Integrating objective health measurement using sensors, devices and pervasive computing in large-scale surveys

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Abstract: While large-scale population studies provide a wealth of insight and knowledge about the health and wellbeing of the aging population, they typically rely on self-report which has been found to be unreliable, especially among older adults. In addition, the assessment strategy usually occurs sporadically, spaced years apart to reduce patient and investigator burden. Finally, the data itself is not fully ecologically relevant being prone to test situation biases. To overcome these shortcomings of self-report and procedural limitations many new developments using pervasive computing and continuous remote sensing strategies, incorporating high dimensional ("big data") analytics show great promise for transforming health data capture and follow-up. By assessing health and behavior continuously, objectively and longitudinally, it becomes possible to generate more robust models on the inter-relationships between health and behavior. This review describes the various behaviors and parameters that can be collected via continuous assessment and the devices and assessment strategies that are used to capture key behaviors. Using the framework of wellbeing, we review strategies to assess behaviors that fall into three key categories of wellbeing. These include physical and physiological function, cognitive and intellectual wellbeing, and social behaviors and function. Thus, specific behaviors that can be assessed objectively and more continuously include body composition or weight (an example of a basic physiologic measure), medication adherence (an example of an everyday cognitive-functional task as well as an important medical outcome), and time out-of-home (and example of a measure of social engagement with the world). Devices and assessment strategies that are used to capture these key behaviors include an array of wearable devices, in-home sensor platforms, internet based surveys, computer tracking software, and "smart" devices. We review the applicability of these data collection methods to Health and Retirement Study and give suggestions for future avenues of research.

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I. Introduction

Large-scale population survey studies provide the critical data needed at multiple levels to guide governments and society in the health and wellbeing of its citizens. The Health & Retirement Survey (HRS), established in 1992, is perhaps the canonical example of these studies in the United States. The HRS was originally designed as a nationally representative longitudinal cohort survey of Americans over 50 years of age. The main purpose has been to study the changes in participation in the workforce and changes in health as people transition out of their working years and into retirement. The design and methodology employed to meet this mission has relied on relatively widely spaced assessment intervals (every two years) using standard brief questionnaires. Over the many years, the HRS has had to adapt to the times to ensure that it continues to provide the best indicators to meet its mission. Accordingly, several waves or subpanels have been added to address specific needs. New methodologies have been adopted to accommodate changes in communication behavior and technology. For example, in 2006 HRS added face-to-face interviews for all participants at every other assessment year (every four years). This face-to-face interview allows for the collection of blood based biomarkers, physical measures, and psychosocial information. These new protocols have been important additions; other large longitudinal surveys and cohort studies have mirrored this evolution.

Despite the important modifications made to the HRS and similar studies to continually improve its data, the basic paradigm for data capture - episodic brief survey periods with many self-report based measures - remains unchanged. This approach has inherent limitations. The sparsely spaced assessment intervals allow for capture of only brief snapshots of function. This limits the ability to identify potentially complex *trajectories* of change and more high resolution features of that change. Thus, interval data such as circadian or seasonal patterns may be difficult to detect. The low granularity of data capture reduces the ability to explore intra-individual trends and change. During interviews (whether in person or via telephone) much data relies on self-report which for many domains of health is unreliable or highly variable. In-person examinations, when performed, are obtrusive, performed more at the convenience of the assessors (not on weekends or holidays), and can be in an artificial setting although some of the supplemental studies (for example the Aging, Demographics and Memory Study) include in-home clinical interviews [1]. The assessments use surrogates or indirect measures of function (e.g., a timed walk with a stopwatch as a measure of mobility). Although one attempts to obtain best effort responses from survey volunteers, many of the scales and ratings are not particularly engaging and can even be stressful to complete. They do not represent tasks that people perform in their usual day-to-day lives. As such these assessments lack ecological validity. Because the longitudinal data capture may rely on human assessors or raters, inherent testing bias and test-to-test variability is continually introduced. Finally, the approach to data collection is limited by being unable to directly and dynamically integrate knowledge across related domains of a multitude of factors significantly affecting important outcomes (i.e., sleep, socialization, physical activity, physiology, and environment). That is, these constantly changing domains cannot be captured with conventional assessments in a format which is conceptually compatible with a continuous, aligned, time-stamped time-series.

