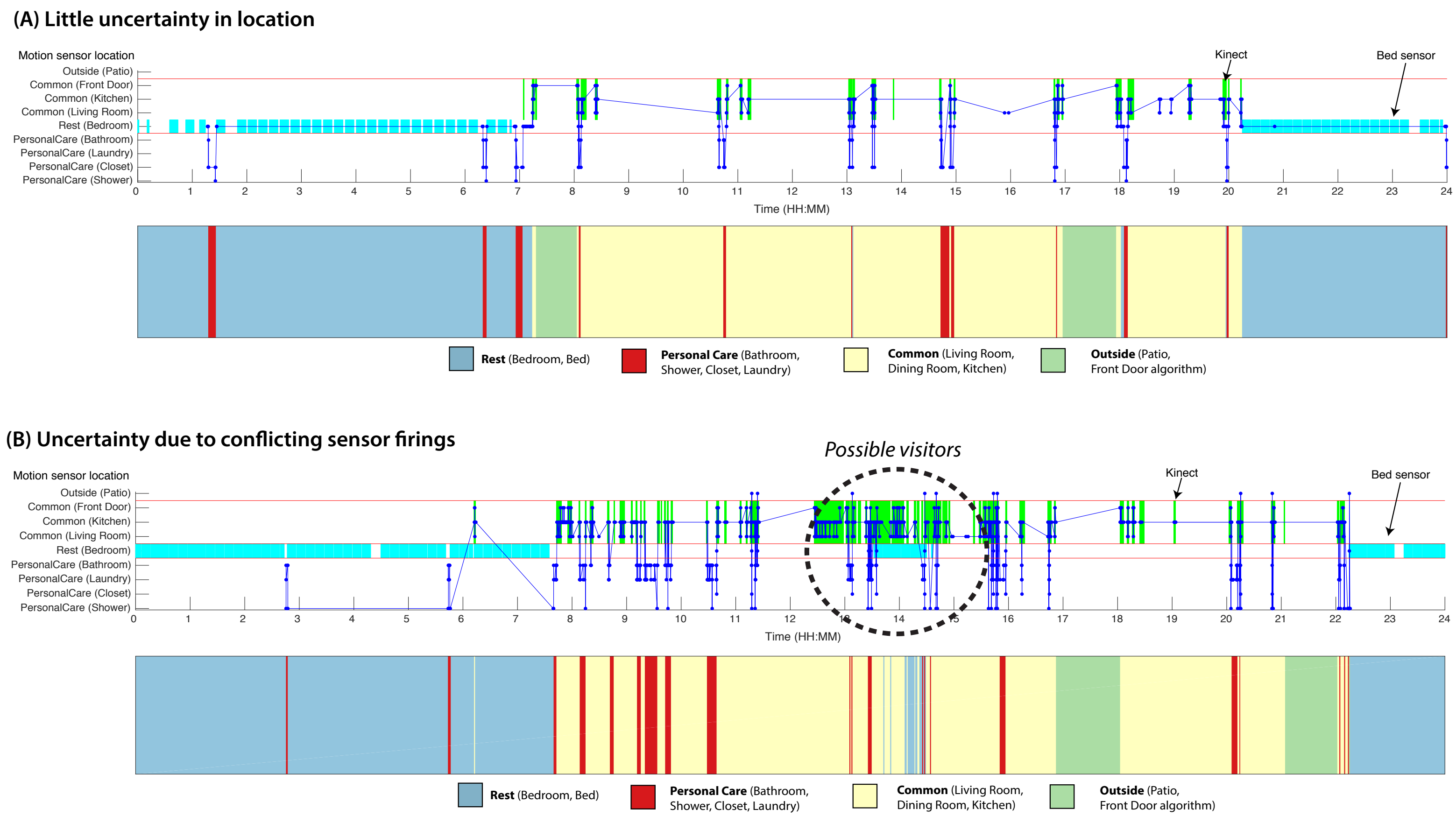

Figure 8. Sensor data coded into daily routine areas with little uncertainty and uncertainty due to conflicting sensor firings. Examples of two separate days of 24-hour raw sensor data (top plot) and post-processed areas (bottom plot). A) Little uncertainty about resident's location since motion, Kinect and bed sensor firings fired consistent with each other. (B) Uncertainty in location of the resident, since bed sensor in the bedroom and Kinect sensor in the living room fired at the same time around 13:30 possibly due to multiple people in the apartment.

