

*Development and Validation of an Unobtrusive, Continuous
Model of Loneliness among Older Adults*

By

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For Tamara,

Who challenged me to overcome my weaknesses,
encouraged me to improve my strengths,
and believed in me when I did not believe in myself.

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ABSTRACT

Socialization is a very important part of healthy aging, but due to normal changes in health and life style, elderly individuals are at increased risk of becoming lonely—a qualitative state characterized by a subjective deficit in the social relationships. In the elderly, loneliness predicts morbidity and mortality [1-3], is associated with decreased cognitive functioning [4], impairs sleep quality [5, 6], decreases mobility [7, 8], and reduces quality of life. As a result, it is increasingly important to identify and assist lonely individuals. While surveys exist to measure loneliness [9, 10], they are given in a sporadic, infrequent, and impersonal fashion, making early detection of loneliness difficult. It is therefore necessary to improve current methods to identify lonely individuals.

Recently, we and others have developed techniques to continually monitor older adults in their home environment using unobtrusive sensing technologies [12, 13] designed to help older adults maintain independence [14, 15] by tracking activities and behavioral patterns in the home on a daily basis. Unobtrusive technologies allow us to collect many types of data that relate to a person’s interaction with others, but this information has never been related back to the current state of the art loneliness assessment. The focus of this thesis is to develop techniques to assess loneliness based on data from motion, contact, phone and computer sensors in the home, setting the framework for unobtrusively measuring loneliness among older adults. In this way, the model of loneliness will be a great contribution to the paradigm of continuous assessment, allowing for a well-rounded view of functional ability and independence in the aging population.

The first step in unobtrusively assessing loneliness is to understand which behaviors are both associated with loneliness and can be monitored unobtrusively.

However, many of the variables we can monitor using this array of sensors, such as frequency of visitor contact and phone use, relate directly to the level of social isolation, not the loneliness level per say. Social isolation is a quantitative construct that captures the number of personal contacts and the frequency of interactions an individual has. However, the association between loneliness and social isolation is not clear as relatively few longitudinal studies analyzing the relationship between loneliness and social isolation have been performed. Thus, we first investigate the longitudinal relationship between both the level of social isolation and *deviations* (relative to an individual's median) in the level of social isolation and loneliness using innovative longitudinal analysis techniques, and demonstrate that loneliness is closely related to both the overall level of isolation and deviations in that level. Next, we develop methods to monitor behaviors associated with loneliness, including phone use, time out-of-home, and visitors to the home. Using these developed metrics (among others), we analyze the relationship between the behavior and loneliness of 16 older adults monitored in their own homes for 8 months. Here, we demonstrate the close relationship between in-home behavior and loneliness ($R^2 = 0.428$), suggesting in-home technology can be used for continuous assessment of loneliness in older adults.

Chapter 1: Introduction

SUMMARY

Because the focus of this thesis is on the development and validation of an unobtrusive model of loneliness, this section provides a detailed background on the concept of loneliness and its health consequences. This background includes a definition of loneliness which differentiates it from solitude, and clarifies the difference between loneliness and other key social concepts including social isolation, social support and social network. Next, this section details the numerous negative health outcomes associated with loneliness and their possible mechanisms, and discusses techniques that have been employed to assess loneliness levels among older adults. Because of the shortcomings with current approaches to assess loneliness, an overview of in-home assessment is provided which describes how loneliness might be assessed unobtrusively using an array of sensors in the home. This section concludes by outlining the specific contributions of this thesis, and detailing their significance in the field.

Humans are designed for social interaction [20]. We crave attention, acceptance, and companionship. Often, we derive meaning and purpose from our interactions with others—both from the giving and receiving of support [21]. We attend events, join sports teams, form reading groups, volunteer time; all to meet and interact with other people. But sometimes, our social relationships are not fulfilling. We feel isolated, alone, lonely. And this feeling of aloneness is acutely painful. Mother Teresa once said, “Loneliness and the feeling of being unwanted is the most terrible poverty”, and very few people have never experienced the poverty of loneliness.

Still, certain groups of people are particularly susceptible to loneliness. Young adults--especially college freshmen who have just left the nest and are attempting to find themselves in the world—may feel alone and isolated on their new college campus. Single mothers are also prone to loneliness, feeling they are alone in the struggle to make ends meet. But perhaps the most vulnerable population is older adults. While many adults continue to lead energetic, fulfilling lives well into old age [22], for many, socializing becomes more and more challenging as health declines and vision and hearing fails [23]. Older adults are also particularly vulnerable to traumatic life events such as the death of friends, especially friends who feel irreplaceable at such a late stage of life [24]. After retirement, the network of friends may become smaller as access to the working social network is reduced, and the sense of purpose and self-respect may become reduced without the fulfillment provided by regularly working. In this phase of life, forming and maintaining new friendships becomes particularly challenging, especially when the failing health of *other* older adults may make kinship with the peer group seem less desirable [25]. The painfully isolating experience of loneliness among older adults is captured in the word cloud in Figure 1.1, generated from 358 responses from 58 older

isolation, not the isolation itself per se, that brings about the negative consequences associated with loneliness [11].

Second, loneliness is caused by a *deficit* in relationships. Weiss et al. defined two types of loneliness: a social loneliness which arises from a perceived lack of a friend network, and an emotional loneliness which arises from the lack of a significant other (for example a spouse or partner) [27]. Others have simply defined loneliness as arising when there is a discrepancy between an individual's desired levels of support and the support they perceive [26, 28]. In both cases, the key point is that the social relationships are lacking in some way. Potential sources of the mismatch between perceived and desired support may include negative life events (e.g. death of a friend or loved one), chronic diseases which reduce the ability to socialize, and relocation [30]. Addressing and mitigating loneliness can therefore take two paths: either the older adult can adjust their expectations for support (becoming satisfied with lower levels of support) or change the level of achieved support from the network.

The experience of loneliness is also *painful*, thereby distinguishing it from solitude. As Paul Tillich [31] noted in The Courage to Be, "Language... has created the word 'loneliness' to express the pain of being alone, and it has created the word 'solitude' to express the glory of being alone". While being alone is often associated with loneliness, spending time away from others can be a positive experience, and has been linked to measures of wellbeing and life satisfaction. The preference or tolerance for solitude differs on an individual level[32, 33]; thus the amount of isolation tolerated before loneliness is experienced will differ by individual as well.

Concepts Related to Loneliness

In addition to understanding what loneliness is, it is equally important to understand what it is not. In the literature, there are several concepts that are related,

but not synonymous, to loneliness. These include social network, social engagement, social isolation, and social support. This section will define these variables and how they relate to loneliness.

Social network refers to the group (or groups) of people with whom an individual has contact. This network provides the means of **social engagement**, which refers to the frequency and number of social activities in which one participates [34]. In addition, the social network provides the basis for **social support**, which is defined as the availability of people on whom one can rely [35]. Like loneliness, social support is typically subjective, evaluated using participant reports on the perception of support from the social network. In contrast, **social isolation** is typically defined as a quantifiable construct pertaining to the number of social network members and the frequency of contact [36, 37]. By this definition, an individual is socially isolated if they have relatively small social network, or if they interact with their social network infrequently. This will be the working definition of social isolation for this thesis. Assessing an individual's level of isolation through this method simply entails evaluating their social network and the frequency of contact with the network, which can be performed using assessments such as Hirsch's Social Network List [38]. However, the reader should note that in the literature, social isolation is frequently interpreted not only as a measure of size and frequency of contact with the social network, but also the perceived closeness of the network members [36]. For example, Hawthorne's Friendship scale [39], which he developed to assess social isolation, asks questions such as "I have someone to share my feelings with". These questions relate to the *perception* of isolation, not the actual amount of isolation per se. In fact, many of the same questions appear in measures designed to assess loneliness [9, 10, 40] as those designed to assess isolation.

Health Consequences of Loneliness and their Mechanisms

When attempting to monitor loneliness, it is important to understand the health outcomes associated with loneliness and how they might be inter-related. Here, we discuss several outcomes associated with loneliness and their hypothesized mechanisms.

Loneliness has frequently (but not uniformly [41]) been shown to predict morbidity and mortality [1-3], with an increased risk of mortality due to loneliness *similar to that of smoking and obesity* [18, 19]. There are two main models for how loneliness and lack of social relationships influence health: the *main effects* and *stress buffering* models [42]. In the main effects model, a positive influence on health comes as a direct result of being part of a social network, through the indirect protective effects the social network provides. That is, the social network may encourage members to engage in positive health behaviors [43, 44] (although some studies have shown that negative health behaviors may also spread through the social network [45, 46]), may provide support or resources when issues arise thereby mitigating potential effects of disease, and may provide purpose and meaning to the members, which directly increases life satisfaction [47]. Because lonely individuals may be less trusting of their social network and perceive less support, they are less likely to receive the positive benefits associated with being part of a social network. This model is consistent with prior research connecting loneliness to an increased risk of placement in nursing home facilities [48], and increased risk of emergency hospitalization [49], possibly because the support derived from the social network is lacking.

On the other hand, the stress buffering model posits that social relationships provide support which buffers the negative responses to stressful life events. In this model, it is actually the *perception* of support (which is directly tied to loneliness) that reduces negative health outcomes. For example, the perception that others will provide

resources may reduce the perceived stress of a given situation, thereby reducing the negative health outcomes. In addition, the perception of support may dampen the physiological changes associated with stress [42], even if the support is coming from a pet rather than another human being [50]. This model is consistent with prior research on loneliness and health, which indicates that loneliness increases blood pressure [51] and diminishes immunity [52], and prior studies on social relationships which indicate that the *quality* of an individual's relationships is more important for determining key health outcomes than the sheer quantity [53]. In addition, studies on loneliness in young adults show that while lonely and non-lonely individuals engage in the same number of stressful activities, lonely individuals *perceived* more stress from the same situations [54]. More recent models indicate that loneliness influences health through both pathways [55, 56]. It is also interesting to note that the older adults themselves perceive both pathways as acting to influence health [57].

In addition to increased morbidity and mortality, multiple studies have also found that loneliness is associated with decreased cognitive function [4, 58-61], possibly due to a decline in socialization, which has been associated with increased cognitive reserve [59, 62]. Cognitive reserve refers to the number of available mechanisms to process a given task. If more mechanisms are available, more damage can be sustained before clinical expression of damage occurs [63]. Thus, individuals who have more cognitive reserve would present with superior cognitive function for a given level of disease pathology [64]. This is consistent with the 'use it or lose it' hypothesis, which suggests that increasing social activities will protect against dementia [17, 65], possibly due to the increase in cognitive reserve.

Loneliness is also associated with poor sleep and increased frequency of micro-awakenings [6]. Poor sleep, independent of loneliness, is hazardous in its own as it is

associated with obesity [66, 67], hypertension [68], cognitive impairment [69], and poor quality of life [70]. The poor sleep among lonely individuals may be directly related to the feeling of perceived isolation, which results in hyper-vigilance and distrust, thereby increasing the number of micro-awakenings to ensure a safe sleeping environment [11]. The hyper vigilance felt by lonely individuals may partially explain the increased cortisol levels the morning after a self-report of loneliness among middle-aged [71] and older adults [72]. This is also consistent with results from Friedman et al. showing that interleukin-6, an inflammatory factor that is linked to increased risk of disease and mortality, was most elevated in individuals experiencing both poor sleep quality and poor quality social relationships. In this study, the interleukin-6 levels were reduced to normal if the participant either perceived support from their social relationships or exhibited good sleep quality [73], further highlighting the beneficial effects of quality social relationships.

Perhaps in part due to the influence of loneliness on sleep quality and the relationship between health limitations and loneliness, individuals experiencing loneliness also report lower quality of life, life satisfaction [47], and increased levels of depression [74].

Current Measurement of Loneliness

While this thesis is on the development of a new technique to monitor and understand loneliness, it is important to appreciate how loneliness is measured currently, as the current techniques will provide the gold standard in validating the new approach. There are two main approaches currently used to assess loneliness [75]: self-labeling using direct questions of loneliness, and the employment of scales or surveys designed to indirectly assess loneliness.

The self-labeling technique typically asks a question about whether the participant has felt lonely within a certain time frame (e. g. the past week), with answers generally ranging from never to always. While this technique has excellent face validity and has been employed in numerous studies, it also has several drawbacks. First, assessing loneliness via a single question assumes that loneliness is a unidimensional construct so the only difference between lonely individuals is the frequency or intensity of perceived loneliness [76]. However, Weiss argued that loneliness is in fact multi-dimensional, encompassing both an emotional loneliness (the loneliness for significant attachment figure such as a spouse) and a social loneliness (the loneliness for close friends) [27]. For example, women who move to a new town for their husbands' work frequently report loneliness for friends despite having the significant attachment of the husband, while recent widows will report loneliness for their deceased spouse despite having a strong friend network. Assessing loneliness via a single question cannot capture these differences in the type of loneliness experienced.

Individuals experiencing loneliness are also perceived as weaker, less attractive, and more passive than their non-lonely counterparts. Due to these social stigmas associated with loneliness, it is possible that many subjects will avoid reporting loneliness even when they are quite lonely, leading to an underestimate of loneliness in the population, and erroneous estimation of the association between loneliness and health outcomes. Several researchers have also argued that loneliness may be present even without the awareness of the individual [26, 77]. which would also lead to underestimation of the true levels of loneliness in the population (although others have argued that the subjective nature of loneliness indicates that loneliness can only be present by self-report of the individual [78]).

Because of the numerous shortcomings associated with directly assessing loneliness, several scales have been developed to indirectly assess loneliness. The two most commonly used scales are the UCLA Loneliness scale[9] and the De Jong Gierveld Loneliness Scale [10], although other scales have also been employed [27, 79]. The UCLA Loneliness Scale is a 20-item unidimensional scale [40] which has been employed in numerous studies of loneliness among older adults [80-83]. In contrast, the De Jong Gierveld Loneliness Scale is an 11-item scale which covers two domains [84] following Weiss's theoretical model of loneliness to capture both emotional and social loneliness [27]. Both scales have short forms consisting of a minimum of 4 items [9, 10] which have also been used extensively in the literature. While these scales may not encounter the same level of stigma associated with directly asking participants whether they are lonely, they still depend on self-report from the subjects, and thus are subject to desirability bias[85, 86], memory problems[65], and under or over estimation[87]. Relying on self-report to assess both loneliness and social isolation makes it challenging to assess the differential effect these constructs have on health—for example an individual experiencing loneliness may perceive infrequent contact with friends regardless of the true amount of contact. Clearly, a more objective method to assess loneliness in older adults is required to advance the field.

Objective Assessment of Loneliness

Recently, ambient in-home sensors have been developed to continuously and unobtrusively monitor inhabitants [15, 88, 89]. The goal of such systems is typically to monitor behavior more frequently than otherwise possible (e.g. hourly or minutely), and identify behaviors that may be associated with increased risk of cognitive decline [90-92], low mood, [93] or other negative outcomes . The nature and type of sensors used in such platforms can vary widely. For example, several research groups have proposed

video cameras[94] and body worn tags[95, 96] as viable options in in-home monitoring. Video cameras[94] installed in key areas of the home enable assessment of various gait parameters, may be used to detect falls, and allow the identification of different individuals moving through the home. However, most individuals consider the use of video monitoring a violation of privacy even when discriminating features of the video data are removed prior to processing. Body-worn tags (e.g. RFID, UWB, Wi-Fi) [95, 96] have also been proposed for in-home assessment as they track how an individual moves throughout the home and are sensitive to multiple individuals at the same time. However, among older adults this technology poses challenges to long term tracking as seniors forget to wear sensors or take them off when they become uncomfortable. In contrast, inexpensive wireless movement detectors and contact sensors can detect a subject's activities in the home on a daily basis without being overly invasive (no cameras) or requiring participants to remember to wear or charge devices. However, they give no information about who (or what) is causing the sensor to fire, and may be subject to high levels of noise. Thus, they are most effective in single person homes. Because older adults living alone are the most vulnerable to feelings of loneliness or social isolation, this technology is ideal for unobtrusive monitoring of loneliness and isolation in older adults.

Using an array of such unobtrusive motion and contact sensors, we at the Oregon Center for Aging and Technology (ORCATECH) have developed methods to detect important behaviors such as walking speed [97], sleep quality [98], mobility [99], total activity [100, 101], and medication adherence [102] in the home. While we have previously related the behavioral metrics derived from the sensors to physical [103] and cognitive health outcomes [12, 101], it may be that some of the behaviors which can be assessed using in-home sensors relate directly or indirectly to loneliness. For example, sensors on the phone would enable the unobtrusive assessment of daily time spent on

the phone and total calls, an important measure of socialization which may be associated with loneliness. Because phone use also requires the dialing of distinct numbers for each contact, this would also enable unobtrusive assessment of an individual's social network. While multiple studies have shown that loneliness is not strongly associated with social network size, through unobtrusive and continuous monitoring of social network, it may be possible to detect *changes* in social network characteristics (e.g. the loss of a friend, relocation, retirement) which have been qualitatively linked with loneliness. Additional behaviors that may relate to loneliness include computer use [104], time out-of-home [105], visitors to the home, and sleep[11].

Chapter Outline

The focus of this thesis is therefore on the development of an unobtrusive model to assess loneliness in older adults. To that end, **Chapter 2** is devoted to furthering the understanding the longitudinal relationship between social isolation and loneliness. While some studies find loneliness is significantly associated with measures of social isolation, others downplay their association. Most of the studies on the relationship between loneliness and social isolation that have been performed to date are cross-sectional in nature, precluding understanding of the longitudinal interaction between social isolation and loneliness. Because many of the social variables that can be monitored unobtrusively are measures of social isolation (e.g. phone use, computer use), it is important to understand the longitudinal association between loneliness and social isolation. Thus, this chapter will establish the plausibility of monitoring loneliness by detecting changes in social isolation on a population basis using data from the Cardiovascular Health Study, a longitudinal study of 5,888 older adults in the United States.

Based on the results of the second chapter, Chapters 3-5 cover the development of methods to monitor the mediators or covariates of loneliness. **Chapter 3** will present the development of a logistic regression classifier to assess the total daily hours spent outside the home using the in-home sensor data. This algorithm will also be used to assess the relationship between loneliness and time out-of-home among 33 older adults, showing that loneliness is significantly related to time out-of-home. Next, **Chapter 4** will present longitudinal data on the relationship between phone behavior (the daily number of incoming and outgoing phone calls) and loneliness, showing that higher daily phone use is associated with lower levels of loneliness. Finally, **Chapter 5** will present the development of an SVM classifier used to detect the presence of visitors in the home using key features from the in-home data. This chapter will demonstrate that while the algorithm performed reasonably well at detecting visitors for one subject, it did not perform well for the other subject the algorithm was trained on. Future work attempted to collect superior ground truth from additional participants to thoroughly develop a visitor detection method, but unforeseen challenges in the data collection precluded the finalization of a robust visitor detection algorithm. As a result, this section is auxiliary to the rest of the thesis as visitors will not be included in the final model of loneliness.

Using the developed metrics (among others), **Chapter 6** analyzes the relationship between in-home behavior and the loneliness of 16 older adults participating in a randomized controlled trial who were monitored in their own homes for 7 months. This chapter will show the feasibility of using in-home data to assess loneliness. The thesis will be concluded in **Chapter 7**, which will discuss future directions for research, including additional in-home behaviors that could be employed in a larger study to assess the relationship between behavior and loneliness.

Thesis Contribution

This thesis presents several contributions to the field: three engineering contributions, one basic science contribution, and one applied research contribution. These are each discussed in more detail below.

Engineering Contributions:

In Chapter 3, an algorithm to detect the total daily hours spent outside the home using data from an in-home sensor platform is developed and validated. This technique is an important contribution as the total time spent outside the home has been linked with quality of life [106], life satisfaction [105], and cognitive function [107-111]. By unobtrusively monitoring time out-of-home using this developed technique, it may be possible to continually assess these important health outcomes in older adults. This work has been published in the IEEE Journal of Biomedical and Health Informatics [81].

In Chapter 4, we present a novel method to assess the telephone use of older adults using a landline phone sensor. While studies have previously used data collected from mobile phones to quantify social groups and their evolution [112, 113], infer friendship networks [114], and even assess mental health [115], these techniques only work with mobile phone data which is not typically employed by the older adult population. Our technique therefore advances the field in assessment of phone use among older adults, while demonstrating the relationship between phone use and loneliness in this population. This work has been submitted to Aging and Mental Health.

In Chapter 5, a classifier to detect the presence of visitors in the home is presented. As noted, this algorithm was not fully validated due to challenges in the collection of ground truth visitor data. Still, this work represents key results on behaviors that may change when visitors are present in the home, and could be used to inform priors in future models of visitors in the home. This work has been published at the IEEE

Engineering in Medicine and Biology Society Annual Engineering in Medicine and Biology Conference.

Basic Science Contribution:

In Chapter 2, we present the results of a longitudinal study on the relationship between loneliness and social isolation. In this study, we reveal that deviations from an individual's normal level of isolation significantly affect the probability of reporting loneliness. That is, individuals who begin at a low level of isolation and then become highly isolated over time are more likely to report loneliness than those who begin at a low level of isolation and remained there. In addition, this paper found that life events such as the death of a friend which affect the social network significantly impact the probability of reporting loneliness. These results advance the field of social gerontology by demonstrating that a key component in loneliness is change in the social network. This work has been submitted to Journals of Gerontology Series B: Psychological Sciences.

Applied Research Contribution:

In Chapter 6, we present the results of the longitudinal study on the relationship between loneliness and behavior. This study demonstrates that behaviors such as the daily time out-of-home, daily computer use, daily number of calls, among others, are closely related to the loneliness of the individual. This work is especially important as it presents a novel loneliness assessment technique that does not require input from the individual, thereby overcoming the societal stigmas associated with admitting to feeling lonely. In addition, this model makes a great contribution to the paradigm of continuous assessment as loneliness is a key variable in numerous health outcomes that may be important to monitor longitudinally such as cognitive function and physical wellbeing.

Chapter 2: Longitudinal Relationship between Loneliness and Social Isolation: Results from the Cardiovascular Health Study

SUMMARY

Conflicting results on the association between loneliness and changes in the level of social isolation have been reported in the literature. While some studies find loneliness is significantly associated with social network, others indicate that loneliness can present with both large and small social network, downplaying their association. However, many of the social variables (e.g. telephone use, visitors to the home) that can be monitored unobtrusively are measures of social isolation, and thus may not relate directly to loneliness. The focus of this chapter is therefore to clarify the longitudinal association between loneliness and social isolation using data from the first five years of the Cardiovascular Health Study, a longitudinal study of 5,888 older adults in the United States. The loneliness question from the CES-D depression scale [116] was dichotomized and used to assess loneliness, while social isolation was measured using six items from the Lubben social network scale [117]. Variables were created to capture both the median level of social isolation and the deviations in the level of social isolation for each year. Using longitudinal logistic regression models, we show that a higher median level of isolation network score is associated with increased odds of reporting loneliness. In addition, increases in the level of isolation relative to an individual's median are associated with increased odds of reporting loneliness. This result has significant implications for monitoring loneliness using unobtrusive in-home sensing technologies, and suggests that variables such as phone use, email use, and time out-of-home, which are closely related to social isolation, may also be closely associated with loneliness among older adults.