Despite these limitations, the HRS has provided a wealth of insight and knowledge about the health and wellbeing of the aging population. Having historically evolved with the times, it currently stands in a position to consider what may be the next best opportunities to address some of the limitations that have been a part of the past. In this review, we consider how the current episodic, sparsely-spaced, self-report-anchored assessment paradigm may be transformed to a more continuous, objective and ecologically valid data capture system. The grist for this transformation lies in recent and rapidly developing innovations in sensing and pervasive computing methodologies, wireless technologies and high dimensional ("big data") analytics.

This review covers a large field within many intersecting and cross-cutting themes and "movements": digital health, mHealth, the Internet of Things, etc. The following sections provide highlights of how transformative technologies may improve the conduct of the HRS and related studies. We provide a perspective, not a systematic review. Many of these technologies and innovations are relatively new and lack large-scale evidence of their efficacy. Still, the trajectory of change and the opportunities are clear. We illustrate many of these opportunities, borrowing liberally from our own work as well as others in the field.

II. Overview of Objective Assessment of Behavior and Function Using Pervasive Computing and Embedded Sensing

A useful way to conceptualize potential new assessment modalities is to consider the domains of function that are most important to health, wellness or wellbeing and then how technologies may enhance the capture of relevant data to inform these domains. There are several classification schemes of the construct of wellness or wellbeing (e.g., Miller, 2010). Most encompass a number of common domains to consider: Physical/Physiological, Emotional/Psychological, Cognitive/Intellectual, Social, Spiritual, Occupational, Environmental, Cultural and Economic. In this selective review we focus on three key domains: Physical/Physiological, Cognitive/Intellectual, and Social Behaviors. Of course, many of the behaviors that we discuss may fall into or cut across multiple categories. For example, when discussing objective means to measure social behavior, we present the use of driving sensors which can track the details of a person's driving habits. By tracking places visited, it would be possible to build a model of socialization and social habits. However, driving capability can also be related to cognitive function, and by assessing characteristics of driving over time (frequency, distance traveled, routes taken), it may be possible to detect declines in cognitive function that are associated with variations in driving patterns. For simplicity of this review, we cover each behavior in only one section. This review also focuses more on technologies and approaches that are currently available with an eye toward those approaches that might be closer to scalability in population studies within the next few years. Details surrounding issues such as implementation schemes, costs and data handling are beyond the scope of this overview.

1. Physical/Physiological Function

One of the most important indicators of health and wellbeing is the physical and physiologic function of the individual. Physical function in this context represents an individual's ability to perform physical activities such as walking or climbing a flight of stairs. In contrast, physiologic function relates to the proper functioning of the body and organs. The two variables are highly interrelated as physiologic variables such as high blood pressure are typically closely tied with physical variables such as increased weight or an inability to walk long distances.

The importance of physical function is evident in the fact that individuals with greater physical ability are less likely to be admitted to a nursing home [2], have a reduced fall rate [3, 4], and are less likely to develop cognitive decline [5, 6]. In addition, physical activity is linked to numerous aspects of health and wellbeing such as self-rated health [7], cardiac function [8], and functional independence [9]. Traditionally, physical function is assessed with tests such as the Timed Up and Go (TUG) where the time to rise from an chair, walk out 3 meters and come back and sit down is recorded [10, 11]. These tests are currently performed biannually by the HRS. The importance of basic physiological functions are well known. In routine practice each time a patient visits their doctor, their blood pressure, heart rate, respiration rate, and weight are commonly collected. Changes in these vital signs may herald the onset of diseases such as hypertension or cardiac failure.

Because of the importance of these kind of metrics for health and wellbeing, a substantial amount of research has been devoted to continuous tracking of both physical and physiological function. By developing and implementing techniques to continuously monitor these metrics, it may not only be possible to detect the earliest warning signs of disease, but may also improve outcomes for individuals already diagnosed with a disease. For example, continuous monitoring of heart rate may improve outcomes for those with cardiac failure or other heart conditions while continuous monitoring of walking speed may herald changes in the fall risk of the individual. In this section we review metrics of various physical and physiologic functions that can be assessed more continuously and the techniques that have been developed to track them.