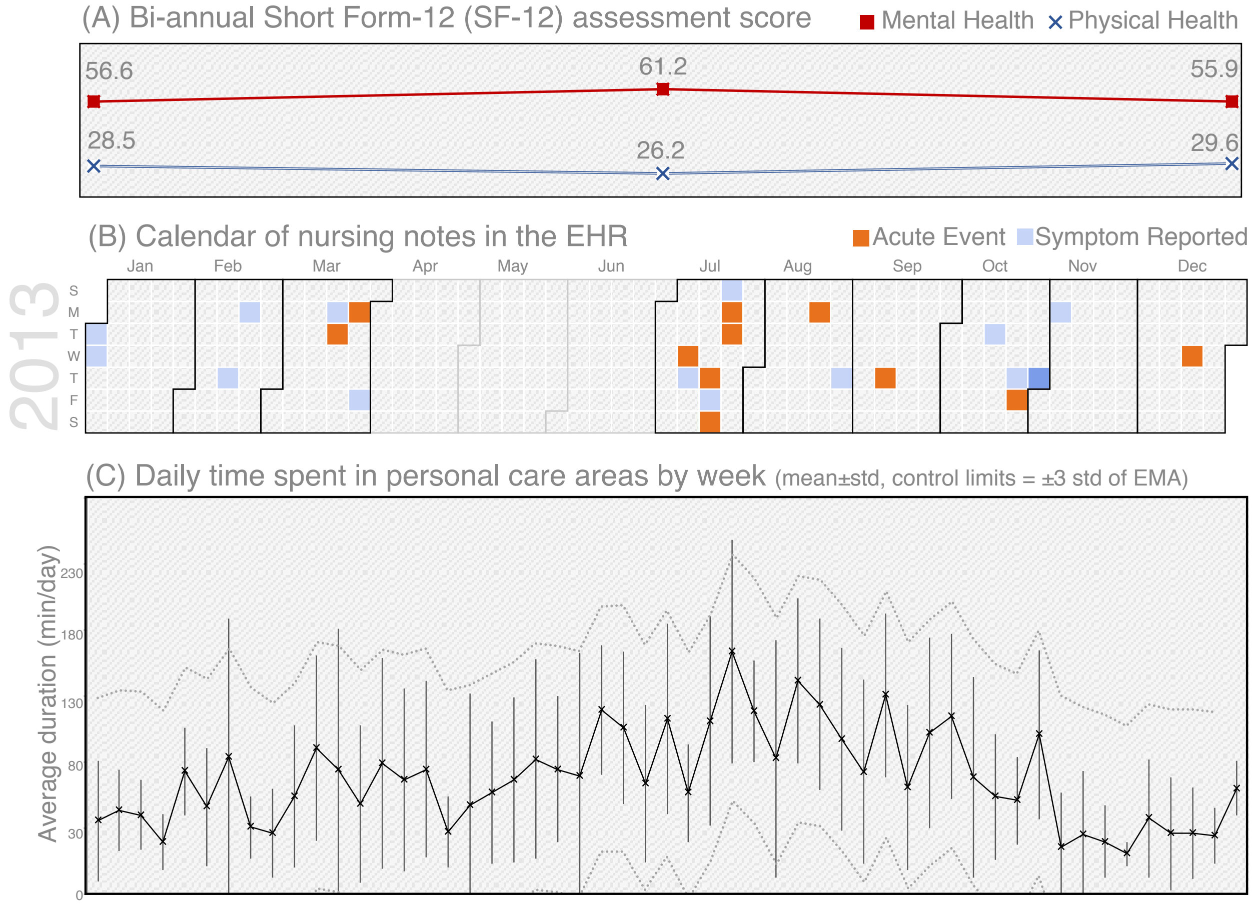

Figure 9. Comparison of clinical and sensor data for an 88-year-old female for one calendar year.

(A) SF-12 scores (Jan 2013, July 2013, and Jan 2014) based on self-report of physical and mental health (range 0-100, higher values = better health). (B) EHR notes plotted in a yearly calendar show temporal clustering of reported symptoms (light blue) and recorded acute events (orange). (C) Time series of sensor-derived total amount of time spent in personal care areas [bathroom, shower, closet, and laundry] in minutes per day aggregated into weekly means (solid line) and standard deviations (error bars). Control limits (dotted lines) are set to 3 standard deviations of exponential moving average with lambda = 0.3.