INTRODUCTION

Social relationships are important at all ages, and are considered a key element in successful aging [100, 118]. Yet many older adults have diminished opportunities for social relationships, and may become lonely. Loneliness has been defined as a subjective state resulting from a deficiency in the social contacts [26]. A large body of literature has focused on understanding the relationship between loneliness and health among older adults [119]. Loneliness, has been associated with poor sleep quality [5, 6], decreased mobility [7, 8], increased risk of placement in nursing home facilities [48], and increased risk of emergency hospitalization [49]. Loneliness has frequently been shown to predict morbidity and mortality [1-3], although not uniformly [41]. Loneliness is also associated with decreased cognitive function [4, 58, 59].

Another important aspect of the social lives of older adults is their level of social isolation. While loneliness is a subjective state, social isolation is a quantitative construct arising from a deficit in social contact. Much like loneliness, social isolation has been found to have significant consequences for health: individuals who are socially isolated tend to have increased morbidity and mortality with the increase in mortality similar to that of smoking [19], exhibit poor sleep quality [73] and have increased risk of cognitive decline [120]. Social isolation is typically defined as one end of a continuum encompassing the objective size of the network and the frequency of contact [36, 37]. However, by reducing the continuum to a binary state (isolated or not), it is possible to lose relevant information regarding the level of isolation. Thus, in this paper we will not

dichotomize the continuum but instead use overall level of isolation, a measure of both the size of the social network and the frequency of contact.

While it might seem self-evident that social isolation co-occurs with loneliness, they are in fact distinct constructs [26]. Several studies have examined the relationship between social isolation and loneliness [58, 121-123], many of which focus on the relationship between loneliness and the size of the social network (one aspect of social isolation). For example, Berkman et al. suggested that the social network lays the foundation for support [34], arguing that while one may perceive a lack of support despite a large social network, without any social network one cannot have support. Perlman and Peplau also argue that the size of the social network is one of the key determinants of loneliness [26] such that individuals with smaller social networks are more prone to feelings of loneliness. Other studies have found that individuals with no friends or children were more likely to report loneliness [124] and that having small social network was significantly associated with loneliness [125], especially among those suffering from ‘social’ loneliness [126].

Despite findings suggesting a relationship between loneliness and social isolation, only a handful of objective, longitudinal studies on this relationship exist [127-129]. In 2002, Holmen & Furukawa found that loneliness was closely tied to not having a good friend to talk to in a longitudinal study of residents of Stockholm [127]. Social network was also found to be associated with loneliness among Israeli populations [128]. More recently, loneliness was found to be associated with social network score among British populations [130], although this study only had two time points spaced eight years apart. Because the manifestation of loneliness may be influenced by culture [131-133], the results from non-American cohorts cannot be generalized to the American older adult population. In the United States, a single study by Cacioppo et al. found

social isolation was associated with both loneliness and depression [74]. However, the main outcome of this study was to understand the relationship between loneliness and depression, not to understand the complex relationship between loneliness and social isolation. Remarkably, none of the longitudinal studies investigated the relationship between *change* in isolation (measured either via life events that directly or indirectly impact the social network or a change in social network score) and loneliness—a particularly important relationship to understand, especially given that changes in social network (which would manifest as changes in the level of isolation) are related to health outcomes independent of baseline network size [22, 134]. Still, there is some evidence to suggest that loneliness is closely tied to changes in the overall level of isolation: a qualitative study on the causes of loneliness in older adults found that the greatest causes of loneliness were ‘life events’ that cause changes in either one’s ability to interact with the available social network or in the social network itself [23].

In this paper, we examine the relationship between both median level of isolation (across individuals) and deviations in the level of isolation (within an individual) with self-reported loneliness among a large group of American older adults surveyed yearly for five years. We hypothesize that individuals who have recently experienced a life event that would cause a change in the level of isolation (e.g. the death of a friend) will be more likely to report feelings of loneliness. We also hypothesize that both higher average levels of isolation (across individuals) and increases in the level of isolation from the median (within the same individual) will be associated with a higher probability of reporting loneliness.

METHODS

Study Design

Data for this study came from the first five years of the Cardiovascular Health Study (CHS), an ongoing observational study on the risk factors for cardiovascular disease in American adults aged 65 and older. A total of 5888 participants were enrolled from Medicare eligibility lists in four communities: Sacramento County, California; Allegheny County, Pennsylvania; Forsyth County, North Carolina; and Washington County, Maryland. In 1989/90, 5201 participants were enrolled from these communities, and an additional 687 African American participants were enrolled in 1992/1993. Exclusion criteria at baseline included institutionalization, receiving hospice care or radiation chemotherapy for cancer, and not expecting to stay in the area for the next three years. Participants were also excluded if they were not ambulatory at home or if they were not able to be interviewed. All participants received up to ten annual in-person interviews and 6-month telephone calls until 1999 when they started receiving telephone calls twice per year. Demographics collected at baseline include age, sex, race, and education. The institutional review board (IRB) of each of the sites and the Coordinating Center approved the study. In addition, the IRB at Oregon Health & Science University approved the reanalysis of the dataset described here (IRB #10006). Details of the study design and sampling methods have been described elsewhere [135, 136].

Participants

During the first five years of the study, participants were asked questions regarding social network and life events which were discontinued after five years. The current study uses these social data to examine the relationship between change in isolation and loneliness. A complete descriptive summary of the demographic characteristics of the cohort at baseline and during the four years of follow up is provided

in Table 2.1. Each year, only those participants who answered the loneliness question (described under ‘Measures’) are included in tables or analyses.

Measures

Loneliness

Subjective loneliness was assessed using a question from the Center for Epidemiological Studies Depression (CES-D) scale [116]. The question asks “In the last week, I felt lonely” with answer options (i) rarely/none of the time, (ii) some or a little of the time, (iii) a moderate amount of time, and (iv) most of the time. We dichotomized loneliness to ‘not lonely’ (i) versus ‘lonely’ ((ii), (iii), (iv)).

Social Isolation

Social isolation was measured using 6 items from Lubben’s social network scale [117], which was developed as a modification to the Berkman-Syme social network index to specifically target older adults [137]. This questionnaire asks ten questions: three questions regarding family relationships, three targeting friend relationships, three looking at independent social support, and one identifying living situation (with others or alone). Each question is answered categorically and converted to a score ranging from 0 to 5. Because this analysis is specifically looking at the relationship between the level of isolation and loneliness, and because perceived support may change in tandem with changes in isolation, the three questions targeting social support were not included in the summary isolation score. This ensures that any relationship between loneliness and social isolation is due to changes in the social isolation, not changes in perceived support. In addition, living situation was included in the analysis separately as a binary variable. The scores on the six questions regarding friend and family relationships were summed to give a summary ‘network score’ between 0 and 30.

In order to understand how both overall social isolation and change in social isolation affect loneliness, we included two variables, one to represent an individual's median level of isolation (across years), and a second to represent the deviation from the median level social isolation each year. We first calculated each individual's median isolation score over the t as a measure of average level of social isolation. For each individual, we then calculated each year's offset from the median as a representation of *deviation* in the level of isolation from the individual's median (see Figure 2.1). We used difference in level of isolation from the median level instead of the difference in isolation level from the previous year because this captures longer term trends in isolation levels (not simply the previous year, but the average over the time period) and allows usage of the each year of the dataset (the first year is lost due to lagging when considering the difference between years). By including both the median value and the offset from the median, we capture the relationship between loneliness and both *average* isolation and *deviations* in level of isolation over time.

Life Events

Five questions were included in the model regarding major life events in the last six months: (i) "Did somebody close to you die", (ii) "Did a significant relationship become considerably worse", (iii) "Did someone close to you have an illness", (iv) "Was a grandchild born", and (v) "Have you been caring for a sick or disabled person". Each question was answered as 'yes' or 'no' each year, and included in the model independently.

Additional Covariates

We included variables in the models that might confound the relationship between loneliness and social isolation. Because cognitive function has been shown to impact one's ability to form and maintain relationships [120], it was important to control

for cognitive function in the model. Cognitive function was measured using the Modified Mini-Mental State Examination (3MSE) [138] in years 1-4. Because the 3MSE was not used at baseline, values from year 1 were lagged backward to the baseline year as scores on this measure change very slowly. Scores on the 3MSE range from 0-100. The 3MSE score in this cohort was 90.6 ± 8.6 at year 1. Health status at each year was determined by calculating whether or not a participant had any prior report of cardiovascular disease, cancer, chronic obstructive pulmonary disease, kidney disease or was taking any medication for diabetes.

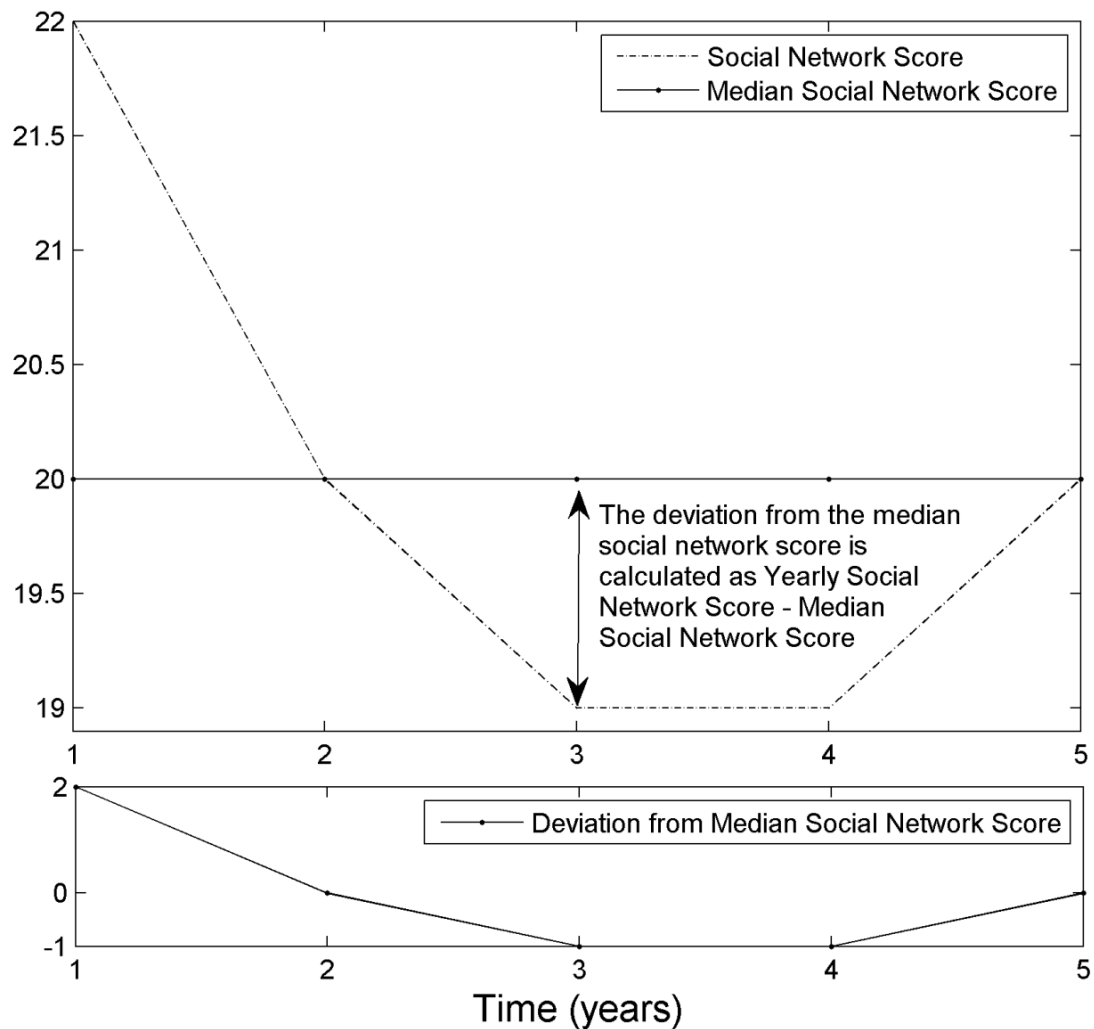


Figure 2.1: Example data from one participant showing the social network score for each time point, the calculated median social network score (per participant), and the calculated deviation from the median social network score (calculated for each year).

Data Analysis

Descriptive analysis:

We first computed descriptive statistics for all variables included in the model. Because the scores on the social network questionnaires are highly skewed to the left (large social network), we computed the median and inter-quartile range (IQR) for the social network scale. These are computed yearly on the available data for all participants who completed the corresponding year's CES-D loneliness item. We also computed the percent of positive and negative responses (the remaining percent of 100 corresponds to the percent missing) for all life events variables for all years.

Transition probability analysis:

To understand how stable feelings of loneliness are in this cohort, we created a transition probability graph describing the probability of transitioning between lonely and non-lonely states. Transition probabilities were computed between adjoining years (e.g. from year 2 to year 3) by calculating the total number of participants who transitioned between states (e.g. lonely to not lonely) and dividing that number by the total number of participants who were in the starting state (e.g. lonely) in the first of the two adjoining years *and* answered the CES-D loneliness question both years. For each possible state change (lonely to non-lonely, non-lonely to lonely), a total of four transition probabilities were computed: one for each year pair. The overall transition probability across years was computed as the average transition probability across the four years of follow up data. The probability of remaining in the same state (e.g. the probability of reporting loneliness in two consecutive years) is taken as $1 - P(\text{Transition})$. We also computed the percent of subjects who are chronically lonely as the percent who reported loneliness *each year* they responded to the CES-D loneliness question. We also computed the percent of subjects who are chronically lonely as the percent who reported loneliness *each year* they responded to the CES-D loneliness question.

Logistic regression mixed effects models

Longitudinal mixed effects logistic regression models were employed in Stata (StataCorp, Texas, Version 13) to examine the relationship between loneliness (measured using the dichotomized CES-D question) and the level of isolation over time. The mixed effects regression framework allows for repeated measures of the same individual by including individual-specific offset terms. Thus, all available data from all years (those shown in Table 2.1) were included in the model, allowing the model to fit both group and individual changes over time. The variables used in the first model were missing an average of 2% of cases each year (max: 7.6%, min: 0%). In order to avoid biases associated with list wise deletion and to maximize efficiency, chained multiple imputation was employed on all variables used in the first model with missing data due to nonresponse (imputation was not employed on participants who died or were lost to follow up). The outcome variable was not imputed. Ten imputed datasets were generated to ensure reliability and consistency of the imputed results. The average number of observations per individual was 4, and the minimum number of observations was 1. In order to ensure coefficient estimates were not biased by multicollinearity, the variance inflation factor (VIF), a standard diagnostic tool for assessing the level of collinearity of the independent variables, was computed for all independent variables. The VIF for all variables was below 2.5, indicating any bias from multicollinearity can reasonably be ignored [139]. A *p*-value of 0.01 was considered significant.

RESULTS

Descriptive Statistics

As shown in Table 2.2, the mean participant age was 72.8 ± 5.6 years at baseline; 57% of the cohort was female, and 70% was married. By the end of the analysis period, the mean age was 75.9 ± 5.3 years, the proportion of females had increased to 59%, and

Table 2.1: Descriptive statistics of the variables included in the model of loneliness and social isolation at each assessment year. Only individuals who answered the yearly CES-D loneliness question are included in the table each year.

	Baseline (n=5194)	Year 1 (n=4894)	Year 2 (n=4659)	Year 3 (n=5059)	Year 4 (n=4600)
<i>Age (years)^a</i>	72.8 (5.6)	73.6 (5.4)	74.5 (5.4)	75.1 (5.4)	75.9 (5.3)
<i>Gender (% Female)^b</i>	57.0	57.1	57.6	58.7	59.3
<i>Marital Status (%)^b</i>					
Married	69.1	69.7	69.2	66.5	66.7
Widowed	23.0	22.5	22.7	24.2	24.1
Divorced/Separated	3.8	3.6	3.7	5.2	5.2
Never Married	4.1	4.2	4.3	4.1	4.0
<i>Education (years)^a</i>	13.9 (4.7)	14.0 (4.7)	14.0 (4.7)	13.9 (4.7)	14.0 (4.7)
<i>Race (%)^b</i>					
Black	4.7	4.3	4.4	17.3	16.0
Non-Black	95.3	95.7	95.6	82.7	84.0
<i>3MSE Score^a</i>	--	90.6 (8.6)	90.8 (9.5)	89.7 (10.0)	90.6 (10.3)
<i>Living Situation (%)^b</i>					
Alone	9.8	22.2	25.1	27.8	28.8
With Others	76.7	75.6	74.8	72.1	69.6
<i>Felt Lonely (%)^b</i>					
Most of the time	3.0	3.9	3.8	4.2	3.9
Moderate amount of time	4.3	4.9	4.8	4.8	4.9
At least some of the time	14.5	15.2	15.1	16.4	15.7
Rarely/Never	78.2	76.0	76.4	74.6	75.5
<i>Social Network Score^c</i>	20 (6)	20 (6)	20 (6)	21 (5)	21 (5)
<i>Somebody close died^b</i>					
Yes	30.6	25.4	26.3	27.9	27.5
No	69.2	74.5	73.5	72.1	72.3
<i>A significant relationship became considerably worse^b</i>					
Yes	6.6	4.1	3.8	4.8	4.3
No	93.2	95.8	95.9	95.1	95.5
<i>Somebody close had illness^b</i>					
Yes	30.9	25.4	29.3	26.6	25.4
No	69.0	74.6	70.6	73.3	74.3
<i>A grandchild was born^b</i>					
Yes	9.2	11.2	10.8	12.6	12.0
No	90.7	81.2	89.0	87.3	87.6
<i>Been caring for a sick/disabled person^b</i>					
Yes	14.5	7.6	7.7	9.5	6.8
No	85.3	92.1	92.1	90.3	93.1

^aContinuous variables are presented as the mean and standard deviation

^bCategorical and binary variables are presented as percent in each category. The remaining percent of 100 for these variables corresponds to the percent missing.

^cThe social network score is presented as the median and IQR due to the skewness in the responses

the proportion of married individuals had decreased to 67%. An average of 23% of the participants (averaged across years) reported feeling lonely at least some of the time. Only an average of 3.8% of the participants reported feeling lonely most of the time in the previous week. The median social network score was 20 (out of 30 possible points) with an IQR of 6 at baseline, and increased to 21 (IQR 5) by the last year of the analysis.

An average of 27.5% of the cohort reported that somebody close died within the last six months (averaged across years), and similarly an average of 27.5% of the cohort reported that somebody close had an illness. Having a significant relationship become worse was relatively uncommon, with only an average of 4.7% of the cohort reporting this each year. The birth of a grandchild was also a rare event, with only 11% of the cohort reporting this each year. Finally, an average of 9.2% of the cohort reported they had been caring for a sick or disabled person during the last six months. The life events variables were missing an average of 0.5% of the observations.

Transition Probability

Figure 2.2 shows the average annual probability (p) of transitioning between states of loneliness from one year to the next. Only an average of 13% of individuals who were not lonely one year transitioned to feeling lonely at least sometimes in the next year, while 87% of those who were not lonely one year remained not lonely the next year. In contrast, an average of 40% of individuals reporting loneliness one year transitioned to not lonely by the next year, while 60% of the individuals reporting loneliness one year remained lonely in the next year. Although there was a greater probability of resolving than developing loneliness, overall there was a slight increase in loneliness over time (from 22% to 25% of the cohort) because of the larger number of individuals in the non-lonely group.

Between 4% and 10% of the participants are suffering from chronic loneliness, meaning they reported feeling at least some loneliness *every year*. The true number of individuals suffering from chronic loneliness falls within this range but could not be calculated exactly due to missingness in the outcome variable. That is, while 4% of original cohort always answered the loneliness question (no missing data, not lost to follow up), and always reported feeling lonely, it may be that some who had missing data on one or more years were also chronically lonely (they would have reported loneliness if they had not been lost to follow up or did not fail to answer the question. Thus, the maximum proportion of individuals suffering from chronic loneliness is 10%, where all of these reported feeling lonely each time they answered the survey, but some did not answer the loneliness question on one or more years.

Loneliness and Social Isolation

The results of the longitudinal logistic regression between loneliness and social

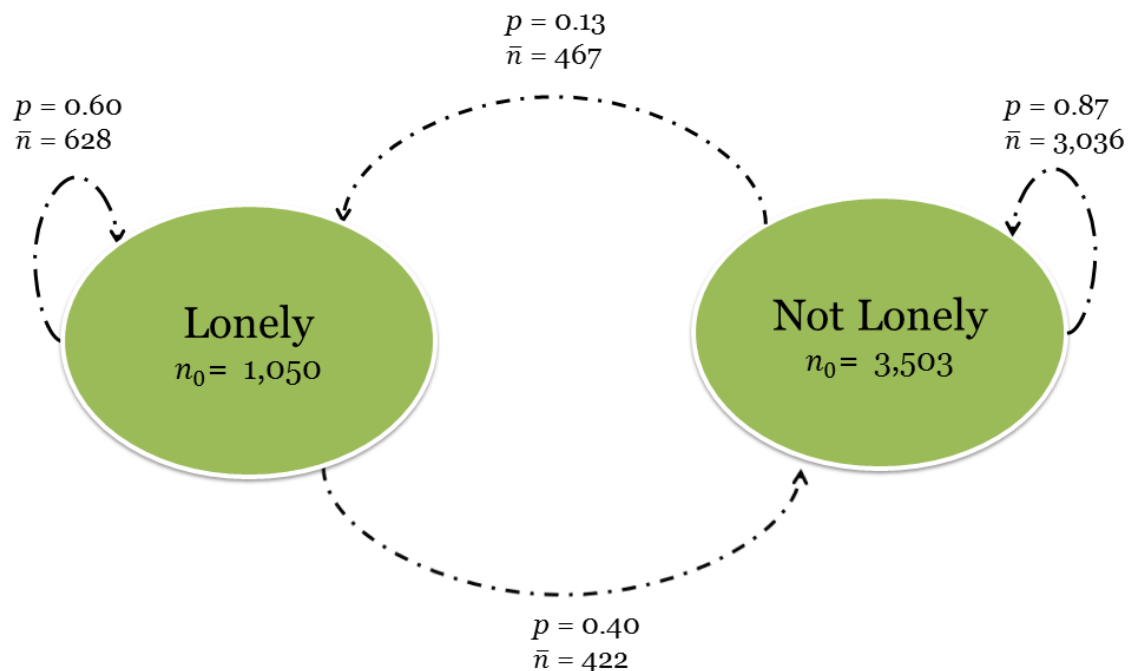


Figure 2.2: Graph of the average annual transition probability (p) between states of loneliness. The variable, n_0 , represents the number of people in each category at baseline, while $\bar{n}$ represents the average number of people transitioning between each category across years.

isolation are shown in Table 2.2. The variable most strongly associated with loneliness was living alone, which was associated with 79% higher odds of reporting loneliness. Loneliness was also significantly related to both between and within person effects, calculated as each individual's median level of social isolation across years (between person effect) and each year's deviation in the level of social isolation relative to the individual's median (within person effect). These variables are shown in Table 2.2 as 'Median Lubben Social Network Score' and 'Deviation in Lubben Social Network Score', respectively. Across individuals, those with one additional point in their median social network score (which corresponds to a lower level of social isolation) had 11% lower odds of reporting loneliness. Thus, compared to those who are fully connected (score of 30 on the social network score), those who are completely isolated (score of 0 on the social network score) have a 97% higher odds of reporting at least some loneliness.