Weight and body mass index

Weight is possibly one of the simpler metrics for continuous assessment. The development of ‘smart scales’, such as the BodyTrace (BodyTrace, Inc New York, NY) or the Withings Smart Body Analyzer (Withings, Inc, Cambridge, MA) that upload each weight reading to the cloud service of the manufacturer makes it possible to continuously track weight simply by placing a scale in the home environment. Studies testing the reliability of such smart scales have found high concordance between the in-home measured weight and the weight measured in the clinic demonstrating high reliability of in-home scales [12]. However, this technique relies on each individual to weigh herself at regular intervals which may not be a realistic expectation, especially as the frequency of weighing is tied to current body mass index [13]. In addition, many scales require a steady weight reading requiring the participant to stand quietly on the scale before outputting a result. Among older adults (especially those with balance issues), it may be difficult to maintain a steady posture long enough for the scale to register a reliable weight and output the weight to the cloud. Nevertheless, given the ease of deployment and data retrieval and the reliability of the weight data, an in-home wireless scale to frequently assess weight or body mass may be an important advance for studies to implement in order to regularly and objectively assess this basic health indicator at a higher resolution.

Heart Rate

Heart rate or pulse is a critically important physiological parameter. For example, temporal changes in resting heart rate may portend future morbidity or mortality [14]. Assessing heart rate during sleep is also important as heart rate may slow or stop in conditions such as sleep apnea. Detecting heart rate during sleep will be discussed in the section on sleep, below. Here we discuss various ways researchers have developed to assess heart rate using both wrist-worn devices and in-home sensor platforms focused more on continuous monitoring potential. Snapshots of heart rate or pulse can be obtained using smartphones with several apps that are freely available for Android and iOS devices (e.g., https://play.google.com/store/search?q=heart%20rate%20monitor&c=apps&hl=en), but currently most older adults do not own or use these devices.

Multiple wrist-worn devices exist that can assess heart rate whenever the device is worn [15]. Among athletes, such devices are especially appealing as they enable the athlete to monitor their heart rate throughout exercise, which may help accomplish specific fitness goals. However, these devices typically require the user to remove the device to charge it regularly, which may make them problematic for older adults or those who are less motivated who may subsequently forget to put the device back on. Thus, other techniques to assess heart rate have been developed. For example, the smart scales discussed above can have the ability to sense heart rate whenever the user steps on the scale, provided there is nothing between the scale and the feet (the subject must be barefoot). One advantage of this approach is the participant does not need to remember to place the device back on the wrist regularly. Still, this approach has the same disadvantages discussed under *Weight and body mass index* above in that participants may forget or avoid weighing themselves. In addition, participants with pacemakers cannot use this scale barefoot because of possible effects of external electrical currents on pacemaker function.

Other groups have developed techniques to continuously assess heart rate using WiFi sensors placed strategically throughout the home [16]. For example, by emitting a low power wireless signal and measuring the time it takes for the signal to reflect back, Vital-Radio can detect both the heart rate and breathing rate of individuals who are holding still in their home environment. The system takes advantage of the minute changes in chest motion during breathing and heart contractions. Thus, while breathing in, the chest cavity expands, reducing the reflection time for the wireless signals. After exhalation, the chest returns to its resting position and the reflection time increases. This causes a sinusoidal reflection time signal, from which respiratory rate and heart rate can be extracted. This approach has numerous advantages over other approaches in that it does not require any body-worn devices or interaction from the participant. In addition, it can detect both the heart rate and respiratory rates of multiple individuals at the same time, making it ideal for multi-person scenarios. However, the technology is still in its infancy and requires additional testing and validation before it could be deployed at scale. Thus, currently the best approach to longitudinal pulse monitoring which balances user interface with functionality may be a wrist-worn device which can monitor the heart rate while optimizing battery life and data transfer.

Walking Speed and Steps

Walking speed has been called “the sixth vital sign” [17]. Because walking speed is closely related to scores on the functional mobility measure, the Timed Up and Go test, many groups have developed techniques to assess this key behavior objectively. Assessing walking speed objectively and more continuously overcomes several shortcomings of clinic-based assessments: lower frequency of observation, cost of clinic visits or home visits by researchers, and the possibility of change in walking speed in a clinical setting [18]. Frequent measurements are key because there is a large amount of variability in walking speed that could mask long-term trends if not sampled often enough [18].

Approaches to assessing walking speed objectively include in-home sensing platforms [19, 20], wrist-worn or body worn accelerometers [21-23], gyroscopes [24] and GPS systems [25]. In our own research we use an array of four motion sensors aligned in a straight line on the ceiling of a participant’s home to estimate the participant’s walking as they walk through the array of sensors [20, 26]. Because this approach captures walking speed each time the participant passes through the line of sensors, multiple estimates of walking speed can be collected each day. Thus, instead of having a single yearly estimate of walking speed, it is possible to have thousands of estimates of walking speed over the course of a year, allowing researchers to track trends and changes in walking speed and their relationship to various outcomes of interest [20, 27, 28]. Other in-home approaches to walking speed assessment have employed a Doppler radar system [29, 30] or a Kinect (Microsoft, Seattle WA) [31] placed in a hallway of the home. These systems also track variables such as step time and stride length.