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CONCLUSION TO DISSERTATION

The dissertation addressed a gap in evaluating tele-monitoring technology to assist older adults with complex health needs to remain safely and independently in the place of their choosing. It proposed a conceptual framework for understanding the relationship between behavior and health, shaped by the everyday management of chronic conditions. The framework was applied in a secondary analysis of data from an existing project using smart homes for health tele-monitoring. The results supported our theoretical proposition that changes in the stability of an individual's daily routine may serve as behavioral indicators of health decline. However, multiple factors confounded the generalizability of insights, such as lack of information about critical environmental variables and technical implementation of the monitoring system. This opens avenues for future work that requires multidisciplinary collaboration. To move the field forward, we presented theoretical, clinical and practical implications of this dissertation in three manuscripts.

The first manuscript, titled "Trajectories of Daily Routines in Older Adults: A Model for Monitoring with Technology," describes a conceptual model for the evaluation of health tele-monitoring systems. It was based on four existing theories grounded in public health, gerontological, and nursing knowledge. We presented conceptual definitions of health trajectories and daily routines of older adults to be measured with sensor data, and clarified assumptions behind their dynamic temporal relationship. Different phases in the course of health over time can affect stability of everyday activity patterns that are shaped by the person and their living environment. In-home monitoring technology can support the individual's health through early detection of changes to guide timely intervention and prevention of further decline. The major contribution of our model is the delineation of extraneous factors that can affect baseline patterns, which is important to correctly identify deviations relevant to health decline. It may be a useful framework for both clinicians and technology developers in future work.

The second manuscript, “A Case Study of In-Home Monitoring Technology Reveals Health-Related Changes in Daily Routines of Older Adults,” presented a method of applying the proposed conceptual model to secondary data. We used qualitative and quantitative methods to retrospectively examine electronic health records and corresponding in-home sensor data for ten participants from an ongoing smart home project. We identified that participants reported non-specific symptoms within a week of an acute health event in 59% of cases. Weakness, urinary problems, pain, wondering and low mood were reflected in deviations from baseline daily routine, captured with in-home sensors. Tele-monitoring for these changes may alert clinicians to intervene on time to control symptoms and prevent acute events in the future. However, the study also found that it is critical to establish a personal baseline by accounting for multiple environmental factors that affect daily behavior to make detection of anomalies effective.

The last manuscript, “Considerations for the Effective Smart Home Health Monitoring of Older Adults,” discussed the details of implementing this technology for long-term use in older individuals with multiple health needs. Based on a critical review of the current work in the field and our experiences working with secondary data, the recommendations emphasized the importance of interdisciplinary collaboration for effective deployment and evaluation. Both clinical and technical researchers should carefully consider the target population for tele-monitoring, practicality and reliability of sensor deployment in dynamic real world environments, and sources of data for clinical outcomes to evaluate technology. This discussion is critical to disseminate in the wider community for effective translation of this technology from research to clinical practice.

Multiple limitations in this dissertation study affected external validity of findings. We discussed considerations for the sample, setting, instrument reliability and data quality in the third manuscript. Another confounding factor is the study design. A retrospective descriptive approach yields little control over extraneous variables, and multiple case studies do not generalize to the whole population. Moreover, analytical parameters were set based on assumptions about behavior, such as seasonality, that may not hold true in all cases. However, this design allows to inductively explore theoretical propositions clearly with clearly stated assumptions for generating hypotheses that can be then deductively tested in larger samples.

There are many possibilities for future work. Our proposed approach is generalizable to other similar in-home monitoring systems, which opens opportunities to pool data, increase sample and diversity of participants. This would to quantify effect sizes of change that is meaningful and to identify sub-groups of individuals with similar health and behavior characteristics. This information would be useful in building robust and personalized predictive models of deviations from daily routines. Future prospective cohort studies using these tele-monitoring systems would test the effectiveness of early detection of health changes, while experimental studies can quantify which interventions would be timeliest, most appropriate and cost-effective in preventing further decline. With practical systems supported by evidence, researchers then can focus on exploring the translation of tele-monitoring in the real world setting, such as cost-benefit analysis of interventions, reimbursement mechanisms and integration into the healthcare delivery system.

The success of current and future research depends on effective interdisciplinary collaboration. Multiple stakeholders are involved in development, implementation of this technology yet they differ in scope, goals, language, methods and approaches to generating evidence. This dissertation study illustrates possibilities and limitations offered by in-home health monitoring technology for older adults. It calls for clinical and technical researchers to first build bridges to join their respective discipline's knowledge domains in order to produce practical innovations that align with the needs of a diverse population of older adults.