Within the same individual, years where the social network score was higher than that individual's median social network score across years (indicating lower than normal levels of social isolation) had 3% lower odds of reporting loneliness per unit increase in social network score relative to the median. Thus, for the individual shown in Figure 2.1, the odds of reporting loneliness in year 1 are 6% lower than that in year 2 (social network score is 2 points higher than the median in year 1), and 3% higher in year 3 as compared to year 2. The most anybody deviated from their median was 17 points in either direction, indicating the maximum effect of this variable was a 40% change in the odds of reporting loneliness.

Among the life events variables, the variable most strongly associated with loneliness was reporting that a significant relationship became considerably worse, which was associated with a 125% higher odds of reporting loneliness (see Table 2.2). Caring for a sick or disabled person was also associated with 54% higher odds of

reporting loneliness, although reporting that somebody close had an illness was not a significant predictor of loneliness levels. Reporting that someone close died was associated with 22% higher odds of reporting loneliness. Surprisingly, those who reported a grandchild had been born in the last year also had 17% higher odds of

Table 2.2: Longitudinal association of loneliness and social isolation. Based on 24,323 observations from 5,870 individuals.

	Odds Ratio	z	95% Conf. Interval	
Median Social Network Score (per unit; 30 points total)	0.89**	-12.75	0.87	0.90
Deviation in Social Network Score (per unit)	0.97*	-3.48	0.96	0.99
Someone close died in last year	1.22**	3.87	1.10	1.35
A significant relationship became considerably worse	2.25**	8.37	1.86	2.72
Somebody close had illness in last 6 months	1.14	2.46	1.03	1.26
A grandchild was born in the last 6 months	1.17	2.16	1.02	1.36
Been caring for a sick/disabled person	1.54**	5.58	1.33	1.80
Not Living Alone	0.21**	-18.33	0.18	0.25
3MSE Score	0.98**	-6.42	0.97	0.98
Health Status	1.45**	5.62	1.27	1.65
Male	0.46**	-9.35	0.40	0.55
Education (years)	0.97**	-3.35	0.95	0.99
Marital Status (married)				
Widowed	1.61***	4.56	1.31	1.98
Divorced/Separated	1.01	0.03	0.71	1.41
Never married	0.74	-1.61	0.51	1.07
Race (non-black)				
Black	0.88	-1.06	0.70	1.11
Age	1.006	0.92	0.99	1.02

*p<0.01, **p<0.001

reporting loneliness, although this result was not significant ($p > 0.01$).

Consistent with other studies on factors associated with loneliness, widowhood was associated with a 61% increase in the odds of reporting loneliness relative to being married (shown in Table 2.2), being male was associated with 46% lower odds of reporting loneliness relative to females, and each unit increase in 3MSE score (associated with higher cognitive function) was associated with 2% lower odds of reporting loneliness. Having significant chronic diseases was also associated with 45% higher odds of reporting loneliness, and each unit increase in years of education was associated with 3% lower odds of reporting loneliness. In this full model, age was not significantly related to loneliness. This result was not consistent with prior studies on loneliness, leading to a post-hoc analysis investigating the univariate association between age and loneliness. In this analysis, age was significantly associated with loneliness (results not shown).

DISCUSSION

In this paper, we have shown that loneliness is closely tied to both the median level of isolation, and deviations from an individual's normal level of isolation. We also found that life events which would directly or indirectly affect the level of isolation are closely related to the probability of reporting loneliness. In our first analysis, we presented a transition probability graph of loneliness, showing that loneliness is a relatively stable state: 60% of participants who report loneliness one year will also report it the following year. We also found the percent of participants reporting loneliness was gradually increasing each year, ending at nearly 25% reporting at least some loneliness in the final year of the analysis.

Both the median social isolation and *deviations* from an individual's median level of isolation were significantly related to loneliness. We found that relative to those experiencing the highest level of isolation, those with the largest possible social network score had 97% lower odds of reporting loneliness. In addition, a decrease in social network score relative to an individual's median score (which may arise due to changes in the number of connections or the frequency of seeing the available connections) significantly increased the odds of reporting loneliness. Thus, individuals who began at a low level of isolation and then became highly isolated over the time period are more likely to report loneliness than those who began at a high level of isolation and remained there for the entire monitoring period (holding all other variables constant). Still, the effect of being very isolated was larger than the effect of *becoming* isolated over the monitoring period. This may be because of the relatively short time period studied, which may wash out the effect of current changes in the social network score due to changes that occurred prior to the beginning of the monitoring period. That is, individuals currently exhibiting a low social network score may have experienced changes and loss prior to the monitoring period that made them feel lonely. Then, once the monitoring period began their social network score may be constant, thereby increasing the effect of the median social network score on loneliness and decreasing the effect of the deviation variable. Participants exhibiting low social network scores also have limited ability to become more isolated, but may be more impacted by changes in the social network score. Future studies should investigate the relationship between changes in social isolation and loneliness among those who are already experiencing social isolation.

It may also be that the effect of the deviation variable is smaller because some changes in the social network such as the loss of a close friend who is then replaced by a new friend would not show up in this measure of social isolation. This is highlighted in

the significance of the life events variables, which dramatically affected the odds of reporting loneliness. These results are consistent with previous longitudinal studies on the relationship between loneliness and social isolation [74, 140], and suggest that future studies investigating the relationship between health and loneliness or social isolation should account for the correlation between these two variables.

In addition to finding the level of isolation was associated with loneliness, we also discovered that participants who experienced a life event that impacted their level of isolation were considerably more likely to report loneliness. These life events included events that would directly affect the social network such as having a significant relationship become worse or losing a close friend or family member. Of course, it is natural and even healthy to mourn the loss of a close friend or family member. However, given the close relationship between loneliness (especially chronic loneliness) and health, it is important to help individuals suffering from loss to engage in their community and build new relationships. Methods to identify and help such individuals in a meaningful way may become increasingly important as the number of older adults continues to rise. Some interventions have been designed which specifically target individuals suffering from bereavement [141]. A better understanding of loneliness and its causes may help in the design and implementation of meaningful interventions for bereaved persons.

We also found that life events that *indirectly* affect the level of social isolation, such as caring for a sick or disabled person which may hamper the frequency with which one can interact with the available social network, were also significantly associated with loneliness. Many studies have investigated the relationship between caregiving and quality of life, and have found that care-giving, especially for a friend or family member, reduces well-being [142, 143] and quality of life [144], and increases stress [145] and

depression [146, 147]. The results presented here also suggest that care-giving increases the likelihood of feeling lonely, which is consistent with qualitative studies on loneliness and caregiving [148]. This highlights the need to provide resources and support for those who are caring for a family member or loved one.

Consistent with previous work, gender, cognitive status, marital status, education, and health status were all associated with the probability of reporting loneliness. In the full model, age was not a significant predictor of loneliness. However, in a univariate model of age and loneliness, increased age was associated with higher odds of reporting loneliness. This suggests that the relationship between loneliness and age that has been found in previous studies may be due to changes in health status, social network or life events that are more likely to accrue with increased age.

This study has some limitations. First, the data included in the analysis is from 1989-1992; over 20 years old. An entirely new generation has moved into old age, with possibly different values, beliefs, and means of socializing (for example online communities). It is possible that the results reported here will not generalize to the new generation of older adults. As noted, the study also included only 5 years of data, and therefore may not have been sensitive to the full relationship between loneliness and changes in isolation. Future studies should investigate these relationships over longer time periods. In addition, the social network scale used as part of the CHS only has 6 questions on social isolation, and does not include measures such as community involvement or church attendance which are frequently included in measures of social isolation. Future studies should investigate how changes in these aspects of isolation affect loneliness.

Finally, self-labeling of loneliness using a direct question on whether or not each individual currently felt lonely was used to distinguish those who felt lonely from those

who did not. While this loneliness assessment technique has excellent face validity and has been employed in numerous studies, it also has several drawbacks. First, individuals experiencing loneliness are frequently perceived as weaker, less attractive, and more passive than their non-lonely counterparts. Due to these social stigmas associated with loneliness, it is possible that many subjects will avoid reporting loneliness even when they are quite lonely, leading to an underestimate of loneliness in the population, and erroneous estimation of the association between loneliness and health outcomes. In addition, assessing loneliness via a single question assumes that loneliness is a unidimensional construct so the only difference between individuals is the frequency or intensity of perceived loneliness [76]. Weiss argued that loneliness is in fact multidimensional, encompassing both an emotional loneliness (the loneliness for significant attachment figure such as a spouse) and a social loneliness (the loneliness for close friends) [27]. Assessing loneliness via a single question cannot capture these differences in the type of loneliness experienced, or the differences in the relationship between loneliness and isolation in these two different types of loneliness. Previous work by Dykstra and Fokkema noted that individuals who were experiencing social loneliness were affected by the size of their social network, while those experiencing emotional loneliness felt lonely independent of the social network [126]. This study only captured one time period among married and divorced older adults, and therefore could not assess the relationship between longitudinal changes in social isolation and emotional or social loneliness. Future studies are required to fully understand the relationship between changes in social isolation and the experience of emotional and social loneliness.

In this paper, we have shown that loneliness is associated with both the level of isolation and deviations in an individual's level of isolation. These results have important consequences for future studies on loneliness, especially on the identification of lonely

individuals. Because loneliness may change in response to many life events and is closely related to social isolation, it may be more timely and informative to identify lonely individuals by tracking changes in the social network or other daily behaviors using unobtrusive monitoring techniques [12, 81]. For example, tracking call history would enable assessment of social network size and frequency of contact—the two major components of social isolation scales. Other behaviors that may relate to loneliness that can be tracked unobtrusively include time spent outside the home [81], computer use [149], and sleep quality [6]. Such approaches to loneliness identification would have dramatic consequences for the understanding of loneliness, enabling researchers to monitor and assess loneliness levels on smaller time scales such as daily or even hourly.

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Chapter 3: Unobtrusive In-Home Detection of Time Out-of-Home with Applications to Loneliness and Physical Activity

SUMMARY

This section details the work performed to unobtrusively assess daily time out-of-home using the in-home sensing platform. Using features from the in-home data stream, we first develop and validate a logistic regression classifier to assess whether someone was in the home or not for each 5-minute interval. This approach was both sensitive (0.939) and specific (0.975) in detecting home occupancy across over 41,000 epochs of data collected from 4 subjects monitored for at least 30 days each in their own homes, although it worked best for individuals who were not living in the assisted living portion of a retirement community where regular nurse visits caused large amounts of noise in the data. Once the classifier was developed and validated, we used it to compare the loneliness of the cohort with their daily average time out-of-home over the four days up to and including administration of the 20-item UCLA Loneliness scale [9], and found that people who are lonelier tend to leave the home for fewer hours on average each day ($r = 0.442$, $p=0.011$). We also studied the relationship between time out-of-home and physical activity, and discovered that self-reported level of physical activity is significantly associated with time out-of-home, but may be subject to recency effects. These results indicate that time out-of-home is an important covariate to loneliness, and that by monitoring time out-of-home and its covariates longitudinally, it may be possible to infer loneliness.

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INTRODUCTION

Loneliness, or perceived social isolation, is a common condition that is particularly prevalent in elderly where retirement, the death of friends, and the subtle decline in health pose challenges to forming and maintaining friendships. Indeed, nearly 20% of seniors self-report as occasionally lonely [150], while 5-15% of elders report frequent loneliness [123]. In this population, loneliness is particularly problematic since it predicts morbidity and mortality [1-3], causes decreased cognitive functioning [4], impairs sleep quality leading to daytime dysfunction [5, 6], decreases mobility which increases risk of falls [7, 8], and reduces quality of life. For these reasons, detection and mitigation of loneliness is critical, as the deleterious effects of loneliness can be reversed with an appropriate intervention [11]. However, physicians currently do not assess loneliness in the clinical setting and many of the aforementioned correlates of loneliness can cause lonely people to go unnoticed by people and programs attempting to reach out to them, making detection of lonely individuals difficult.

Smart homes, which have the ability to continuously and unobtrusively monitor inhabitants [15, 88, 89], present an ideal means to monitor and detect loneliness at the earliest phases. While multiple approaches to smart home technology exist [96, 151-153], memory problems and privacy concerns in the elderly hamper the efficacy of devices worn on the body and cameras in the home. For this reason, our research focuses on unobtrusive and passive sensing of loneliness based on data from motion sensors, contact sensors, computer sensors, and phone sensors. Using this array of sensors, we are developing methods to monitor the covariates of loneliness—for example, sleep

quality [98], frequency of visitor contact [154], total activity [101], and time out-of-home—with the goal of developing a robust model of loneliness that can be employed to continuously and unobtrusively detect loneliness in the home. Such a platform would allow lonely individuals to receive much needed help prior to experiencing a host of negative health effects.

The focus of this paper is on using passive sensors for objectively and unobtrusively detecting time spent out-of-home, a critical component of loneliness. This is in large part because loneliness often presents with a decline in physical activity [155], decreased motor function [7], and increased risk of depression [80], all of which are associated with more time spent in the home. Loneliness is also associated with sleep disruptions and daytime dysfunction [5]. Daytime dysfunction may not only increase time spent inside the home, but also reduce activity while in the home. For this reason, accurately detecting when an individual leaves the home will allow us to control for time out-of-home when estimating daytime dysfunction.

While our primary focus is on characterization of loneliness, measuring time out-of-home is also important for other applications. For example, fewer outings has been linked to decreased cognitive functioning, suggesting its importance for detecting cognitive decline [107]. More generally, measuring time spent out-of-home across a large number of individuals allows investigation into general behavioral patterns such as how elderly spend their time during the day, what the regularity of these patterns is over the course of the day, and what sort of changes exist between weekday and weekend out-of-home profiles. In fact, as we suggest below, larger variability in out-of-home profiles may allow detection of individuals at higher risk of loneliness.

Taken together, these applications support the need for an accurate, objective and unobtrusive method for detecting time out-of-home, especially in elderly

populations. In the following we describe and validate a method for detecting time spent out-of-home using a logistic regression based classifier with inputs derived from passive sensor data. After describing the sensor data collection and video ground truth, we discuss the rationale for incorporating different inputs into the classifier followed by a performance assessment. We follow by showing several applications of our methodology to loneliness and physical activity, and conclude with a summary of the contributions of this work.

METHODS

In this section, we describe the data collection, the model development and experimental validation.

Data Collection

The data used in this study were collected from the homes of the Intelligent Systems for Assessing Aging Changes (ISAAC) cohort [156] and the ORCATECH Living Lab. These two cohorts currently comprise around 150 seniors living independently in the Portland community who have been monitored for the past 3-5 years. A core set of technologies is continually maintained in all homes, including pyroelectric motion sensors (MS16A, x10.com) in each room and contact sensors (DA10A, x10.com) on the refrigerator and doors to the home.

To collect ground truth data, motion activated video cameras (Logitech C600) were installed over the door in the homes of four different subjects. This allowed us to capture when residents entered and exited the home while minimizing privacy issues by only recording video for 5 seconds when motion was detected. At installation, we verified that the field of view of the camera was appropriately positioned to detect when people passed through the door. Each individual video file was first labeled with a home

identifier and time stamp and then automatically uploaded to our data server. Using these data, outings from the home were hand-annotated. An outing was defined as any period where the resident left the home and closed the door behind them, leaving nobody else in the house. Thirty days of valid video data were collected from each home.

While the cameras collected data, data from motion sensors in each room of the home as well as contact sensors on the doors of the home were simultaneously collected. The infrared motion sensors function by firing a signal each time movement is detected, with a refractory period after firing of about 6 seconds. The contact sensors are magnetic, and fire a different signal when the two magnets are together (the door is closed) than when they are apart (the door is open). These contact data also have heartbeats: if no event occurs within about an hour, the contact sensor emits a signal corresponding to whatever state it is in at present. To remove heartbeats, consecutive data points with the same signal were removed from the data stream.

Feature Selection

To derive the features used in the model development, the sensor data from each home was first divided into 5 minute epochs. Because most out-of-home events last at least 30 minutes, this window size was small enough to capture the outing events with high sensitivity, while remaining large enough facilitate data processing and analysis. For each epoch, thirteen features were calculated—five initial features and the forward and backward lags from four of them—and used in the model development.

The first feature included in the model corresponds to the number of sensor firings during each five minute interval. Because the motion sensors in the home are event driven, the number of sensor firings should be very low or zero when nobody is present in the home. On the other hand, the number of sensor firings should increase when someone is present in the home provided they are moving about. To account for

periods where the subject is both home and not moving (e.g. during naps or overnight), our second feature corresponds to whether the subject was in or out of bed, as calculated using the heuristic approach developed by Hayes et al [98].

Our next two features correspond to the firing of door sensor events and are designed to capture entry and exit events from the home. Two key observations can be made regarding the door sensor and outings from the home. First, when the subject leaves the home, the *last* sensor firing in the home during the departure epoch should be a door sensor. Second, when the subject arrives back home, the *first* sensor firing in the home during the arrival epoch should be a door sensor. In between these two events, few, if any, sensor firings should occur. However, simply looking for these events to happen consecutively is not enough as door sensor firings are noisy and can be missed. For example, if a door opening event is not recorded, the corresponding door closing event will be treated as a heartbeat and removed from the sensor stream. To create the most robust model, we therefore incorporated two separate door sensor features into the model. The first, corresponding to a leaving event, operates on the intuition that periods of inactivity following a door sensor likely correspond to out-of-home events. For this feature, we looked for periods where the door sensor was the last sensor that fired during the epoch. All epochs between this event and the next movement event, where movement is defined as at least 3 consecutive sensor firings, were labeled as ‘1’, corresponding to epochs where the person was likely out of the home. Our second door sensor feature corresponds to an arrival event, and operates on the intuition that periods of inactivity preceding a door sensor firing likely also correspond to out-of-home events. For this feature, we looked for all epochs where the door sensor was the first sensor in the epoch and labeled all epochs between this event and the *previous* movement event as ‘1’.

The final feature included in the model simply indicates whether the last recorded sensor firing occurred in a room from which the subject could leave the house. This feature was calculated independent of the true home layout. Rather, rooms that were deemed unlikely to leave the home from without first tripping a different sensor (e.g. a bedroom) were labeled ‘o’ while those a resident may be able to directly leave the home from (e.g. the living room) were labeled ‘1’. Each epoch was then labeled according to the value of the last sensor firing. This feature was important to distinguish events where the resident arrived home and opened the door from those where the resident was in the home but not moving when someone else arrived and opened the door. Although using the home-specific layouts could provide better labeling for training purposes, this approach would not readily generalize to new homes.

In order to capture some of the time-series nature of outings from the home, forward and backward lags of one epoch for each feature except the bed feature were also used in the classifier.

Model Development

We treated the problem of detecting outings as a binary classification on each epoch. Multiple methods to classify binary data exist (support vector machines, neural networks, logistic regression, etc.), each with its own advantages and disadvantages. However, the focus of this paper is not to compare the different classification techniques, but rather to demonstrate that the features described can be used to separate out-of-home epochs from in-home epochs with high sensitivity and specificity. Because of the ease of interpretability of the results, we chose to use logistic regression, a well-known technique often used for binary classification [157], to classify the data. Logistic regression is based on the assumption that the “log-odds” of the outcome is linear in the

parameters. From this assumption, the conditional probability follows a logistic distribution given by

$$P(y_i = 1 | \mathbf{x}_i) = \frac{\exp(\mathbf{x}_i \beta)}{1 + \exp(\mathbf{x}_i \beta)}. \quad (3.1)$$

where y_i is a binary indicator variable corresponding to ‘1’ if nobody is in the home during epoch i (the participant is out-of-home) and ‘0’ otherwise, $\mathbf{x}_i$ is the feature vector for epoch i , and, β represents the vector of model parameters which can be estimated using maximum likelihood.

To optimize model performance and applicability, we trained on the same number of out-of-home events as in-home events. This resulted in training on $\frac{1}{4}$ of the in-home epochs (7745 of 30,980 epochs), and $\frac{3}{4}$ of the out-of-home epochs (7678 of 10,198 epochs). We tested on all the remaining data. For all model fits, we used 1000 fold repeated random sub-sampling to determine mean out-of-sample performance, parameter estimates, and 95% confidence intervals for sensitivity and specificity with a decision threshold of 0.5 (that is, samples with a probability greater than 0.5 were classified as ‘out-of-home’, and those with a probability less than 0.5 were classified as ‘in-home’).

Initially, the logistic regression model was trained using all the data and all the features discussed above. Parameter estimates and 95% confidence intervals for each feature were calculated using these data. All features with parameter estimates whose 95% confidence intervals included zero were removed from the model, and the model was refit using the reduced feature set. This process was continued until all included features proved significant. Through this process, four features were removed: the forward and backward lags of the number of sensor firings, the backward lag of the first

door sensor, and the forward lag of the last door sensor. All other features were significant. The results of the model with the final feature set are presented below.

RESULTS

The logistic regression based classifier performed well with a sensitivity of 0.939 (95% CI: 0.931, 0.947) and specificity of 0.975 (95% CI: 0.973, 0.977). This high performance can also be visualized in the ROC curve shown in Figure 3.1. The ideal threshold for classifying this data is likely 0.51. After this point, a small increase in sensitivity causes large drops in specificity, quickly resulting in dramatic overestimation of time out-of-home.