Additional approaches designed to assess walking speed or steps per day require participants to remember to wear a device - a major shortcoming in older adult populations where cognitive impairments may make it challenging to remember to wear a new device. The rapid evolution of wrist-worn devices, smartwatches or fitness bands, will likely make this approach a more feasible component of mobility assessment in the future as power requirements and usability improve. An alternative avenue will be to employ smart phone applications such as Moves (ProtoGeo Oy, Helsinki, Finland) or Noom Walk Pedometer (Noom Inc, New York, NY USA) which continuously track variables such as number of steps, walking speed, distance traveled, and calories burned while a phone is carried. As noted above, older adults have been slow to adopt new technologies such as smart phones [32]. However, as the baby boomer generation ages (a generation with higher smartphone adoption), the next generation of longitudinal studies may increasingly find use of an array of smart phone applications designed to intermittently, but frequently assess variables such as walking speed, calories burned, step count, and distance traveled while carrying the phone.

Pain

Another key functional outcome of interest is the level or intensity of pain that may be experienced with aging. Pain is not only an unpleasant state to be in, when chronic it can contribute to multiple negative health outcomes including poor sleep quality [33], reduced cognitive function [34], negative mood [35], poor cardiovascular health [36], and reduced quality of life [37]. Traditionally, pain is assessed through self-reports such as numerical rating scales (rated on a Likert scale from 0-10), the “FACES” scale (pain is rated on a scale from 0-5 with pictures to help explain what each level of pain expression looks like), or the verbal pain intensity scale (participants rate pain on a scale from ‘no pain’ to ‘worst possible pain’ where each intermediate level is given a description) [38]. However, self-report of pain may be biased as individuals may intentionally over or under estimate their level of pain [39]. To move away from using self-report to assess pain, a large body of research has focused around more objective pain assessment protocols such as assessing the frequency of ‘pain behaviors’ [40-43]. Pioneered by Keefe and Block this pain behavior research typically revolves around counting the frequency of specific behaviors related to either the expression of pain to others or the preservation of the body when experiencing pain [44]. Five key behaviors are typically studied: (i) ‘guarding’, where movement is observed to be abnormally slow or stiff, (ii) ‘bracing’, where the participant is observed to distribute their weight in a non-uniform fashion to alleviate pressure in the pained area, (iii) ‘rubbing’ where the participant touches, rubs or holds the painful part of the body, (iv) ‘grimacing’ where the participant makes an obvious facial expression of pain, and (v) ‘sighing’ where the participant exhales a large volume of air. The frequency of such pain behaviors is more closely related to the self-reported level of disability due to pain than the self-reported level of pain intensity [41]. This suggests that assessing pain by evaluating pain-related *behavior* may provide a measure of pain intensity that is more immune to a participant’s tendency to under or over-report pain. However, this objective measurement of pain is highly time-consuming as participants must be recorded on video, and trained clinicians must score each video for the occurrences of the five pain behaviors. Thus, while this may overcome some shortcomings with self-report, it does not enable pain assessment regularly over long periods of time. It is not scalable.

In our research, we have used in-home sensing platforms to more continuously assess pain intensity related behaviors in older adults such as in-home walking speed and time out-of-home, both of which are reduced when people self-report higher levels of pain. This finding is consistent with the presence of ‘guarding’ behaviors when people are in pain. Still, a completely unobtrusive and continuous technique to assess pain intensity frequently is not yet fully validated. However, given the importance of pain intensity for numerous health outcomes in older adults, querying pain levels more often than biannually may be an important, advance especially as the self-report of past pain is highly affected by current pain [45].

One way to increase the frequency that older adults are queried about pain (as well as other internal states, health status and life events) is to ask a question regarding pain online. We have found among elders (mean age, 83) online that brief (force-choice) responses to a number of relevant life events including pain in the past week are reliably completed on a weekly basis over a year or more [46]. Among other questions, we query participants through an emailed questionnaire where they report their pain intensity in the last week (Likert Scale) and the degree to which their pain interfered with their regular activities of daily living. This technique to pain assessment relies on the participant to regularly check their email and answer the questions on the form. Currently, this frequent query may not be easily achieved in large panel surveys such as the HRS, especially among the oldest old. Nevertheless, it is anticipated that the number of older adults online will continue to grow steadily. Notably, even almost a decade ago, among those HRS participants who reported using a computer, there was a high acceptance rate to completing web based surveys, indicating the applicability of the approach for all participants who use a computer (30% of the HRS cohort in 2007 [47]). Because pain is ultimately an internal, subjective experience, this approach would allow for the tracking of changes in pain levels over time within the same individual, but may not as readily allow comparisons across individuals. Still, the increased sampling rate of this approach may enable a large array of new research for example into longitudinal trajectories of pain over time, how pain levels change immediately after retirement or full time employment, or how the perception of pain changes surrounding major life events like the loss of a loved one.