While reporting sensitivity and specificity is important, the true goal of this model is to estimate how much time an individual spends out of the home. For that

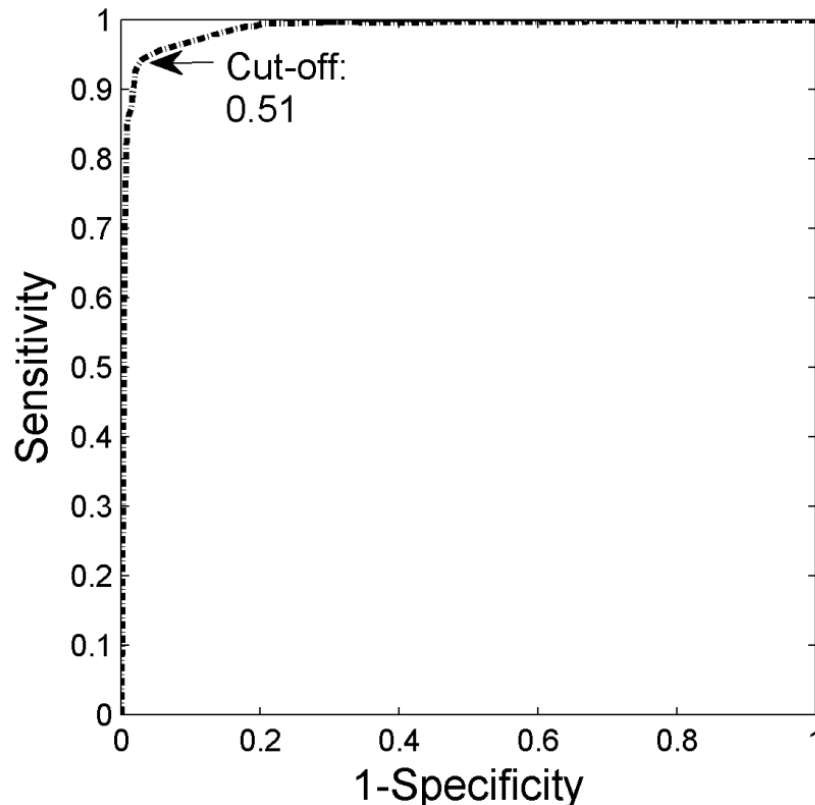


Figure 3.1: Receiver operating characteristic (ROC) curve of the model performance.

reason, calculating the difference between the estimated time out-of-home and the true time out-of-home is important. This difference will vary as a function of the proportion of time spent out-of-home. That is, for individuals who go out frequently, the low sensitivity may cause underestimation of time out-of-home, while we may over-estimate the time out-of-home for those who seldom leave. To compute the expected bias in minutes we estimate the probability of false positive $(1 - s_p)(1 - p)$ and of false negative $(1 - s_e)(p)$ and evaluate their difference multiplied by the number of minutes in a day:

$$\bar{b} = 1440 \left[(1 - s_p)(1 - p) - (1 - s_e)(p) \right]. \quad (3.2)$$

Here, s_p is the specificity of the model, s_e is the sensitivity of the model, and p is the proportion of time spent out-of-home. Using this estimate of the bias,

Figure 3.2 shows the relationship between true daily time out-of-home and the estimate of time out-of home for a sensitivity of 0.939 and specificity of 0.975. In our population of four subjects, the lowest average daily time out-of-home was 3 hours per day. For this subject, the classifier will overestimate their time out-of-home by 19.8 minutes per day on average. On the other hand, the highest average time out-of-home was 8 hours per day, and the classifier will *underestimate* this subject's time out-of-home by 5.1 minutes per day on average. Across subjects, the classifier will overestimate time out-of-home by 5.5 minutes per day on average. Within the range of probable average daily time out-of-home, this classifier performs very well at estimating the true time out-of-home.

This performance gives some indication of the noisiness of the sensor data. For example, many of the false negatives (periods classified as 'in' when nobody was actually in the home) occurred when sensors would fire in the home while the resident was out, likely due to sources of heat inside the apartment (e.g. space heaters, pets, or sun through the window). Indeed, in two separate homes, we discovered sensors that often fired while the resident was out of the home – one likely due to a computer turning on and causing a change in heat patterns in the room, and the other likely due to sun

through the window. Because it is nearly impossible to detect and eliminate all misfirings, we did not remove any of these events from the sensor stream. Instead, our performance gives an indication of how the model will perform under true conditions, which are typically noisy.

In general, we were able to handle these noise issues as well as noise associated with the door sensors themselves by accounting for both arrival and departure events. If the arrival door event was excluded from the model, the sensitivity dropped only slightly to 93.1% while the specificity dropped considerably to 82.6%. Exclusion of the departure door event dropped the sensitivity to 90.67% while the specificity remained largely unaffected at 96.6%. This difference between the arrival and departure door sensor events indicates more errors occur with door sensors when subjects are leaving the home

than
they
back

when
arrive
home.

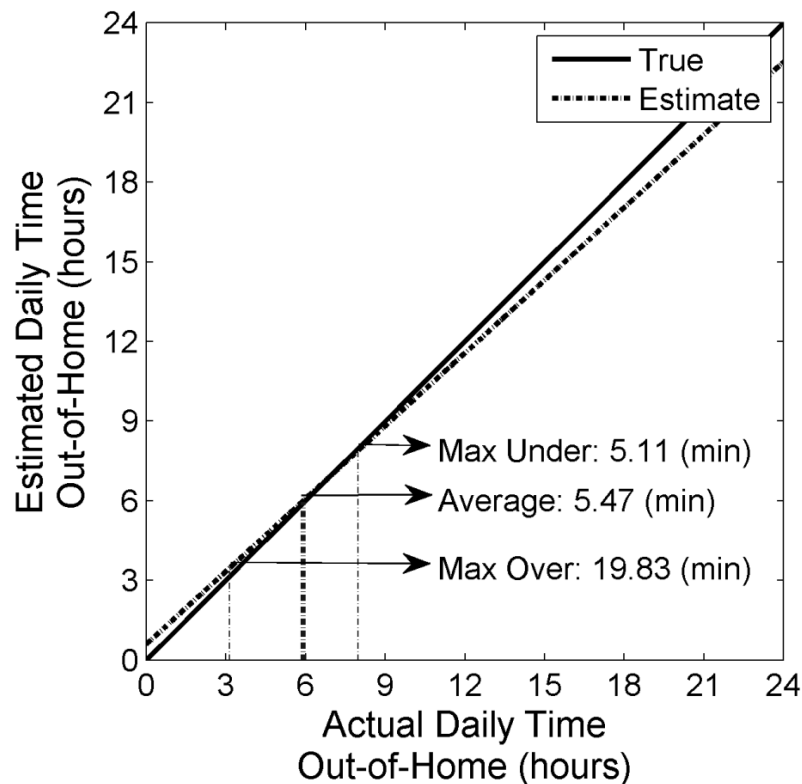


Figure 3.2. Estimated daily time out-of-home as a function of actual daily time out-of-home. For the individual from this population who leaves the most, the classifier underestimates their time out-of-home by 5.11 minutes. For the individual who leaves the least, the classifier overestimates their time out-of-home by 19.83 minutes. On average, the classifier will overestimate time out-of-home by 5.47 minutes.

Model Applications

We have shown that our classifier can detect outings from the home with high accuracy. We now examine applications of this model.

Loneliness and Outings

In June of 2012, subjects from both the ISAAC cohort and the ORCATECH living lab were administered an online version of the UCLA loneliness scale [9], a well validated survey for assessing loneliness. This survey asks questions such as “I do not feel alone” and “There are people I feel close to”, where response options are: (1) Never, (2) Rarely, (3) Sometimes and (4) Often. Because this survey was administered online rather than in-person, we also added a response for ‘do not wish to answer’. After reversing the value of positive questions, the value of each answer was summed across the twenty questions to give a loneliness score ranging from 20 to 80, with 80 being the loneliest. The least lonely individual scored 21 on this survey, while the loneliest individual from our cohort scored 60. The mean value was 35 with a standard deviation of 7.87, which is consistent with values obtained by Russell et al in validating the UCLA Loneliness Scale for the elderly [40].

We chose to correlate loneliness score with the average time spent outside the home over the five days up to and including survey administration. This interval was chosen to provide the most robust summary of average outings while eliminating as much recall bias as possible. The current analysis included only those subjects with valid sensor data who answered all questions on the questionnaire (34 people) and who live alone. Of those 34 individuals, two were traveling away from home for at least three of the five days prior to filling out the survey and were therefore excluded from this aspect of the study. This left a total of 32 subjects who completed the loneliness survey and had

valid sensor data. We used these subjects' data to explore the correlation between outings and loneliness.

Figure 3.3 shows the correlation between the average time spent outside the home over the course of the four days up to and including survey administration and the corresponding loneliness score. As can be seen, average time outside the home is negatively correlated with the loneliness score, indicating those who spend more time at home tend to be lonelier. This is consistent with research showing a negative correlation between loneliness and physical exercise, social activity, and mobility. Still, the correlation is significant ($p=0.011$) but modest ($r = -0.44$). Obviously it is possible for some individuals to stay at home but not experience loneliness. Including other factors that influence loneliness such as social contact with others, sleep disturbances, and daytime dysfunction would assist in creating a more complete model of loneliness in the

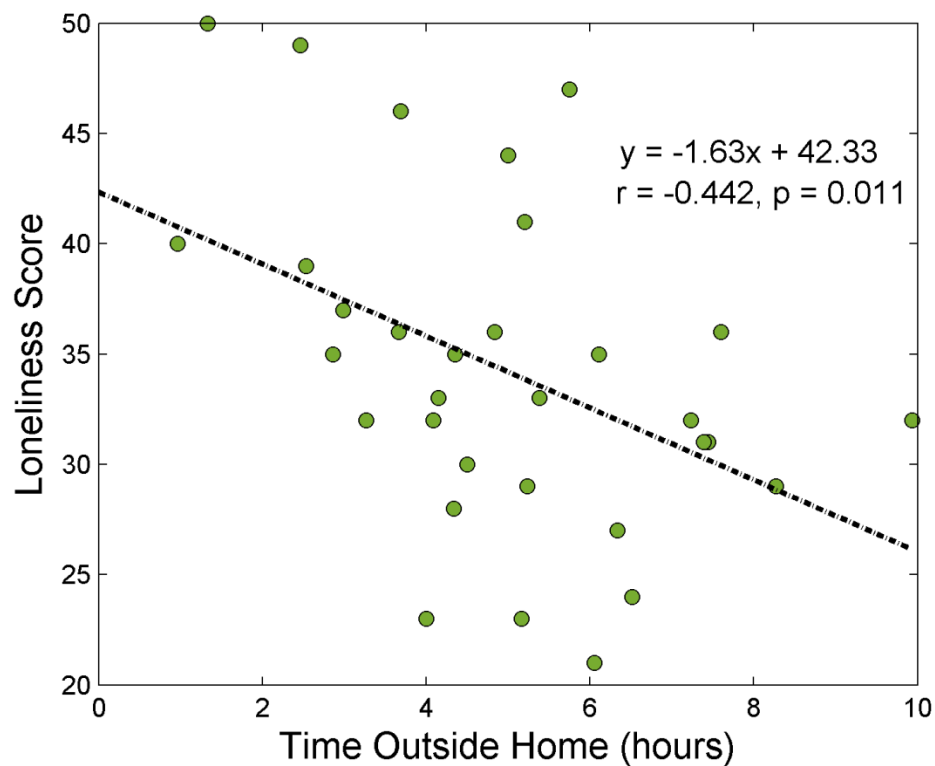


Figure 3.3: Loneliness score as a function of average time spent outside the home over the five days up to and including survey administration. Loneliness is negatively correlated with time out-of-home.

home.

Outings by Time of Day

While the total time spent outside the home is important, various factors can influence the time spent outside the home. For example, in retirement communities people typically take meals in the central dining hall. Leaving simply to eat a meal may not influence loneliness the same way that leaving to play games with close friends would. For this reason, it is also important to view outings as a function of the time of day.

For this aspect of the study, we used our outing model to compute outings, y for every five minute interval over the thirty days prior to completing the loneliness survey where $y=1$ if the individual was out of the home, and $y=0$ if the individual was in the home. By averaging the corresponding y values for each subject and day, we were able to generate a picture of the probability of leaving the home as a function of the time of day. Figure 3.4 shows the probability of leaving over the entire population of 51 individuals living alone in the community who completed the survey and had *any* full days of sensor data during the 30 day period prior to survey completion. Clear peaks can be discerned at around noon and 6 p.m., corresponding to the lunch and dinner hours, respectively. The probability of being out of the home at these times was 0.5, indicating that at noon and 6 p.m., an average of 50% of our elderly population is outside the home on any given day. Further, these subjects are more likely to be out of the home in the early afternoon, perhaps when most errands are completed. Not surprisingly, Figure 3.4 also shows that our cohort is almost certainly at home during the night, consistent with sleep patterns.

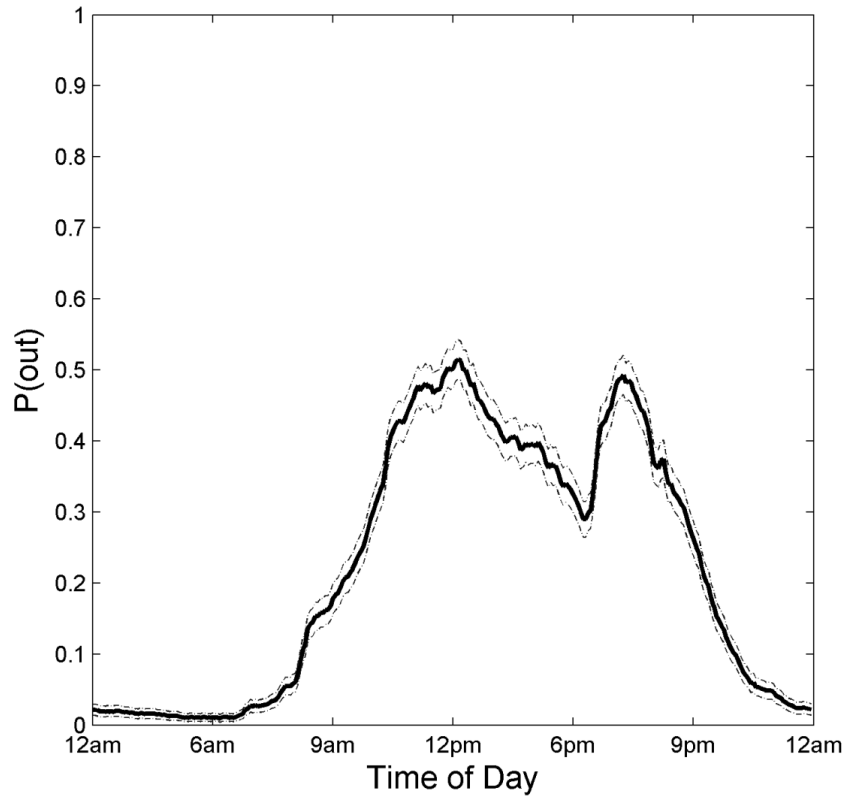


Figure 3.4: Mean and 95% CI of the probability of being out of the home as a function of the time of day for 51 elderly subjects over the course of 30 days. For this cohort of elderly, roughly half the population is out of the home at lunch and dinner times on any given day.

While trends across the population are important for summarizing how elderly spend their time, individual trends are also important. To illustrate the variability of outing patterns of lonely and non-lonely individuals, we chose to plot the probability of being out for a representative sample of five subjects with varying loneliness scores. Their loneliness scores and corresponding probability of being out of the home are shown in fig. 5(a-e). Clear meal times and an obvious regularity can be discerned in fig 5a-d, but this regularity is largely absent in fig 5e—the loneliest individual plotted.

It is worth noting that the individuals in Figure 3.5a, c, and d live in retirement communities where they could take meals in the local dining hall. While the individual plotted Figure 3.5a leaves the home regularly in the late afternoon, the main peaks in Figure 3.5c surround the lunch and dinner mealtimes. This mealtime regularity is also

seen in Figure 3.5d, although this individual rarely leaves the home at all. This may suggest that outings other than simple mealtime outings are important in assessing loneliness for individuals living in a retirement community. On the other hand, mealtime outings for individuals living alone in the community may represent an important aspect of socialization, and contribute greatly to decreasing loneliness. This is seen in Figure 3.5b. This individual lives alone in the community and, even though his most common outing times surround the mealtimes, he is not lonely. Likely he is getting a great deal of socialization when he leaves his home to get a meal with a friend, which helps ward off loneliness. Taking into account these different lifestyles may be important in unobtrusively modeling loneliness in the home.

Outings and Physical Activity

Many physical activities are done outside the home, so we tested how outings from the home correlate with self-report of physical exercise. Concurrent with the administration of the UCLA loneliness scale, subjects also completed a physical activity survey from Berkman's Social Disengagement Index [158]. This fifteen item survey

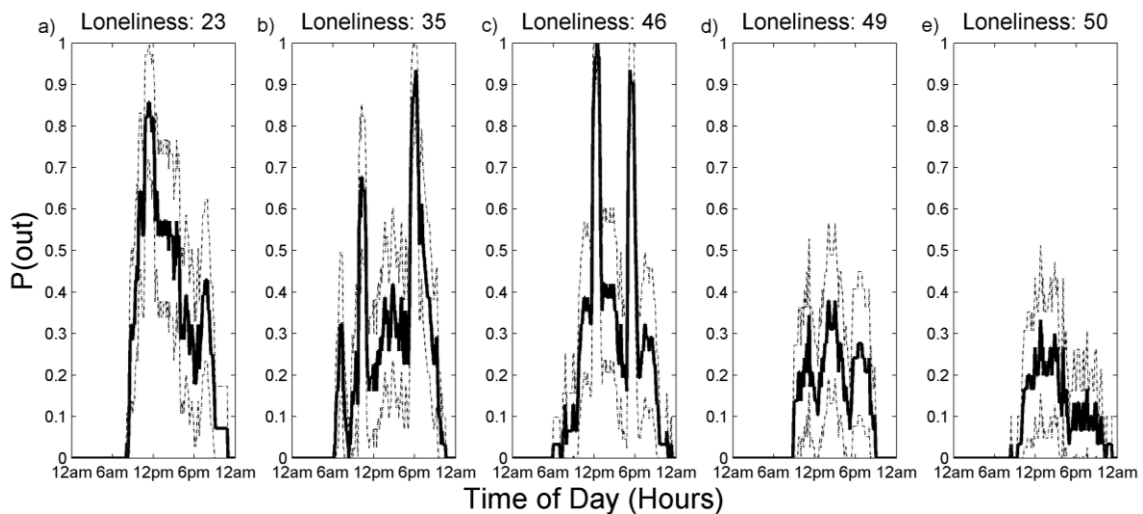


Figure 3.5: Average probability of being out of the home as a function of the time of day for five different individuals over 30 days with varying loneliness scores. 95% CI in this measure is plotted in grey. Meal time outings can be seen on plots (a-d) whereas subject (e), the loneliest of the group, is the most variable and the only one with no clear mealtime peaks.

queries subjects regarding activities they do both in and outside the home. To get a composite score of outside activities, scores on three questions were reversed: (i) How often do you prepare your own meals, (ii) How often do you read books, magazines, or newspapers, and (iii) How often do you watch television, as these are activities likely done inside the home. After reversing these scores, the scores on all questions were summed to give a total outdoor activity index.

A plot of the correlation between the physical activity score and the average time spent outside the home over the four days up to and preceding survey administration is shown in Figure 3.6a. As can be seen, physical activity score is positively correlated with average time spent outside the home ($r=0.415$, $p=0.031$), indicating outings are also an

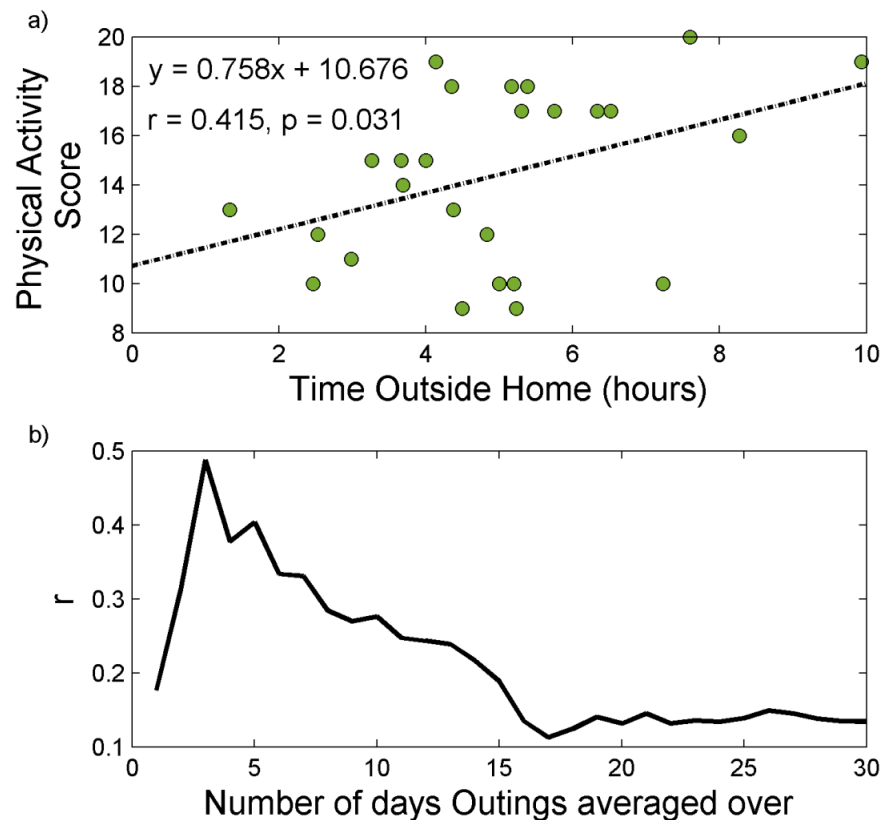


Figure 3.6: (a) Physical activity score as a function of average time spent outside the home over the four days up to and including survey administration. (b) Pearson's correlation coefficient (r) between average time outside home and physical activity score. As more days further from the survey date are included in the window and averaged, the correlation drops off. This suggests recall bias.

important measure of physical activity. This correlation is also prone to recall bias. Figure 3.6b shows a plot of the correlation as a function of the window of observation. While looking at only the same day as the survey generates the worst correlation, the best correlation is seen when averaging around 3-7 days of outing activity. The correlation then drops considerably until it plateaus at around 18 days of outing data. This result is consistent with the salience effects seen by Eagle et al. in their correlation of self-report of proximity patterns of other individuals with Bluetooth phone logs [114], suggesting human recall favors the recent events.

CONCLUSIONS

We have presented and validated a logistic regression based classifier to detect outings from the home on longitudinal data from subjects currently monitored in their own homes. Our classifier performs very well with a sensitivity of 0.939 and specificity of 0.975, but it depends heavily on door sensors firing when they ought. Simple tests for door sensor functionality should be employed prior to using this model.

We also discussed several practical applications of our approach. Specifically, we have shown that time outside the house is negatively correlated with loneliness, indicating the utility of time out-of-home in any unobtrusive model of loneliness. We have also demonstrated a general pattern of out-of-home behavior in an elderly population consistent with prior research, and shown that outing patterns vary substantially on an individual level which may be useful in detecting individuals at increased risk of loneliness. We correlated time out-of-home with physical activity, and were able to demonstrate that an individual's self-report of physical activity may be subject to recall bias. In conclusion, we expect that being able to accurately detect out-of-home events will improve point-of-care in the home setting, particularly for loneliness

and other adverse health outcomes whose symptoms present with an increased, decreased, or more variable pattern of out-of-home behaviors.

ADDENDUM

In this chapter, we discussed various errors that may occur in the sensor data that would reduce the sensitivity and specificity of the time out-of-home classifier. For example, if a sensor in the home fires repeatedly when the subject is out-of-home, those epochs may be classified as ‘in-home’ when the participant is in fact out-of-home. This type of error would drop the sensitivity and if it occurred in applications of the algorithm, would lead to mis-estimation of the total daily time out-of-home. Another source of error would be malfunctioning door sensors, which would dramatically reduce the algorithms ability to detect the periods where the subject is not home, thereby reducing the sensitivity of the algorithm.

In one of the homes included in this analysis, a sensor would frequently fire while the subject was not home. To demonstrate the algorithm performance in the presence of such noisy data, we performed a round-robin train and test of the classifier, where we trained the classifier on data from all but one subject and tested the performance of the classifier on the data from the remaining subject. The results of this analysis are presented in Table 3.1. As can be seen, the classifier performed well for three of the four subjects (Subjects 1-3), with an

average sensitivity of 94.35 and average specificity of 98.41. However, for the last subject (Subject 4), the sensitivity of the classifier dropped dramatically to

Table 3.1: Comparison of sensitivity and specificity of classifier when trained on 3 subjects and tested on the remaining subject.

	Sensitivity	Specificity
Subject 1	93.25	96.55
Subject 2	94.02	99.36
Subject 3	95.8	99.31
Subject 4	79.67	99.07

79.67. In practice, if these noisy sensors can be identified and removed from the dataset the classifier sensitivity can be expected to return to within the 95% confidence intervals reported in this chapter (pg. 45). In this home, if the offending sensor is removed from the dataset, the sensitivity of the classifier increases to 93.8 for this home, while the specificity remains high at 98.5.

For completeness, we also include here the beta coefficients of the classifier, shown in Table 3.2. However, we note that one should not expect to achieve the same performance as that reported here if using these coefficients in their own data.

Table 3.2: Beta coefficients from final out-of-home logistic classifier.

Feature	Coefficient
Number of Sensor firings	-0.0811
Bed Indicator	-1.8315
Leaving Door Sensor	0.9552
Arriving Door Sensor	3.5483
Room Indicator	-1.4233
Forward Lag Arriving Door	1.0958
Backward Lag Arriving Door	1.3985
Forward Lag Room Indicator	-1.0818
Backward Lag Room Indicator	-2.0337
Constant	-1.1932

Chapter 4: Phone Behavior and its Relationship to Loneliness in Older Adults

SUMMARY

In this section, we study the relationship between loneliness and objective measures of phone behavior. Using data on the total daily number of calls as recorded by in-home phone monitors on the landline phones of 26 older adults, we show that increased loneliness is associated with fewer total calls (both incoming and outgoing). In particular, individuals with the highest possible loneliness score of 60 had half (0.52) the number of calls each day on average compared with individuals with the lowest possible loneliness score, holding all other variables at their means. A follow up analysis shows loneliness is significantly related to both incoming and outgoing phone calls. This work shows that total phone use should be included in the longitudinal model of loneliness. Future work on phone use and loneliness should assess how changes in social network (for example changes in the numbers dialed) relate to loneliness. In addition, this work included data from landline phones only, and the results should be verified among cell phone users as the behavioral profile of cell phone use may differ from that of landline phones.

INTRODUCTION

Loneliness and social isolation have each received considerable attention in gerontology due to their association with numerous negative health outcomes [159]. For example, individuals experiencing loneliness have been found to exhibit increased morbidity and mortality [1], reduced sleep quality [5], increased daytime dysfunction [6], and increased rates of cognitive decline [4]. The relationship between loneliness and health may be in part because lonely individuals perceive less support from their social network [122], and therefore experience increased stress levels compared to non-lonely individuals [71]. Likewise people who are socially isolated tend to have increased morbidity and mortality with the increase in mortality similar to that of smoking [19]. Socially isolated people also exhibit poor sleep quality [73] and increased risk of cognitive decline [120]. These associations with health may be a direct result of a poor social network, as isolated individuals have less access to resources and less encouragement to engage in healthy behaviors [42, 55, 56]. But while both loneliness and social isolation are associated with significant negative health outcomes, it is difficult to isolate the contribution each state has on health in part due to problems with the assessment of loneliness and social isolation.

While loneliness is typically understood to refer to a subjective feeling of a deficit in social relationships [26, 28, 29], the term ‘socially isolated’ refers to a quantifiable state where the number of network members or frequency of contact with the network is small [36, 37]. As a result, while loneliness is typically assessed using subjective scales, assessment of social isolation has been performed simply by counting the number of network members and the frequency of contact with the network [38]. However, most of

the techniques currently used to assess social isolation rely on subjective self-report of the number of contacts and frequency of contact with the network. Relying on self-report to assess both loneliness and social isolation makes it challenging to isolate the impact each of these constructs has on health. For example, an individual experiencing loneliness may perceive (and report) infrequent contact with friends regardless of the true amount of contact. Thus, the development of an objective means to assess social isolation would advance the understanding of the relationship between loneliness and social isolation, and their differential effect on health.

One aspect of behavior that directly relates to the level of isolation is telephone use. Because people use the phone to call their network members, monitoring phone calls would provide one measure of the frequency of contact (by monitoring total number of calls), and network size (by monitoring numbers dialed). Of course, this would only assess frequency of contact via the telephone, and network size of those with whom one corresponds via telephone, which may not be a complete picture of the level of isolation. Still, many of the scales used to assess social isolation ask participants how often they contact friends and family by phone in addition to asking how often they are contacted in person, highlighting the importance of telephone contact in measures of isolation. In young adults, data collected from mobile phones has been used to quantify social groups and their evolution [112, 113], infer friendship networks [114], and even assess mental health [115]. These applications typically employ smart phone apps to record phone calls, Bluetooth proximity logs (records when the phone is close to another Bluetooth user), and GPS or cell-phone tower information. However, older adults still largely use landline phones and flip phones (as opposed to smart phones): while 69% of those 65 and older own a cell phone, only 18% owned a smart phone in 2012 [160]. Thus the smart phone apps developed to assess phone use do not currently work in well this population. Monitoring landline phone use can be performed by installing a device in the home that

records signals on the phone line. This technology can easily be employed with other unobtrusive in-home monitoring systems which detect important behavioral features such as time out-of-home [81], sleep quality [98], visitors to the home [154], or computer use [161], and provides a longitudinal measure of a key behavioral parameter.

In this research, we used phone monitors placed in the homes of 26 older adults to objectively assess social isolation and its relationship to loneliness. We hypothesized that increased levels of loneliness, as measured using the UCLA Loneliness Scale, would be associated with fewer daily calls. As a secondary analysis, we also sought to determine whether loneliness had a differential effect on outgoing or incoming calls. Previous work on loneliness has demonstrated that individuals experiencing loneliness may attempt to overcome their loneliness by reaching out to others [27, 162]. Thus, while incoming calls may decline as individuals become lonely, outgoing calls may remain constant or increase. In the later phases of loneliness, both incoming and outgoing calls are likely to decline as individuals may adjust their expectations for social contact or become resolved in their loneliness [20, 26]. Thus, we hypothesize that loneliness will be significantly related to incoming calls but not outgoing calls.

METHODS

Participants

The participants for this study were recruited from the ORCATECH Intelligent Systems for Assessing Aging Changes (ISAAC) [12] cohort, an ongoing observational study aimed at understanding the relationship between daily behavior and health in older adults. The minimum age for participation in the ISAAC study is 80 years (or 70 for non-whites). Participant inclusion criteria include living independently in a house or an apartment larger than a studio, a minimum score of 25 on the Mini-Mental State

Examination [163], and a maximum score of 0.5 on the Clinical Dementia Rating[164] scale. Participants were also required to be in average health for their age with either no or well-controlled chronic health conditions. Exclusion criteria were health conditions that may limit physical participation or lead to death within three years. Subjects from the ISAAC cohort who agreed to participate in this additional study received phone monitors (Shenzhen Fiho Electronic, Fi3001B) on their landline phone line for up to one year. All subjects signed informed consent prior to participating in any study activity, and the study was approved by the OHSU Institutional Review Board (IRB #4661). A total of 26 individuals agreed to participate; the mean age of the participants was 86 ± 4.5 years, 88% of the cohort was female, and 46% had completed college (see Table 4.1).

Data and measures

Incoming phone calls

Installation of the phone monitors began in December of 2011 and continued on through February of 2012. Once installed, the monitors were left in the home for at least 6 months. During this time, subjects had a mean of 174 ± 87 days of valid monitoring data. The differences in number of days of data between subjects were influenced

Table 4.1: Demographic characteristics of the population

Characteristic	Statistic	Range (Min, Max)
Age (years)	86 ± 4.5	(73, 94)
Gender (% Female)	88%	-
Education (% Completed College)	46%	-
Race (% Caucasian)	100%	
MMSE	29.1 ± 1.04	(26, 30)
Cognitive Z-score	0.28 ± 0.55	(-0.81, 1.39)
Loneliness	35.3 ± 7.6	(23, 60)
Pain Level	1.89 ± 2.2	(0, 10)

primarily by device functionality. That is, the devices occasionally stopped collecting data due to a device failure, and would not turn back on for a period of up to several months. Thus, the missing data mechanism was not related in any way to the study participants or their characteristics. As a result, we assumed the phone call data were missing completely at random, and dropped days with missing data from the model. The monitors plug directly into the phone line, and are designed to record all signals on the line including 'on hook', 'off hook', 'ring start', 'ring stop', and 'dtmf' (numbers dialed encoded as dual-tone multi-frequency). Incoming and outgoing phone calls were counted separately. Because the phone must ring prior to being taken off the hook for an incoming call, all calls where the phone rang and was subsequently removed from the hook within 30 seconds of the final ring signal were counted as incoming calls. It should be noted that missed calls (calls where the resident did not answer the phone) would not be treated as incoming calls in this paradigm. For a call to be treated as outgoing, a number must have been dialed. Because several of our participants live in retirement communities, four digit codes could be used to call within the building to other residents of the retirement community. As a result, a call was treated as outgoing if an 'off hook' signal was followed by at least four numbers dialed and not preceded by a ring signal. It should be noted that there is no signal to detect whether an outgoing call was completed (that is, whether the other end picked up the phone or not). Caller-ID information was not reliably collected, and therefore data regarding the number dialed was not used in this analysis.

Loneliness

Loneliness was assessed online in June of 2012 using the 20-item UCLA Loneliness Survey [9], which asks questions such as "I feel part of a group of friends" and "I do not feel alone". Response options for each question are (1) Never, (2) Rarely, (3) Sometimes, and (4) Often. The survey is scored by first reversing the value of positive

questions and then summing the value of each answer to give a composite 'loneliness' score between 20 and 80, with 80 being the loneliest.. The loneliness survey was administered to participants in conjunction with a regular weekly health form, a questionnaire with 11 questions that was administered online to all ISAAC participants each week. This questionnaire is programmed to appear on participant computers every time they log in to the computer until it is completed. The survey begins to appear each Monday, and once completed will not appear again until the following Monday. For a period of up to 2 months beginning in June 2012, the loneliness survey appeared immediately after completion of the weekly health form. Participants were told the general nature of the ensuing questions and given the option to accept, decline, or postpone survey completion. If a participant opted to postpone survey completion, it appeared after subsequent weekly health forms until either the subject completed the entire survey, declined to complete the survey, or a period of two months passed. Once the participant completed this online administration of the UCLA Loneliness survey once, they were not asked to complete it again. Thus, we collected the UCLA Loneliness Survey data from each participant at most one time, but the date at which they completed it ranged from early June to late July.

Covariates

We included several variables in the model that might confound the relationship between loneliness and incoming phone calls. Individuals with cognitive difficulties might initiate fewer conversations, and those with more physical symptoms might reach out to other people more or less than others would. Global cognitive status was assessed using a composite score including z-scores tabulated from two or three representative neuropsychological tests in each of five cognitive domains. Cognitive domains included working memory: Letter-Number Sequencing (WMS-III) [165] and Digit Span Backward length (WAIS-R) [166]; attention/processing speed: Digit Span Forward length (WAIS-

R), Digit Symbol (WAIS-R), and Trail Making Test- Part A [167]; memory: WMS-R Logical Memory II Story A, WMS-R Visual Reproduction II, and CERAD Word-List Recall [168]; executive function: letter fluency (CFL), Trail Making Test Part B [167], and Stroop color-word conflict [169]; and visual perception/construction: WAIS-R Block Design, WAIS-R Picture Completion, and WMS-R Visual Reproduction I. Individual test z-scores were calculated using group mean and standard deviations of the raw test scores from all cognitively intact participants at study entry into the ORCATECH cohort. All individual participant scores were z-normalized, summed, and averaged to obtain the composite score.

Pain level was assessed weekly using a question from the weekly health form. The question asked participants to rate their pain by indicating the number that best described their pain on average in the last week. Participants answered on an 11-point Likert scale (0-10) with lower scores indicating less pain. In the model, we also included gender, age at baseline, and a flag for weekend days (this was included because weekend behavior is often different from weekday behavior due to work hours, community events, and the availability of resources; this flag will allow the model to fit these behaviors separately).

Data analysis

We first computed descriptive statistics for all variables included in the model. Because the telephone data is left skewed, we calculated the median and interquartile range (IQR) to describe the data. The interquartile range is a robust measure of standard deviation that is given by the 75th percentile minus the 25th percentile of the data. Because the daily number of calls is a count variable, we tested it for over-dispersion to determine whether the Poisson model, a standard model for count data, is a good fit to the data. This was tested using a χ^2 test, with null hypothesis that α (the dispersion

parameter) equals zero. This test indicated the data is over-dispersed ($\chi^2 = 7782$, $p < 0.001$), so a negative binomial regression was used to model the data. We modelled the effect of loneliness on phone use using a mixed effects negative binomial regression, controlling for age, sex, and cognitive function. A total of 4,519 days of data were included in the model, representing an average of 174 days of monitoring for each participant (days of data included in the model differed across participants due to both data outages due to device failure and differences in the date of installation). In our secondary analysis (models 2a and 2b), we sought to determine the differential effect of loneliness on incoming and outgoing phone calls. For this analysis, we ran two mixed effects negative binomial regressions, after testing for over-dispersion in the output for these models ($\chi^2 = 1337$, $p < 0.001$ for model 2a, and $\chi^2 = 936$, $p < 0.001$ for model 2b). The dependent variable in model 2a was the total daily number of incoming calls, while that for model 2b was the daily number of outgoing calls. All analyses were performed in Stata (StataCorp, Texas, Version 13). A p-value of 0.05 was considered significant.

RESULTS

Descriptive statistics

Participants received a median of 2 (IQR: 3) phone calls each day, and placed a median of 2 (IQR: 4) calls each day. The median total calls each day was 5 (IQR: 6), and the correlation (r) between daily number of incoming and outgoing phone calls was 0.47. The average loneliness score in this cohort was 35.3 ± 7.62 , which is consistent with previous studies on loneliness in older adults [40]. The average cognitive Z-score score was 0.276 ± 0.55 , indicating little to no cognitive impairment in this cohort. The median level of pain reported each week was 1, with an inter-quartile range (IQR) of 4.

Mixed effects negative binomial regression on total daily calls

The results of the mixed effects negative binomial regression are shown in Table 4.2. It should be noted that the effective sample size for all cross-sectional variables included in this model (age, gender, loneliness and cognitive function) is 26. From the negative binomial regression, the incidence rate ratio (IRR) represents the proportional change in number of calls for a unit increase in the independent variable. An IRR that is greater than 1 means the number of calls increases for each unit increase in that independent variable, and an IRR of less than 1 indicates the number of calls will decrease for each unit increase in that independent variable. For example, an IRR of 0.5 would mean that for each unit increase in the independent variable, the daily number of calls would decrease by a factor of 0.5. Thus, if the independent variable could vary from 0 to 3, the change in daily calls over this range would drop by 0.5^3 or 0.125.

As can be seen from Table 4.2, loneliness is significantly related to the daily number of incoming phone calls. Individuals with higher loneliness scores received fewer calls on average (IRR=0.99, $p<0.05$; 95% CI 0.99, 1.00) such that the individual

Table 4.2: Results of the mixed effects negative binomial regression on daily number of phone calls

Variable	Incidence Rate Ratio	Std. Err.	z	95% CI	
Loneliness	0.990*	0.005	-1.96	0.980	1.000
Gender (male)	2.026***	0.225	6.37	1.630	2.518
Age	0.982	0.010	-1.81	0.963	1.001
Cognitive Z-Score	1.512***	0.098	6.36	1.331	1.717
Weekend	0.647***	0.017	-17.02	0.616	0.680
Pain Level	1.007	0.011	0.68	0.987	1.028
Date (Normalized)	0.999	0.011	-0.06	0.977	1.022
Constant	5.099	4.322	1.92	0.968	26.854

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

with the highest loneliness score of 60 averaged nearly two thirds the number of calls each day ($0.990^{(60-23)} = 0.69$) compared to the individual with the lowest loneliness score, holding all other variables constant. Other factors also significantly affected the total number of calls each day. Gender was significantly associated with the daily number of calls, with women receiving twice the number of calls that males received (IRR = 2.03, $p < 0.001$; 95% CI 1.63, 2.52). This result should be interpreted with caution, however, as the number of males included in the study was very small ($n = 3$). Due to the small number of men, as a post-hoc analysis we re-ran the model with men excluded to ensure consistency in our estimated coefficients. The results were not significantly different: no coefficient changed to a value outside the previously estimated 95% confidence intervals suggesting the small number of males in the model will not bias the coefficients when accounting for gender. In addition, superior cognitive function was associated with a higher daily number of calls (IRR = 1.51, $p < 0.001$; 95% CI 1.33, 1.72). People also had fewer calls on the weekend than the weekday (IRR=0.65, $p < 0.001$; 95% CI 0.612, 0.680). Age and pain level were not significant predictors of the daily number of calls.

Differential effect of loneliness on incoming and outgoing calls

To test whether loneliness was differentially related to incoming and outgoing phone calls, we ran two additional mixed effect negative binomial regressions, with daily number of incoming phone calls as the outcome for the first regression, and daily number of outgoing phone calls as the outcome for the second regression. The comparative results of this analysis are shown in Table 4.3. Consistent with our hypothesis, loneliness was negatively related to incoming calls but not outgoing calls. The loneliest individual received 40% of the number of calls received by the least lonely (IRR = 0.98, $p < 0.01$; 95% CI 0.96, 0.99). The non-linear relationship between loneliness and daily number of incoming phone calls is shown in Figure 4.1. This figure shows the probability density of the daily number of calls as a function of the UCLA Loneliness

Score, holding all continuous variables at their means (gender was taken to be female and the flag for weekend was held at weekday). That is, at each possible value of the UCLA Loneliness Scale, the probability of receiving a given number of calls (between 0 and 6) is computed and plotted in color, with higher probabilities plotted in red and lower probabilities plotted in blue. The mean is also plotted in black. As can be seen, the average daily number of incoming calls decreases from 4.6 when the loneliness score is 23 (the lowest observed score) to 1.9 when the loneliness score is 60 (the highest observed score). It should be noted that the UCLA Loneliness scale can range from 20 to 80, but no participants scored higher than 60 or lower than 23 in this cohort, so the values plotted do not exceed this observed range.

In this analysis, age was also found to be significantly related to outgoing calls (IRR = 0.97, $p < 0.01$; 95% CI 0.956, 0.99) but not incoming calls. Gender was significantly related to both incoming and outgoing calls, such that women received 60% more calls than men, and placed 128% more calls than men (although this should be

Table 4.3: Comparative results on the relationship between loneliness and incoming/outgoing phone calls

	Number Incoming Calls			Number Outgoing Calls		
	Incidence Rate Ratio	Std. Error	z	Incidence Rate Ratio	Std. Error	z
Loneliness	0.950**	0.009	-2.74	1.001	0.005	0.25
Gender (male)	2.281***	0.440	4.27	1.613***	0.188	4.09
Age	1.014	0.016	0.87	0.972**	0.010	-2.74
Cognitive Z-Score	1.694***	0.171	5.22	1.065	0.076	0.88
Weekend	0.686***	0.018	-14.68	0.625***	0.023	-13.01
Pain Level	1.023	0.012	1.90	0.992	0.013	-0.58
Time	0.888*	1.198	2.84	1.001	0.005	-1.91
Constant	0.950	0.009	-0.09	1.613*	0.188	2.15

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

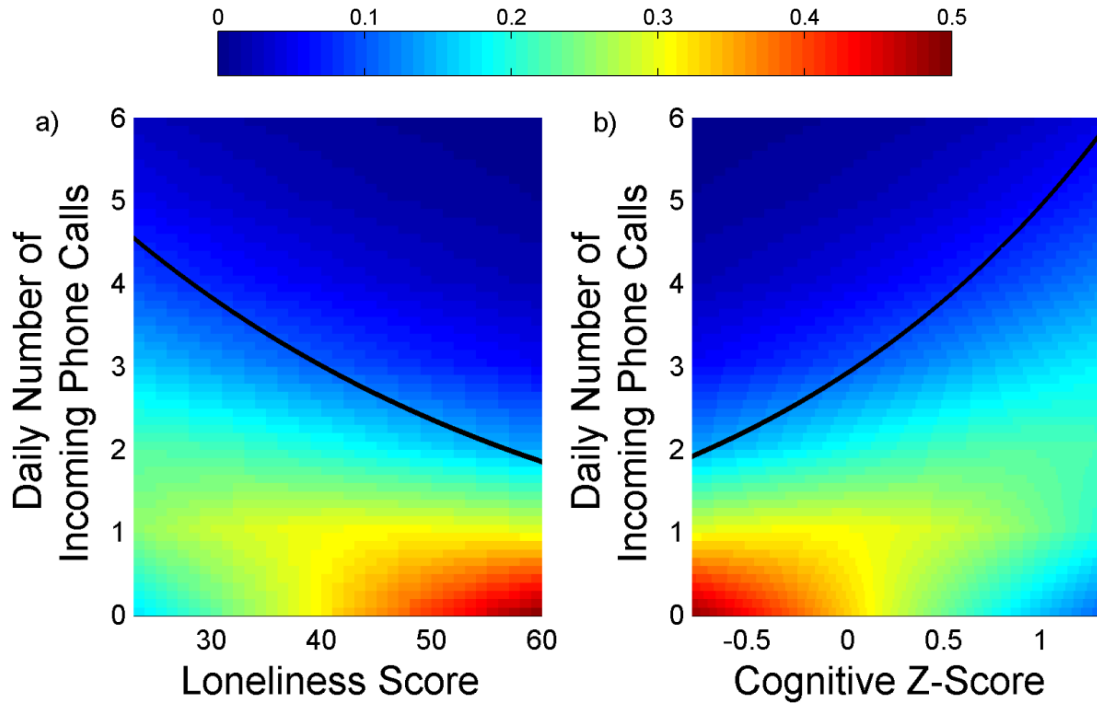


Figure 4.1: Probability density of the daily number of incoming calls as a function of (a) the UCLA Loneliness score and (b) the z-normalized Cognitive score, holding all other variables at their means. Color represents density; discrete probabilities were linearly interpolated for graphical clarity. The mean function, μ (black trace), has been overlaid on the density to show central tendency. Number of incoming calls decreases with increasing loneliness and decreasing cognitive abilities.

interpreted with caution due to the small number of males in the cohort). In addition, cognitive status was significantly related to the number of incoming calls (IRR = 1.69, $p < 0.01$; 95% CI 1.39, 2.06) but not the number of outgoing calls.

DISCUSSION

This paper presents the first results on the relationship between loneliness and objective measures of social isolation using a landline phone monitoring system. We found that increased loneliness is associated with decreased daily phone use, such that the loneliest individual uses the phone nearly two thirds as much as the least lonely. This result supports the work of prior studies suggesting loneliness is closely tied to the quality of the social network [170, 171], and suggests that loneliness may also be closely tied to the level of social isolation. In addition, this suggests that by objectively

monitoring isolation levels longitudinally in older adults, it may be possible to understand the differential effect that loneliness and social isolation have on health. Finally, because loneliness is tied to social isolation, it may be possible to unobtrusively monitor loneliness levels in addition to isolation levels, using both measures of social isolation and emotional well-being (for example time out-of-home [81]).

Consistent with our hypothesis, we also found that loneliness was more closely tied to incoming than outgoing phone calls. This is consistent with previous work on loneliness which suggests that in the early stages of loneliness, people may attempt to overcome their loneliness by forming new social connections, even when meeting new people causes great emotional stress [27, 162]. Attempting to form new connections may manifest as an increase in the number of outgoing calls while the number of incoming calls declines. After a time of being lonely, one may adjust expectations for support, becoming content to have fewer contacts and less support [26]. Thus, while outgoing calls may increase at the onset of loneliness and then decrease over time, incoming calls are more likely to universally decrease with the manifestation of loneliness. Of course, with only one loneliness time point it is difficult to understand how telephone use changes with changes in loneliness levels within the same individual. Thus, future studies on the time-course of loneliness and isolation should investigate the differential relationship between loneliness and incoming and outgoing calls in the earliest phases of loneliness onset.

Among our covariates, age was also found to be significantly related to the number of outgoing calls, but not the number of incoming calls. This may be suggestive of difficulties with using the phone that occur with age, especially with placing calls. For example, while hearing impairments may make it challenging to use the telephone to communicate at all (reducing the total number of calls), arthritis and vision impairments

may cause difficulties in dialing numbers to place outgoing calls, thus reducing the number of outgoing calls to a greater degree than incoming calls.

Increased cognitive function was found to be positively associated with telephone use, which is consistent with work tying the ability to perform instrumental activities of daily living (iADL) including the ability to use the phone with cognitive ability [172]. Thus, as cognitive function declined, phone use also declined. Increased pain was also associated with increased phone use, which may represent the increased support given when people fall, go to the emergency room, or have other adverse events likely to increase pain levels. We also found that women make more calls than men, people receive fewer calls on the weekend than on the weekday, and superior cognitive function was associated with more telephone use.

This study has several limitations. Notably, there were relatively few subjects, and as a result the number of constant or control variables that could be included in the model was small despite the large number of data points (the effective sample size for each cross-sectional variable is 26). Future studies should incorporate data from more subjects with additional potentially explanatory variables to fully understand the relationship between phone use and outcomes of interest among older adults. We also did not explicitly test whether participant characteristics were related to the number of days of monitoring data as this was determined primarily by how well the phone monitor worked in each home. Still, the subjects who have more observed days of data will have the largest influence on the estimated coefficients. Thus, if any participant characteristic were in fact related to the number of days of observed data, the coefficients may be biased. This study did not monitor the duration of each phone call or the number dialed due to shortcomings with the phone monitoring software. Because of the importance of social network on multiple health outcomes [16], developing techniques to unobtrusively

monitor multiple aspects of social network, including number of contacts or longitudinal changes in the social network (addition of new members or loss of old ones) may be increasingly important [22]. Further, the average age of this cohort was 86 years, and the youngest participant was aged 73 years. Despite their older age, everyone in the cohort lived alone and independently (although they may live in a retirement community). In addition, all participants used landline phones only, and did not use wireless telephone devices. The results of this study may not generalize to younger populations, to those whose physical health is imposing more serious limitations on their lifestyle, or to those populations where wireless devices have become the norm.

This work shows that in-home monitoring can be used to objectively analyze the relationship between loneliness and social isolation. Using this approach in longitudinal models on health, it may be possible to understand the differential effect these variables have on health. In addition, using a phone monitor in conjunction with in-home monitoring platforms designed to assess multiple aspects of behavior known to be associated with loneliness (for example, sleep [11], time out-of-home [81], and computer use [149]), it may be possible to monitor loneliness levels unobtrusively and continuously in the home environment. Such models would contribute greatly to the understanding of loneliness and its effectors, time course, and outcomes. By monitoring for loneliness in the home environment, it may also be possible to detect lonely individuals earlier than currently possible, thereby enabling outreach programs to give lonely persons appropriate help and assistance.

Chapter 5: SVM to Detect the Presence of Visitors in a Smart Home Environment

SUMMARY

This chapter describes the work performed to unobtrusively detect the presence of visitors in the home. Because visitors represent an important aspect of socialization, they may be an important feature for assessment of loneliness using in-home sensors. To develop a visitor detection technique, we first develop and validate a Support Vector Machine (SVM) classifier to detect periods where untagged visitors are present in the home. This approach used the dwell time, number of sensor firings, and number of transitions between major living spaces (living room, dining room, kitchen, and bathroom) as features in the model and diary self-report from two subjects as ground truth. The sensitivity and specificity of the SVM classifier was different between the two subjects: subject 1 had a sensitivity of 0.90 and specificity of 0.89, whereas subject 2 had a lower sensitivity and specificity at 0.67 and 0.78, respectively. While the results demonstrated the feasibility of detecting visitors with the in-home sensor data, they also highlight the need for improved ground truth and more advanced classification techniques to detect visitors in the home for all subjects. To that end, we installed motion-activated video cameras over the doors to the homes of six subjects. These cameras were designed to record the coming and going of visitors by recording 5 seconds of video data any time movement was sensed. However, due to the 30 second refractory period of the camera, the arrival and departure of visitors were not always captured, thus invalidating the ground truth. Despite the challenges faced in fully validating a visitor detection algorithm, this work represents key results on behaviors that may change when visitors are present in the home, and could be used to inform priors in future models of visitors in the home. Still, we did not carry this project any further in this project. The next step in developing a visitor detection algorithm would be to install superior video cameras capable of collecting high quality ground truth. Using this data, it would be possible to train a general visitor detection algorithm and enable monitoring the frequency of visitors to the home to include as a feature in a model of loneliness. However, this work was outside the scope of the thesis; thus visitors to the home will not be included in the final model of loneliness and behavior.

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INTRODUCTION

The emerging problem of supporting and caring for an aging population has received a great deal of attention in recent years. The high cost of institutionalization (i.e. nursing homes) and the reduced quality of life in such environments has led to a search for options that allow seniors to maintain their independence. One approach to helping seniors remain in their homes is ambient sensing environments, in which technologies placed in the home provide continuous data about the health status of the residents [12, 15, 173]. This “smart home” approach is most effective when it is unobtrusive, i.e., the seniors are not required to do anything outside of their normal daily activities, and thus unobtrusive technologies that are integrated into the individual’s home play an important role in this approach. Unfortunately, identification of activities using such passive technologies is much more challenging if there are multiple people in the environment [174], since the IR passive sensors cannot differentiate who is moving through the space. Thus, being able to identify when multiple people are present is an important part of interpreting and disambiguating in-home data.

The ability to identify when visitors are in the home is particularly important for assessing socialization in seniors. Socially isolated individuals generally exhibit higher blood pressure [175], higher all-cause mortality [18], and are at increased risk of developing cognitive decline [158]. Since a decrease in visitors to the home often heralds an increase in the isolation of an individual, detecting visitors to the home can allow for early detection of changes in socialization levels, enabling earlier intervention and support.

A number of approaches have been proposed to manage the multi-person identification problem. More complex sensors such as video cameras have the advantage of allowing identification of different individuals moving through the home, but most seniors consider the use of video monitoring as a violation of their privacy. Body worn tags (RFID, UWB, Wi-Fi etc.) can provide good information about the relative location of multiple individuals in the home [95, 96]. In an elderly population, however, this approach is impractical especially for long periods of time as they may forget to wear the sensors or take them off when they become uncomfortable. Alternative approaches not requiring body-worn tags include algorithmic techniques that attempt to disambiguate passively acquired sensor data based on statistical properties. For example, we recently used Gaussian Mixture Models to separate the walking speeds of individuals moving through a sensor line in two-person homes [176]. While this approach was effective for its specific purpose (measuring walking speed), it was not more widely applicable to identifying when visitors were in the home. Crandall and colleagues used graph and rule-based algorithms as well as Bayesian Updating Graphs to estimate the number of individuals present [177]. While effective, this technique required a very high density of sensors, which is not practical for large-scale monitoring. Thus, techniques to identify visitors to the home in passively monitoring environments are still needed.

The main focus of this paper is to develop a method to detect the presence of visitors in the home environment using only the data provided by wireless motion sensors in each room. A support vector machine (SVM) was developed to distinguish these events, using several key features from the sensor data as the input and subject diary entries detailing when visitors were present in the home as the ground truth. The quality of the model is estimated using thousand fold repeated random sub-sampling.

METHODS

Data Collection and Pre-processing

The data used in this study came from the homes of ORCATECH Living Lab subjects. The ORCATECH Living Lab is a group of 31 seniors who have agreed to participate in ongoing research about the role of technology in maintaining independence. A core set of technologies is continually maintained in their homes, including pyro-electric motion sensors (MS16A, x10.com) in each room and contact sensors (DA10A, x10.com) on the doors to the home. Only the motion sensor data were used in this study. For a period of 6 weeks, thirteen subjects completed diary entries twice a day—once at around noon and once around 11:00pm—regarding the specific times visitors were present in their homes. The diaries were incomplete for six participants (for example, the participant would report that they had a visitor but not record the times of the visit), and five participants lived in multi-person homes where there was little time with only one person in the home. Two participants lived alone and had complete diary entries; those data were used for this analysis. Incidentally, these data suggest the difficulty in using self-report as the source of socialization data [85].

Over the course of the six week period, subject 1 recorded 31.75 hours where visitors were present and subject 2 recorded 89.5 hours where visitors were present. These self-report data were used as the ground truth in model development. During this time, sensor data from the motion sensors in these subjects' homes were also collected. All data from any days where any sensor in the house was not functioning properly were excluded. This resulted in the exclusion of two days of data from subject 1 and zero days of data from subject 2. A total 4.75 hours of visitor data were therefore excluded for subject 1.

To create the features used in the model development, the sensor data from each home was divided into 15 minute epochs. Four different sets of features were then calculated for each epoch. The first feature set we incorporated in the model is the total time the subject spent in each room or the dwell time per room. This feature set was chosen because visitor events like dinner guests or a game night would increase the dwell time in the dining room or living room while the visitor is present as well as decrease the dwell time in whatever room of the house the subject normally resides in while alone. Dwell time was calculated by assuming that no sensor firings were missing, and therefore that consecutive firings of the same sensor represented continuous movement in the same room. The dwell times then form a series of triplets $\{R, t, d\}$ where R is the room ID, t is the start of the dwell time, and d is the duration of the dwell time in the room. The duration d is calculated as the difference between the time of the first firing in a room A and the time of the first subsequent firing in a *different* room B . The start time t is the time of the first sensor firing in the consecutive sequence of sensor firings within room A . From this we calculated the total dwell time for each room, for each 15 minute epoch.

The second feature set used in the model is the total number of sensor firings in each room. The underlying hypothesis is that as the number of people present in the home increases, the activity level in the home will also increase, thus increasing the number of sensor firings.

The third feature set used in the model is the number of room transitions for each room couplet. In a house with n rooms, there are $n(n-1)/2$ different room couplets, and the number of transitions was computed for each of these couplets. Transition profiles are expected to change in two ways when visitors are present in the home. First, anytime a visitor is present in the home and in a different room than the resident, the number of

transitions between those two rooms is likely to increase. On the other hand, anytime the visitor and resident are in the house in the same room, the number of room transitions is expected to decrease or remain the same while the number of sensor firings and dwell time for that room will likely increase.

The fourth feature set corresponds to the time of day. Because human activity patterns follow a circadian rhythm, there will be differences in normal activity patterns as a function of the time of day. It is therefore important to include the time of day as a feature in the model design. The time of day was coded as a dummy variable with '1' assigned to the four epochs starting at midnight, 12:15am, 12:30am, and 12:45am, and linearly increasing each hour; thus '24' was assigned to the four epochs starting at 11:00pm, 11:15pm, 11:30pm and 11:45pm.

Model Development

SVM was used to classify the data. SVM [178] is a well-established machine learning technique to classify data which has been used previously in smart home environments to detect abnormal behavioral patterns [14]. In general, SVM is used to determine non-linear boundaries for classification. The theory underlying SVM is based on the notion of mapping the raw data into a high-dimensional space where it can be categorized by a hyperplane decision boundary. When projected back into the original data space, the hyperplane is mapped into a nonlinear surface. The mapping can be performed directly using kernel-based transformation. Because the decision boundary for distinguishing visitor epochs from non-visitor epochs is likely to be non-linear, as illustrated in Figure 5.1, we used SVM with a Gaussian Radial Basis Function kernel with $\sigma = 1$ to map the data into a higher dimensional space to perform the classification.

In order to limit the complexity of the model, we reduced the feature set to include only those features corresponding to rooms that are frequently used when

visitors are present. That is, only the sensor features from the kitchen, dining room, living room, main bathroom and the transitions between these rooms were used in the final model.

Initially, the SVM model was trained using all epochs during all 24 hours of the day to train and test the model. However, because the features included in the model may look considerably different during the night (because the subject is likely sleeping), this could lead to biased results. We therefore also tested the model using only those epochs that occur during the daytime hours—that is, 7am to 11pm—to eliminate potential bias associated with the night hours.

Because there were so many more epochs where visitors were not present (3732 for subject 1 when night hours are excluded) as compared to epochs where visitors were

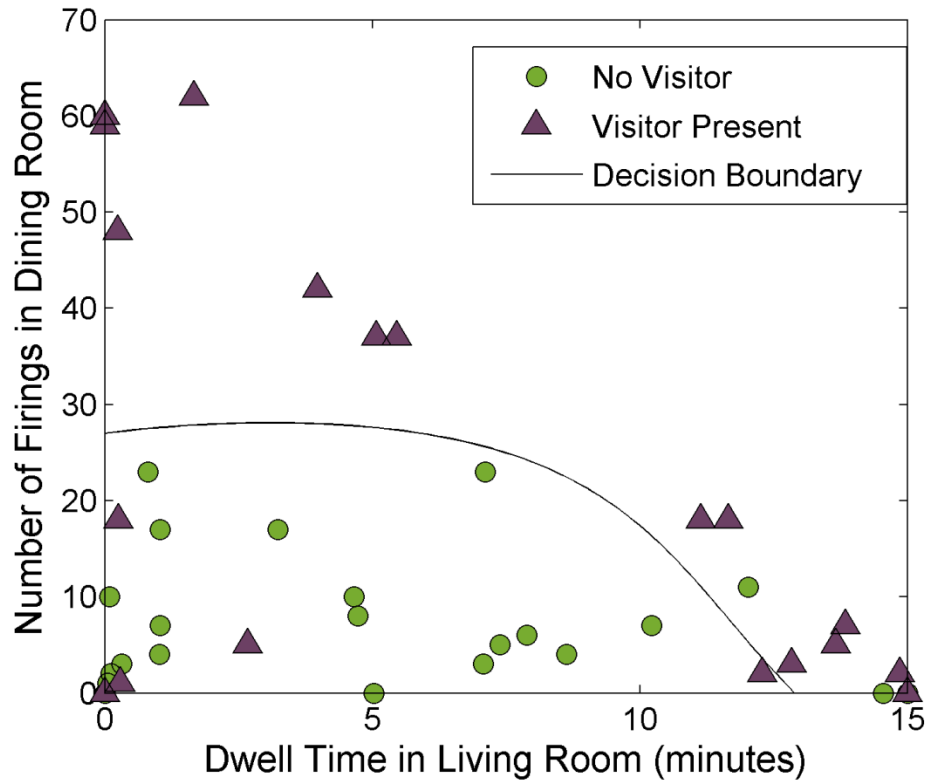


Figure 5.1: An example of total dwell time in the living room versus the total number of sensor firings in the dining room for subject 1 from 5:00-7:00pm for both the case where a visitor was reported in the home and the case where no visitors were reported during this time. The non-linear decision boundary between these events is also shown.

present (108 for subject 1), we trained the model on $\frac{3}{4}$ of the visitor epochs. When nighttime epochs were excluded, we trained on 15% more non-visitor epochs than visitor epochs and 50% more non-visitor epochs than visitor epochs when night hours were included. We tested on all the remaining data. For all model fits, we used 1000 fold repeated random sub-sampling to determine the mean out-of-sample performance and 95% confidence intervals. We report on those results below.

RESULTS AND DISCUSSION

Table 5.1 presents the results of the SVM model for classifying epochs where visitors are and are not present in the home for each subject and both models. As can be seen, excluding nighttime epochs from the model does not significantly affect the sensitivity of the analysis. However, the specificity decreases by about 0.07 when nighttime epochs are excluded for both subjects. This decrease in the specificity when nighttime epochs are excluded is to be expected as the sequences of sensor firings that are likely to occur during the night (e.g. bedroom, bathroom) are very different from those that occur during the day (e.g. kitchen, living room). However, even when the nighttime epochs are excluded, the model still performs reasonably well with sensitivity and specificity of 0.89 and 0.80 for subject 1, and 0.67 and 0.69 for subject 2, respectively.

It is also important to note that the model performs considerably worse in detecting epochs where visitors are present for subject 2 than for subject 1. The average sensitivity for subject 1 is 0.90 as compared to 0.67 for subject 2. There are several possible causes for this difference in sensitivity. First, the ground truth in this model is limited to the self-report of the subjects. It is well known that self-report, especially in the aging population, is prone to inaccuracies [85]. Forgetting to report visitors in the

home would decrease the specificity of the model, while inaccurately reporting the time that visitors arrive and leave would decrease the sensitivity. It is therefore possible that subject 2 did not accurately record the precise times that visitors arrived and left the home, resulting in a lower sensitivity of the model.

The home layout and placement of sensors in these two homes is also considerably different. Subject 1 has an open kitchen that feeds into the dining room and living room. In this layout, it is easy for an individual in the kitchen to interact with individuals in the living and dining rooms. As a result, the number of transitions between these three rooms can increase dramatically when visitors are present. Further, the sensors are well placed so subjects can be detected in any room of the house. Because there are so few dead zones in the house, changes in behavioral patterns due to the presence of a visitor can be detected more easily, resulting in a higher sensitivity of the SVM model in detecting visitors.

In contrast, the sensor layout appears to have problems for subject 2. While there is a sensor in the dining room, its purpose is not to detect individuals in the dining room, but rather to detect individuals leaving the home. The field of view of the sensor is pointed mostly at the front door. As a result, it seems to have high error rate in accurately detecting the presence of an individual in or passing through the dining room. This would dramatically affect the performance of this model in detecting visitors as it is dependent on the transition profiles, number of sensor firings, and dwell times in these

Table 5.1: Sensitivity and specificity of the SVM model for visitor detection for subject 1 for all epochs in a 24-hour period, daytime epochs only and 95% confidence intervals (CI) for 1000 random splits of the data into model fitting and classification sets.

	Subject 1		Subject 2	
	Sensitivity	Specificity	Sensitivity	Specificity
Mean	0.902	0.861	0.672	0.782
95% CI	(0.778, 1.00)	(0.813, 0.893)	(0.589, 0.756)	(0.752, 0.810)

rooms.

These differences in home layouts and in the positioning of the sensors highlight the importance of sensor placement in a smart home. In configuring a smart home, it is critically important to place sensors appropriately to accurately detect the movement of the subject throughout the entire home. Placing a sensor with an occluded or limited field of view is likely to limit the ability to detect behavioral patterns or changes in behavioral patterns in the home environment. As Crandall's study showed [179], a large number of sensors can greatly improve the recognition of subject movements. However, it remains an open question how the number and placement of sensors can be optimized to minimize the intrusion into the senior's home while still allowing for good recognition of visitors.

While the current approach for detecting visitors in the home performs well it still has several limitations. First, the visitors recorded in this study were only daytime visitors—neither subject reported overnight guests. However, the presence of an overnight guest in the home would be incredibly important to identify from both a socialization perspective and to effectively model multiple individuals in the home. The model therefore needs to be generalized for the case where visitors remain in the home overnight.

Further, the model only detects the presence or absence of any number of visitors in the home, but cannot quantify how many visitors are present. Several of the diary entries report varying numbers of visitors present in the home, and accurately detecting differences between large groups of visitors and more personal encounters with small groups is important in assessing socialization practices.

Finally, this model was only tested on two subjects and two home layouts, and therefore needs to be validated on more subjects. Because the behavioral patterns

associated with the presence of visitors in the home will change for different people, the generalizability of the model must be tested for multiple individuals and multiple home layouts. This is especially important as the performance of the model varied considerably between the two subjects tested.

CONCLUSIONS

Because of the multiple health impacts of socialization in the growing aging population, continually and unobtrusively monitoring the socialization practices of elderly individuals is increasingly important. Key to this goal is the detection of visitors present in the home. Using the dwell time, number of firings, number of transitions, and hour of the day as features in a support vector machine, we were able to distinguish periods where visitors are present in the home with 90% sensitivity and 86% specificity for subject 1, while the sensitivity and specificity were lower at 67% and 78% for subject 2, respectively.

In the future, we plan to improve this result by incorporating the door sensors that detect the opening and closing of the front door into the model. Because visitors must enter and exit the home through the doorway, modeling changes in the presence or absence of a visitor in the home around door firings may increase performance of the model and allow for visitor detection at a greater granularity.

Chapter 6: Behavior and Loneliness: How does What We Do Associate with How We Feel?

SUMMARY

In this section, we incorporate all the in-home behaviors studied thus far in addition to other behaviors hypothesized to be associated with loneliness into a longitudinal model on the relationship between loneliness and behavior. While previous chapters used existing data from the ORCATECH Life Laboratory to assess the relationship between key behaviors and loneliness, this study used data from 16 new participants specifically recruited to study the relationship between loneliness and behavior. Each of these participants received the in-home motion and contact sensors as well as telephone and computer sensors. In addition, the participants completed the UCLA Loneliness scale at least 3 times over the 8 month monitoring period. Using this longitudinal dataset, we were able to use eight behavioral variables, including five ‘social’ variables, as independent variables in a mixed effects linear regression with UCLA Loneliness Score as the dependent variable. Our analysis shows that loneliness is significantly associated with both time out-of-home ($\beta = -0.77$, $p < 0.05$) and number of computer sessions ($\beta = 0.87$, $p < 0.01$), although other behavioral variables (in-home walking speed, time on computer, number of calls) were also marginally non-significant. The R^2 for the model was 0.43. We also show that the in-home behavioral variables can predict out-of-sample loneliness scores reasonably well, with a correlation between true loneliness score and predicted out of sample loneliness score of 0.48. This chapter presents the first steps toward an unobtrusive, objective model of loneliness among older adults, and marks the first time multiple objective behavioral measures have been related to loneliness. These results underscore the possibility of using in-home sensor platforms to objectively and continuously monitor loneliness levels among older adults.

INTRODUCTION

Loneliness is a painful and debilitating experience typically arising due to a perceived deficit in social relationships [26, 28, 29]. Among older adults in particular, the experience of loneliness can be especially traumatic, giving rise to numerous negative health outcomes including increased morbidity and mortality [1], reduced sleep quality [5], increased daytime dysfunction [6], and increased rates of cognitive decline [4]. For these reasons, detection and mitigation of loneliness in older adults is critical as the deleterious effects of loneliness can be reversed with an appropriate intervention [11].

While identifying lonely individuals is critical to mitigating loneliness among older adults, the detection of loneliness can be challenging. While it may seem easy to simply ask older adults if they are feeling lonely (using the self-labeling approach to assessing loneliness [75]), it is possible that people will avoid reporting loneliness even when they are quite lonely due to the numerous social stigmas associated with being lonely. For this reason, several scales have been developed to indirectly assess loneliness levels [9, 84]. While these scales may overcome the negative stigmas associated with being lonely, they still depend on self-report which is subject to desirability bias[85, 86], memory problems[65], and under or over estimation[87]. Thus, the development of an objective and continuous method to assess loneliness in older adults may enable identification of loneliness as it occurs, thereby assisting in the mitigation of loneliness at the earliest possible stages. An objective model of loneliness would allow researchers to develop more precise inferences regarding the impact of loneliness on health while enhancing our understanding of loneliness in older adults.

Recently, ambient in-home sensors have been used to continuously and unobtrusively monitor individuals in their own homes [15, 88, 89]. These systems are frequently designed to help seniors remain independent and healthy as long as possible

by capturing meaningful behavioral measures which relate to health outcomes of interest. There are several aspects of behavior that can be assessed using these in-home sensing technologies which may also relate to loneliness levels. For example, our preliminary research shows that both time out-of home [81] and telephone use [180] are associated with loneliness levels among older adults. Other behaviors that may be related to loneliness include computer use [149, 181, 182], visitors to the home, sleep quality [5, 11], and measures of daytime dysfunction [6] which include in-home mobility [99] and in-home walking speed [90, 97]. A diagram of the in-home behaviors hypothesized to be associated with loneliness is shown in Figure 6.1.

The focus of this paper is to understand the relationship between in-home behavior and loneliness. Using data from 16 participants monitored in their own homes

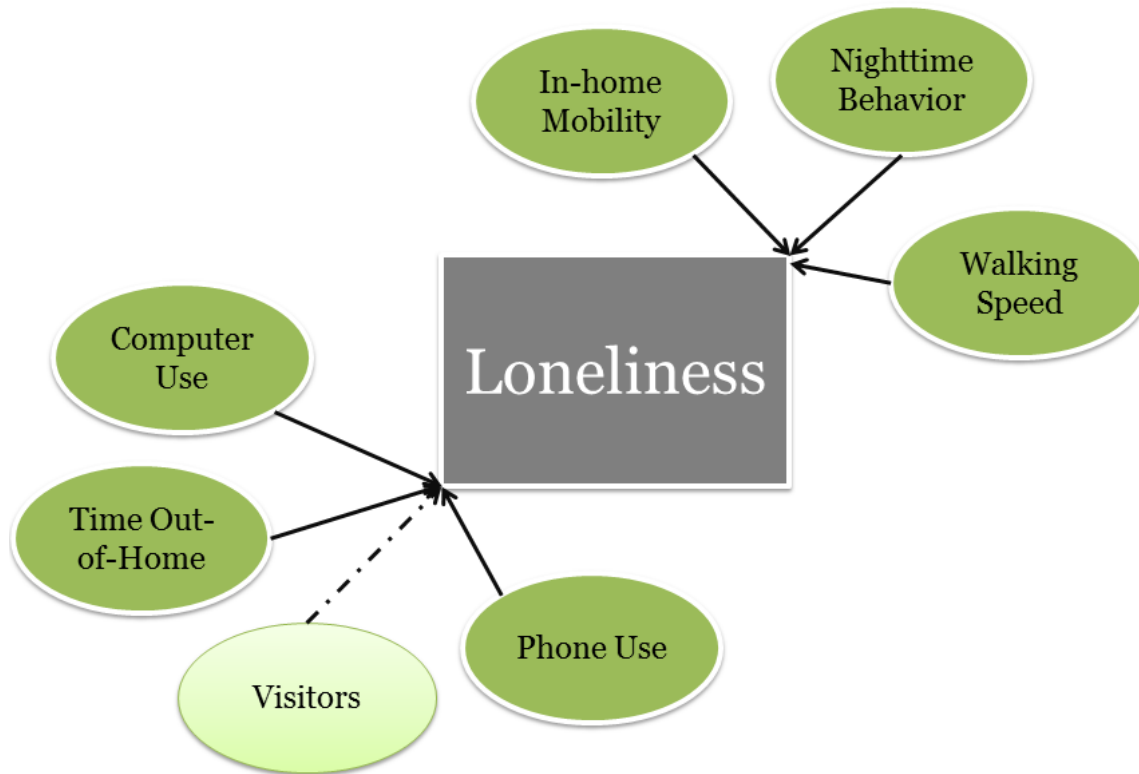


Figure 6.1: Diagram of in-home behaviors hypothesized to be related to loneliness. The node corresponding to visitors to the home is shaded differently because it was not included in the model due to the challenges in the algorithm development discussed in Chapter 5 (pg. 73). Still, it was included in the diagram as it is likely associated with loneliness.

for up to 7 months, we will first analyze which in-home behaviors are most closely associated with loneliness. We hypothesize that the variables most closely associated with social behaviors (those on the left of the graph in Figure 6.1), will be most strongly associated with loneliness. Next we will analyze how well the measures of in-home behavior predict out-of-sample loneliness levels, which will provide a first glimpse into the feasibility of using unobtrusive in-home sensor data to assess loneliness levels in older adults.

METHODS

Participants

Participants for this study were recruited from low-income apartment communities and by word of mouth as part of a loneliness intervention study lasting 9 weeks (the intervention will not be discussed further here). The minimum age for participation in this study was 62 years. Participant inclusion criteria include living alone and independently and a minimum score of 26 on the Mini-Mental State Examination [183]. Participants were also required to be ambulatory and in average health for their age, have internet in their apartments, and know how to use a computer. Eligible participants who knew how to use a computer but did not already own one were given a computer to use for the duration of the study. All participants provided written informed consent before participating in study activities. This protocol was approved by the Oregon Health & Science University Institutional Review Board (IRB #9631). A total of 16 participants were recruited. The mean age of participants was 71.0 ± 6.3 years; 81% were female (see Table 6.1). All participants received a core set of technologies in their home including pyroelectric infrared motion sensors (MS16A, x10.com) in each room and contact sensors (DA10A, x10.com) on the doors to the home. A line of motion sensors was also placed in a straight line in a frequently used walkway. These sensors

were used to assess relevant behavioral metrics discussed in more detail below. Participant enrollment began in January of 2014 and ended in May of 2014. The intervention began on June 30, 2014 and ended August 27, 2014. Participants were followed from enrollment until the end of the 3 month follow up period, which ended November 26, 2014.

Data and Measures

Loneliness

Loneliness was assessed at baseline, at the start and end of the intervention, and at a 3-month post-intervention follow up using the 20-item UCLA Loneliness scale. This survey asks questions such as “I feel part of a group of friends” where response options are: (1) Never, (2) Rarely, (3) Sometimes and (4) Often. At baseline, the loneliness survey was administered in-person: participants were asked to fill out a paper copy of the survey (not via an interview) thereby reducing desirability bias. After consenting to be in the study, participants were added to an email list and study information was gathered through on-line surveys. That is, the survey was emailed to each participant with a subject-specific link to the survey at regular time intervals spaced between one week and 2 months apart. Participants completed the form online in their own homes. One participant who did not

know how to use email
completed a paper copy
of the survey in the first
follow up, and
completed the survey
over the phone in the
subsequent two follow

Table 6.1: Baseline demographic characteristics of the population

Characteristic	Statistic	Range (Min, Max)
Age (years)	71.0 ± 6.3	(62, 80)
Gender (% Female)	81%	-
Education (years)	15 ± 1.5	(12, 18)
MMSE	29.3 ± 0.95	(27, 30)
Socioeconomic Status	45.1 ± 9.75	(33, 62)
Race (% Caucasian)	100%	-

up periods. To generate a composite loneliness score, the value of positive questions was first reversed and then scores on all questions were summed to give a loneliness score ranging from 20 to 80, with 80 being the loneliest.

Time Out-of-Home

Total daily time out-of-home was computed probabilistically using the logistic regression classifier developed in Chapter 3 [81]. As shown in Chapter 3 (pg. 45), this technique has high sensitivity (94%) and specificity (98%), and is completely unobtrusive. Because days where the subject was away from home overnight (e.g. due to hospital stay or vacation) are not representative of daily behavior, these days were excluded from the analysis.

Phone Use

Phone use metrics were collected in one of two ways for each participant. Where available, call records were exported from the phone carrier (e.g. AT&T, Verizon). The phone carriers record the number dialed, time of call, and call duration (generally rounded up to the nearest minute). Not all carriers record whether the call was incoming or outgoing, so this was not included in the model. Whenever the phone carrier logs were not available (two participants use CenturyLink which does not keep track of phone use), the phone monitoring device used in Chapter 4 was used to unobtrusively assess daily phone use. The monitors (Shenzhen Fiho Electronic, Fi3001B) plug directly into the phone line, and are designed to record all signals on the line including 'on hook', 'off hook', 'ring start', and 'dtmf' (number dialed). Because the phone must ring prior to being taken off the hook for an incoming call, all calls where the phone rang and was subsequently removed from the hook within 30 seconds of the final ring signal were counted as incoming calls. It should be noted that missed calls (calls where the resident did not answer the phone) would not be treated as incoming calls in this paradigm. For a

call to be treated as outgoing, a number must be dialed. Because several of our residents live in retirement communities, four digit codes can be used to call within the building to other residents of the retirement community. As a result, a call was treated as outgoing if an 'off hook' signal was followed by at least four numbers dialed and not preceded by a ring signal. It should be noted that the phone line does not detect whether an outgoing call was completed (that is, whether the other end picked up the phone or not).

Computer use

Participants also received computer monitoring software designed to assess the total time spent on the computer, daily number of computer sessions, and the activities performed while on the computer. The software installed was specific to the operating system of the individual's computer. Individuals with Windows-based operating systems ($n = 14$) received WorkTime Corporate (Nestersoft Inc., Ontario Canada), while those with Apple computers ($n = 2$) received RescueTime Professional (RescueTime, Seattle WA). Both programs record the total time spent on the computer by analyzing mouse and keyboard activity. Computer use was logged in sessions, where a given session was considered continuous until the mouse and keyboard were both inactive for a period of 15 minutes or more. Total number of computer sessions each day was computed by counting the number of continuous sessions, and total hours on the computer was computed by adding the total hours spent on the computer in each computer session.

Five participants owned a tablet or other personal computing device. Unfortunately the software used to track computer activity was not compatible with app-based devices. Thus, this activity was not recorded.

Walking Speed

Daily in-home walking speed was calculated using a line of four motion sensors positioned in series on the ceiling. The field of view of the sensors was restricted so they

fired only when the participant passed directly underneath them. The distance between sensors was recorded to allow adequate calculation of velocity as the participant passed through the line of sensors [97]. While the data from these sensors is highly correlated with true walking speed, the variability in sensor placement and refractory period means there is typically a constant offset between true walking speed and calculated walking speed for each line of sensors. As a result, the raw walking speed is typically not comparable cross-sectionally because the constant offset will differ by individual. To account for this, we normalized the measures of walking speed for each individual by the median and IQR of their walking speed over the entire time period [97]. Then, because the participant can walk through the line multiple times in a day, the median normalized walking speed was calculated for each day and used as normalized daily in-home walking speed in the model. Thus, this variable represents the deviation in daily walking speed from an individual's median.

Mobility

In-home mobility was computed by first assuming that the motion sensors only fire when they detect movement from the participant. Thus, consecutive firings from the same sensor indicate movement within a room (indicative of activity levels), and consecutive sensor firings from *different* sensors indicate the participant is moving throughout the home. Under this assumption, total daily mobility can be estimated by summing the total number of consecutive firings from two different sensors each day [99]. However, this measure of mobility will be influenced by the number of hours spent inside the home [184]. That is, the more hour spent inside the home each day, the greater the *opportunity* for mobility. To get a meaningful measure of in-home mobility, it is therefore necessary to divide the mobility estimate by the total hours spent inside the home. This number represents the estimated level of mobility per hour spent inside

the home. Because home layout and sensor sensitivity (which vary by participant) may affect the median number of transitions independent of true in-home mobility levels, this measure was normalized by each participant's median in-home mobility estimate and the IQR, calculated over the entire monitoring period.

Sleep

ORCATECH has previously developed a technique to unobtrusively assess various aspects of sleep including sleep latency, restlessness, and number of awakenings [98]. However, this method only works if participants sleep in a bedroom, not the living room. Unfortunately, many participants in this study regularly slept in the living room. Thus, the previously validated technique was not employed. Instead, total sleep time was determined by adding the hours between 10pm and 9am where sensors indicated the participant remained in either a bedroom or the living room for a period of 2.5 or more hours without transitioning.

Data Analysis

Using all the data from up to 7 months of monitoring for each participant, we first computed descriptive statistics and cross-correlations for all the in-home variables derived from the sensor platform. Next, we ran a longitudinal mixed effects linear regression to examine the relationship between in-home behavior and loneliness using the in-home data from the same day the participants completed the UCLA Loneliness scale. Due to the small sample size, we did not control for any demographic characteristics to allow inclusion of the maximum number of behavioral variables without over fitting the model. Instead, we allowed these characteristics to be captured in the person-specific offset from the mixed effects model. In order to ensure coefficient estimates were not biased by multicollinearity, the variance inflation factor (VIF), a standard diagnostic tool for multicollinearity, was calculated for each independent

variable included in the model, and univariate models were computed for all input variables to ensure the direction of the beta-coefficients were consistent between the full model and the univariate models. The VIF for all variables in the model was below 2.5, indicating any multicollinearity can safely be ignored [139], and the direction of all the beta coefficients did not change between the univariate and full regression models. A p -value of 0.05 was considered significant. In order to determine the effectiveness of the model at predicting loneliness, we computed both the correlation between in-sample and out-of-sample predictions of loneliness and true loneliness levels. To determine the predicted out-of-sample loneliness score, we trained our regression model on data from all but one participant, and then used the coefficients from that model to predict the loneliness of the remaining participant. By iteratively doing this for each participant, we were able to obtain out-of-sample loneliness predictions for all participants, and relate these predictions to the true loneliness scores.

RESULTS

Descriptive Statistics

The descriptive statistics for the behavioral variables, including the correlation between the in-home behavioral variables, are presented in Table 6.2. As can be seen, the average daily time spent outside the home was 3.24 ± 2.84 hours, slightly lower than previous studies on time outside the home in older adults [81]. The average daily number of phone calls was 5.3 ± 4.94 , while the average daily number of minutes spent on the phone was 29.97 ± 35.25 . As expected, the daily number of phone calls was highly correlated with the total daily time spent on the phone ($r = 0.6$). These participants spent an average of 1.95 ± 2.02 hours on the computer each day, which was logged across an average of 3.52 ± 3.7 sessions each day. The total daily hours on the computer had a strong positive correlation with the daily number of computer sessions ($r = 0.55$) and a

Table 6.2: In-home data statistics and cross-correlations.

	Mean (STD)	1	2	3	4	5	6	7	8
1. Time Out of Home (hours)	3.24 (2.84)	1							
2. Number of Calls	5.31 (4.94)	0.06	1						
3. Time on Phone (minutes)	29.97 (35.26)	-0.02	0.6	1					
4. Computer Use (hours)	1.95 (2.02)	-0.20	-0.07	-0.11	1				
5. Number of Computer Sessions	3.53 (3.74)	-0.24	-0.13	-0.12	0.50	1			
6. Time Asleep (hours)	5.87 (3.81)	0.28	-0.06	-0.01	-0.01	-0.16	1		
7. Norm Median Walking Speed	-0.01 (0.29)	0.04	-0.04	-0.04	0.05	-0.01	0.02	1	
8. Norm Room Transitions	0.20 (1.02)	0.10	0.08	0.04	-0.04	0.08	-0.07	0.11	1

negative correlation with the hours spent outside the home that day ($r = -0.20$). On average, participants slept for $5.87 \pm .831$ hours each night. This was divided into an average of 4.25 ± 3.65 hours asleep in the master bedroom and 1.58 ± 31.91 hours asleep in the living room or a secondary bedroom (not shown in table). The normalized median daily walking speed was positively correlated with the hours spent outside the home ($r = 0.24$).

In-home behavior and Loneliness

The results of the mixed effects regression between loneliness and in-home behavior are presented in Table 6.3. A total of 55 data points were included in this model, representing an average of 3.4 data points per participant. As can be seen,

Table 6.3: Results of the mixed effects linear regression between the UCLA Loneliness Score and behavior.

	Coefficient	Std. Error.	z	95% Confidence Interval	
Time Out of Home (hours)	-0.772*	0.340	-2.27	-1.44	-0.11
Number of Calls	-0.141	0.152	-0.92	-0.44	0.16
Time on Phone (minutes)	0.000	0.029	0.02	-0.06	0.06
Number of Computer sessions	0.867**	0.331	2.62	0.22	1.52
Time on Computer (hours)	-0.882	0.622	-1.42	-2.10	0.34
Time asleep (hours)	-0.141	0.244	-0.58	-0.62	0.34
Normalized Median Walking Speed	-2.394	2.210	-1.08	-6.73	1.94
Normalized Room Transitions	0.863	0.862	1.00	-0.83	2.55
Constant	46.199***	2.855	16.18	40.60	51.79

* p<0.05, ** p<0.01

loneliness is negatively associated with the total hours spent outside the home, such that a unit increase in hours spent outside the home results in a corresponding drop in loneliness of 0.77 points. This result is consistent with that found in Chapter 3 (pg. 49), where each increase in hours spent outside the home was found to decrease the corresponding loneliness by 1.63 points. The slight decrease in the relationship between time out-of-home and loneliness is likely due to the inclusion of additional variables in the model, some of which are correlated with time out-of-home. Loneliness was also found to be significantly related to the total number of computer sessions, such that each additional computer session results in an increase in loneliness score of 0.87 points.

The other in-home behavioral variables were not significant in predicting loneliness ($p > 0.5$), although some were only marginally non-significant as shown in Figure 6.2. In this figure, variables are sized by the magnitude of the influence the variable has on loneliness, and colored by the direction of the influence (green = positive influence, purple = negative influence). In addition, the lines connecting each variable to

loneliness are colored by the significance level of the variable in the full model (darker = more significant). As can be seen, time out-of-home and number of computer sessions are the darkest two variables and also the two with the largest influence on loneliness. Still, time on computer, walking speed, and number of calls were all marginally non-significant and had a relatively large effect on loneliness. The variable with the smallest effect was the total time spent on the phone, possibly due to its high correlation with the number of phone calls. Time asleep was also found to be highly non-significant and with

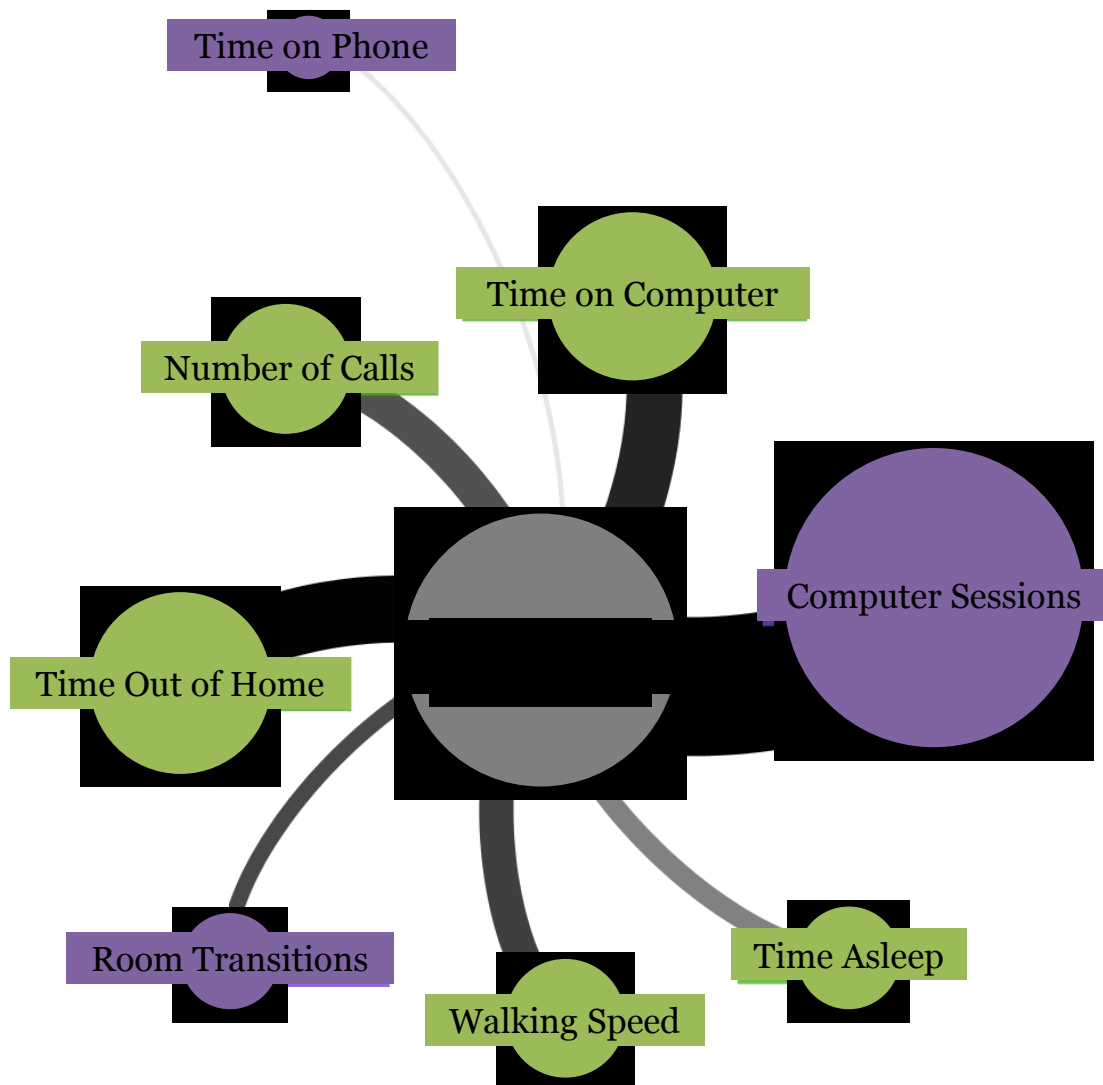


Figure 6.2: Diagram showing the relative influence of the behavioral variables on loneliness. Variables are sized by magnitude of influence and colored by the direction of the influence (green = positive, purple = negative). In addition, the connector lines are colored by significance of the variable, with blacker lines indicating higher significance.

only a small effect on loneliness.

The overall R^2 for the model was 0.428, suggesting a close relationship between behavior and loneliness. The normalized root mean squared error of the predicted loneliness scores (normalized using the standard deviation of the true loneliness scores) was 0.898, and correlation between the true loneliness and predicted out-of-sample loneliness (using leave one out cross-validation) was 0.446, as shown in Figure 6.3. In this figure, it is clear that the model tends to over-estimate the loneliness of individuals whose true loneliness is low, and under-estimate the loneliness of those whose true loneliness is high. This may be due in part to the mixed effects model chosen, which includes an offset for each individual in the model. While this functions well for associative models where the intent is to understand the relationship between variables

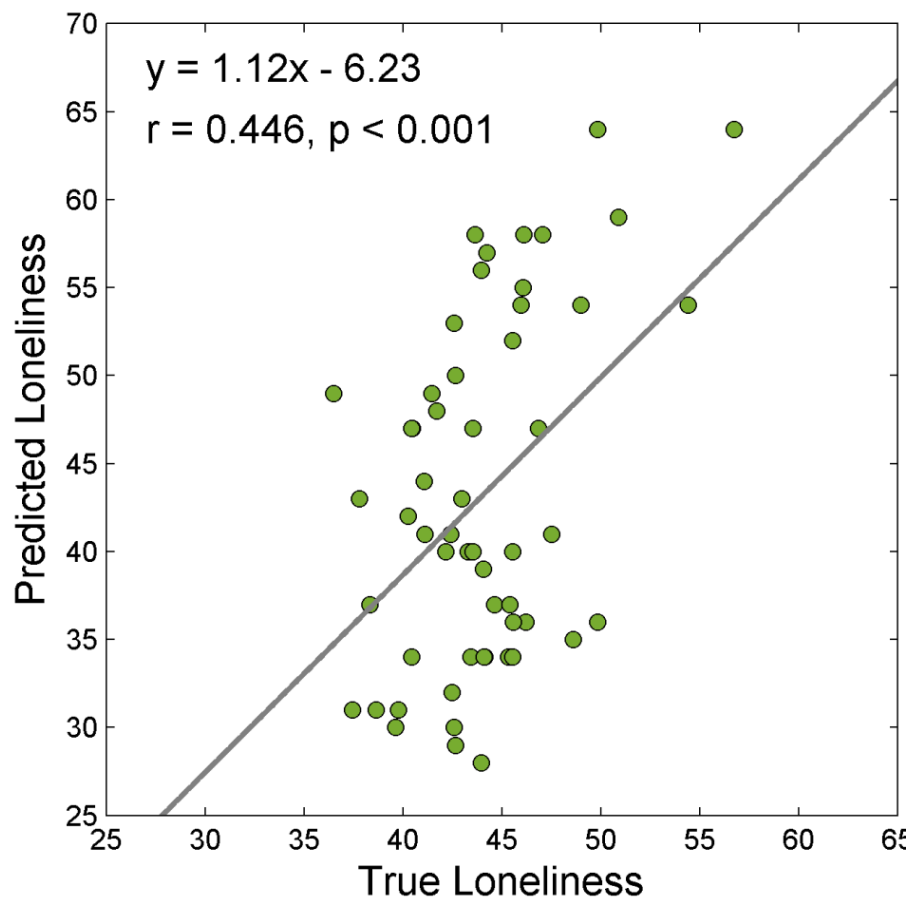


Figure 6.3: Plot of the predicted out-of-sample loneliness against the true loneliness of the 55 data points included in the model from 16 subjects.

(the focus of this chapter), it faces challenges in an out-of-sample predictive framework as the model does not estimate a unique offset for the unseen individual. It should be noted that while we tested the model's ability to predict loneliness out-of-sample, the primary goal of this analysis was to understand the relationship between loneliness and in-home behavior, a fundamentally different goal than optimizing predictive power [185]. Larger sample sizes and study designs optimizing predictive power are required to truly understand how well in-home behavior predicts loneliness.

DISCUSSION

This paper presents the first steps toward an unobtrusive, objective model of loneliness among older adults, and marks the first time multiple objective behavioral measures have been related to loneliness. These results underscore the possibility of using in-home sensor platforms to objectively and continuously monitor loneliness levels among older adults.

In our longitudinal regression model, daily time out-of-home and the number of computer sessions were the only two variables that were significantly associated with loneliness ($p < 0.05$). This result supports our hypothesis that the social variables would be most closely associated with loneliness. However, phone use and hours on the computer were not significantly associated with loneliness. The lack of significance in these social variables may be in part because of the high correlation between the social variables. That is, the number of phone calls was highly correlated with the amount of time spent on the phone ($r = 0.6$), and the number of computer sessions was highly correlated with the amount of time spent on the computer ($r = 0.5$). Including variables that are highly correlated in a model can result in multicollinearity, which can inflate the variance of coefficients, causing variables to look non-significant when they actually are

significant. While we tested all variables included in the model for non-ignorable multicollinearity using the VIF, it is possible that these high correlations still resulted in biases in the variables or their significance. Indeed, removing the total time spent on the phone from the model altogether increases the significance of the total number of phone calls ($p = 0.181$) while the coefficient remains nearly the same ($\beta = -0.148$) indicating the presence of at least some bias from multicollinearity. One way to overcome biases associated with multicollinearity is to increase the sample size, highlighting the need to test these results in a larger, more diverse cohort.

It may also be that telephone use was not significant because a major aspect of phone use, texting, was not captured in this cohort. Ad-hoc interviews with participants revealed that many of these older adults prefer texting to calling, and do most of their communication this way. Future studies on the relationship between loneliness and behavior should incorporate variables that capture texting in the models. In addition, this study was not able to accurately capture the number dialed for all participants. Collecting numbers dialed would enable the incorporation of variables related to the social network such as the overall size of the network (number of contacts), the loss of a contact, or the addition of a new contact. Longitudinal analyses on the effect of network change revealed that losing a network member is associated with depressive symptoms and changes in network composition (both positive and negative) are associated with health outcomes [22]. Thus, monitoring network change using telephone data may not only improve the ability to unobtrusively assess loneliness levels, but also enable the identification of network changes (e.g. the loss of a network member) which herald upcoming health consequences.

As with telephone use, total time on the computer may not have been significant due to our inability to track computer use on tablets and smart phones. Several

participants owned tablets, and two indicated their tablet was their primary device for browsing the internet and playing games. It may also be that monitoring total hours on the computer is not sufficient as the computer can be used for both social and anti-social activities. Previous research on internet use and loneliness has indicated that increased internet use decreases loneliness *only if* the internet is used to communicate with friends and family [104]. Other studies have found conflicting results on the benefits of computer use among older adults, possibly due to differences in activities performed while on the computer [186-189]. Thus, future studies on computer use and loneliness should incorporate variables describing activities performed on the computer.

We also did not find that any non-social variables were significantly associated with loneliness. The non-social variables included total time asleep and two measures of daytime dysfunction: in-home walking speed and in-home mobility. Previous studies on loneliness and sleep indicated that loneliness is not associated with total duration of sleep but instead with the sleep quality [6]. However in this study, we were not able to include a measure of sleep quality as many of the participants regularly slept in the living room and our previously validated algorithm does not work if people do not sleep in a bedroom [98]. Because sleeping in the living room may be associated with poor sleep quality, future work should validate a method to assess sleep quality even when participants do not sleep in the bedroom. In-home walking speed and in-home mobility were also not associated with loneliness. This is consistent with prior work on in-home walking speed and low mood [93], although it may also be due to high levels of noise in these two data streams which drive up the standard error of the coefficients. Future studies using more participants and data points are necessary to thoroughly understand the relationship between measures of daytime dysfunction and loneliness.

This study has several limitations. Notably, the sample size was small and relatively homogenous: only 16 subjects, all Caucasian and living alone, mostly in a low income retirement community. Future studies should validate the results found here in a larger, more diverse cohort. In addition, the study spanned less than one year, with an average of 3.4 observations per participant. Future studies should also assess the relationship between loneliness and behavior over a longer time period to better understand the time course of loneliness, the seasonal effects of loneliness, and the complex relationship between behavior and loneliness. Finally, all participants included in this model volunteered to be part of the study, and agreed to have the sensor system installed in their homes. There may be key differences in characteristics between those who are or are not willing to participate in research studies, especially those involving in-home sensors. Some work has been done to identify the differences between these groups which indicate those who participate are more likely younger and more highly educated [190]. To overcome some of this bias, this study specifically targeted individuals living in low-income retirement communities for recruitment. Still, it is possible that those who refused to participate or were not interested are different in other key characteristics, although a recent study by Claes et al suggested no key differences between those who were willing to participate in unobtrusive monitoring studies from those who were unwilling [191].

While future studies are required to validate these results in a larger, more diverse cohort, these results show potential for using behavioral measures to objectively assess loneliness levels among older adults. An objective model of loneliness has the potential to improve outcomes for older adults as it would provide the opportunity to enhance our understanding of the relationship between loneliness and health outcomes through longitudinal, objective monitoring of loneliness. An objective model would also help in the evaluation of interventions designed to improve loneliness by not only

reducing the number of participants necessary to demonstrate statistically significant improvement in loneliness but also providing insight into behaviors that changed or improved over the course of the intervention. In the long term, unobtrusive in-home sensor platforms could be employed in major retirement communities, assisting staff in the identification of lonely individuals and preventing them from becoming isolated and ignored. Taken together, this objective model of loneliness has the potential to dramatically impact social gerontology as a whole.

Chapter 7: Future Directions

SUMMARY

This thesis has developed new methods to unobtrusively assess behaviors associated with loneliness, and provided insight into how loneliness is associated with behavior. This section first details how this information might be used in future studies of loneliness, including in-depth analysis of the relationship between loneliness, social isolation and health and the validation of interventions designed to assess loneliness. Such applications may dramatically improve outcomes for older adults suffering from loneliness. This section also details ways the model of loneliness could be improved. For example, finalizing the development of a visitor detection method and adding frequency of visitors to the home to the model of loneliness may improve the observed relationship between behavior and loneliness and lead to more robust, unobtrusive models of loneliness. In addition, various aspects of both the computer data and telephone data were not included in the pilot study on behavior and loneliness discussed in Chapter 6 (pg. 84). These additional variables are discussed in this section, along with preliminary data demonstrating their relationship to loneliness.

OVERVIEW

Because of the importance of loneliness and the challenges associated with self-report of loneliness among older adults, this thesis has been devoted to the development of an objective method to assess loneliness in older adults. After analyzing the longitudinal relationship between loneliness and isolation, we developed new techniques to monitor behaviors hypothesized to be associated with loneliness using in-home sensing technologies. We then used behavioral data extracted from the in-home sensor platform using these developed techniques (among others) in a longitudinal model designed to assess the relationship between daily behavior and loneliness, and determined the feasibility of using an objective technique to assess loneliness. The results presented herein demonstrate the feasibility of using in-home monitoring to continuously assess loneliness among older adults. This approach to loneliness assessment opens the door to numerous possibilities for future research.

MODEL APPLICATIONS

Social Isolation, Loneliness and Health

As discussed in Chapter 2, multiple studies have demonstrated that both loneliness and social isolation have serious impacts on health. For example, individuals experiencing loneliness have been found to exhibit increased morbidity and mortality [1], reduced sleep quality [5], increased daytime dysfunction [6], and increased rates of cognitive decline [4]. Likewise socially isolated individuals tend to have increased morbidity and mortality with the increase in mortality similar to that of smoking [19], poor sleep quality [73] and increased risk of cognitive decline [120]. But while both loneliness and social isolation are associated with significant negative health outcomes, it is difficult to isolate the contribution each state has on health in part because assessment

of both loneliness and social isolation has relied on subjective self-report. Thus, an objective model of loneliness would enable longitudinal, objective studies on the inter-relationship between loneliness and social isolation, allowing researchers to determine which problem (loneliness or isolation) is contributing the negative health outcomes. In addition, because the model of loneliness is completely unobtrusive, long term studies ranging from years to decades could be employed to better understand the causal relationship between loneliness and health. In this manner, an objective model of loneliness has the potential to improve outcomes for older adults by providing the opportunity to enhance our understanding of the relationship between loneliness and health outcomes.

Testing the Effectiveness of Interventions

An unobtrusive model of loneliness would also help in the evaluation of interventions designed to improve loneliness. Because the model of loneliness would be able to estimate *daily* loneliness levels, fewer participants would be required to demonstrate statistically significant improvement in loneliness. In addition, the model would provide insight into behaviors that changed or improved over the course of the intervention. Leaving the system in place after completion of the intervention would allow analysis of the long term effects of the intervention. Understanding the long term effects of loneliness interventions would help researchers develop interventions with lasting effects rather than transient effects that decay upon completion of the intervention program.

Identification of Lonely Individuals

In the long term, unobtrusive in-home sensor platforms could be employed in major retirement communities or nursing homes, where they could assist staff in the identification of lonely individuals. By helping the staff identify when an individual is

becoming lonely, it would be possible to intervene and prevent individuals from becoming isolated and ignored. This would be especially important among larger communities where lonely individuals may be prone to withdraw from others altogether, causing them to go unnoticed by the people attempting to reach out to them. Indeed, some retirement communities and companies are already taking advantage of the benefits of unobtrusive sensing technologies. For example, Elite Care, a retirement community in the greater Portland, OR area specifically designed for adults suffering from Alzheimer's disease and other dementias, employs numerous sensors designed to maximize the wellbeing of both the older adults and their family.

FUTURE WORK

While the results presented here are promising, there are several ways the longitudinal model of loneliness could be improved using in-home data. First, our behavioral model of loneliness did not include any demographic data due to the small sample size. However, previous research on loneliness has provided insight into demographic variables that are associated with loneliness in older adults. Demographic variables influencing loneliness include gender [123], income [23], marital status (widows are particularly vulnerable to loneliness) [37, 128, 141], and number of children [192]. Other studies have indicated that childhood experiences may play a large role in the perception of loneliness in adulthood [193, 194]. Personality may also affect the perception of loneliness: individuals who are highly neurotic are more likely to experience loneliness [195] as are those with high levels anxiety [24]. In addition, pet ownership is likely to influence loneliness. For example, pets have been used in multiple interventions designed to ameliorate loneliness as they provide a level of companionship that may be otherwise lacking [196-198]. In the cohort of 16 individuals from Chapter 6, pet ownership was weakly associated with higher loneliness levels ($\beta = 0.77$, $p=0.11$)

when included in the model with the behavioral variables. This result may indicate that those who are lonely are attempting to improve their loneliness through pet ownership. While we did not account for these traits in the full model presented in Chapter 6 due to the small sample size and homogeneity of the cohort, adding them to a larger model of loneliness would likely improve the model's ability to predict loneliness from behavior. Thus, future studies on loneliness and behavior should account for these demographic variables thought to be associated with loneliness.

Visitors to the Home

While we developed a technique to assess visitors to the home, this technique was never thoroughly validated due to issues with the collection of ground truth data. However, visitors to the home represent an important aspect of socialization, especially among those who are home bound. Future work should validate the visitor detection approach developed here using objective ground truth data that does not rely on the self-report of the individual. In addition, more robust visitor detection methods could be developed which employ techniques such as Hidden Semi-Markov Models (HSMM) which model dwell times or Non-Stationary Hidden Semi-Markov Models (NSHSMM) which capture variation in transition probabilities over time[199]. In this way, it would be possible to validate a visitor detection algorithm that works across individual differences in behavior and differences in home layout.

Telephone Use

The model of in-home behavior and loneliness included only basic measures of phone use such as total time spent on the phone and total number of calls. However, if the number dialed can be accurately captured, phone use data could easily be used to generate social network models, such as that shown in Figure 7.1. While some association between social network size and loneliness may be evident from this graph,

the figure is static, representing a single 2 month period of data. The real benefit in such models would be in tracking the loss of important nodes or the addition of new nodes to the social network. Previous work has indicated that the addition of new contacts is beneficial for health and wellbeing [22] and our work in chapter 2 indicates that the loss of a close network members is highly associated with loneliness. Thus, using social network analysis techniques in longitudinal models of loneliness may prove highly

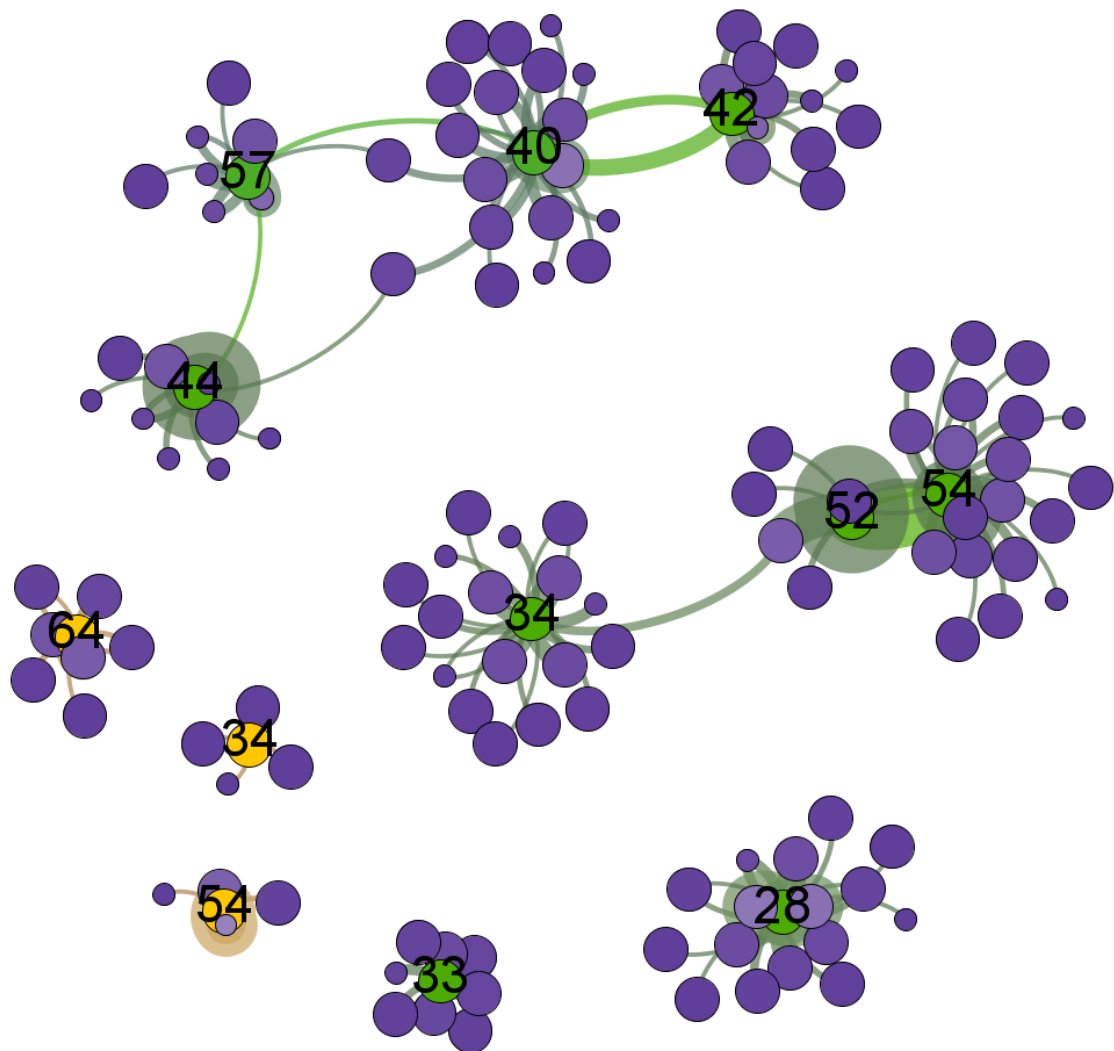


Figure 7.1: Social network graph of 12 subjects whose phone data was collected from the phone carrier. Nodes corresponding to participants whose data was collected are shown in either orange (male) or green (female). All purple nodes represent a contact called by the participant. The thickness of lines between nodes corresponds to the number of calls between the nodes. In addition, nodes are sized by the distance from Portland (smaller nodes mean longer distance). The loneliness scores are displayed in black above the corresponding participant node.

beneficial. With the recent rise in social network analysis, new techniques are being developed to assess longitudinal characteristics of social networks, including determining when a network member should be counted as ‘lost’ or when a new member should be counted as added [200]. Using these techniques, future models of behavior and loneliness may be even more sensitive to changes in loneliness levels over time.

Computer Use

Our model of loneliness also used basic measures of computer use: total time on the computer and number of sessions. However, total time may not relate directly to loneliness as individuals can do

both social and anti-social computer activities. Because RescueTime did not allow separation of specific activities performed on the computer, we were unable to include more sensitive aspects of computer behavior in our loneliness model. Still, we were able to separate the type of activity performed while on the computer for the 13 participants who received WorkTime on their computers and relate these data to loneliness as shown in Figure 7.2. We separated computer

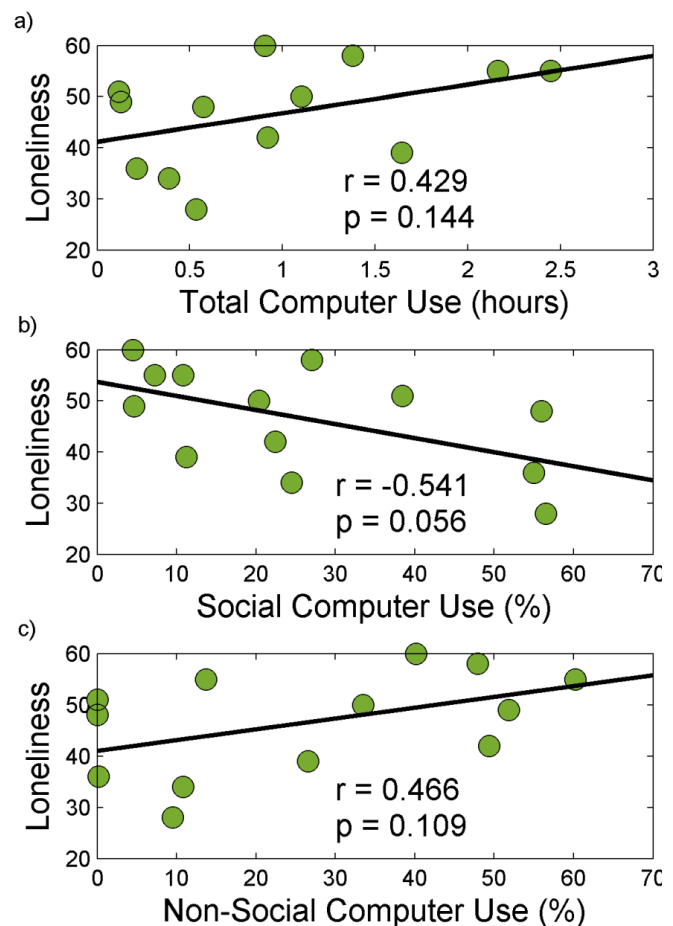


Figure 7.2: Relationship between loneliness and (a) total computer use, (b) percent of total computer use spent socially, and (c) percent of total computer use spent non-socially. Loneliness is positively related to overall computer use and non-social computer use, but negatively related to social computer use.

behavior into ‘social’ and ‘non-social’ activities, where social activities included time spent in email and social networking sites, and non-social activities included games. As can be seen, spending an increased percent of total computer time in non-social activities increases loneliness, while spending more time in social activities decreases loneliness. These results are consistent with previous research on the relationship between computer use and loneliness[104], and suggest that future studies should account for the type of activity performed while on the computer instead of just the total computer use.

CONCLUSION

In conclusion, this thesis has presented new techniques to assess behaviors associated with loneliness, and used these techniques to develop an objective method to assess loneliness from these behaviors. This work has dramatic implications for the field of social gerontology: deepening our understanding of loneliness, improving interventions, and advancing our understanding of the relationship between loneliness and health. We hope this work contributes to a reduction in the number of people suffering from the “terrible poverty of loneliness”.

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