Falls

Falls among older adults can have serious consequences. Common disorders such as osteoarthritis can make bones brittle and more likely to fracture during a fall. Unfortunately, a major fall which results in a fracture can lead to serious injury, hospitalization, nursing home admission or death. A hazardous environment, the use of certain medications, gait and balance disorders, and even poor cognitive function can lead to increased risk of falls among older adults [48]. Because falling is a relatively infrequent event, the precise frequency of falling may not be remembered over the long term, especially over the 2 year sampling intervals that HRS has employed. Thus, reducing the time between querying older adults about whether or not they have fallen may improve the estimation of frequency of falls. This would enable understanding of common triggers of falls, the frequency of falls among older adults with various health conditions or even the trajectory of falling frequency over time.

One way to increase the frequency that older adults are queried about falls is to ask a question regarding falls online. This may become more effective with as noted, continued growth in the older online population with recent surveys reporting that approximately 60 per cent of those over 65 go on-line [32] (although this frequency drops considerably in the old old). As also noted above, we have found that among elders (mean age, 83) online, brief (force-choice) responses to a number of relevant life events including pain (see above) or falls in the past week were reliably completed over a year or more on a weekly basis [49]. In this approach any participant that answers in the affirmative has the opportunity to enter text to describe the conditions around the fall and any negative health outcomes or injuries that occurred as a result of the fall. In this fashion, one may gain detailed information about each person's frequency of falling and the conditions associated with the fall.

Another method to improve fall detection might be to employ a fall detection device. This remains an active area of development focused on developing body worn devices that automatically detect when the wearer of the device falls. Many of these are commercially available and used in the setting of personal emergency response systems (PERS). However, independent objective evidence for their ability to capture falls reliably is not widely available [50]. For the longitudinal health surveillance surveys where intervention and PERS are not appropriately deployed, the simple query of participants at more regular intervals may be the most practical near term future direction to improve the accuracy of estimating fall frequency.

2. Cognitive/Intellectual Function

Cognition is the ability to process information, apply knowledge, and develop mental representation based on experience and is vital at any age. The MacArthur Research Network on Successful Aging characterizes successful aging as freedom from disability and disease coupled with high cognitive, physical, and social functioning [51]. A review of publications about optimal aging found cognitive function to be the second most important predictor of aging well, preceded only by physical disability [52]. Intact cognitive function is critical to preserving independence and a high quality of life. Cognitive impairment is among the strongest predictors of institutionalization among non-demented elderly individuals [53].

Cognitive assessment surveys are often carried out using screening tools such as the Mini-Cog or GPCOG (General Practitioner Assessment of Cognition) [54]. These tools have two major disadvantages. They are typically performed in an unfamiliar environment such as a clinic and they may only be performed once a year. The Health and Retirement Study surveys currently include some questions about cognitive function, including meta-memory measures and memory or recall items (http://hrsonline.isr.umich.edu/sitedocs/surveydesign.pdf). The addition of continuous home-based monitoring of cognition would strengthen the capacity to capture real-world cognitive function which has been called “everyday cognition”. Importantly, this ability to assess inherently cognitively laden activities in the course of daily routine provides a unique opportunity to bring ecological validity to the assessment. In this context, we discuss various tasks and routines that can be objectively assessed at home to index cognitive function. These include walking (speed), medication taking behavior (medication adherence; prospective memory), computer use, and sleep.

Walking Speed

While walking may seem automatic or ‘mindless’, this task requires a large amount of cognitive engagement. This is evident in the difficulties people have with walking when they develop cognitive decline or have a cognitive load of some kind (e.g. “talking while walking”; trying to walk while counting backward from 100 by 7’s). As a result, walking speed is frequently assessed during cognitive assessments as one of a multitude of indicators of cognitive decline. Indeed, continuous assessment of walking speed has revealed that slowed walking independently predicts later disability and loss of independence [55-57] as well as dementia consistent with Alzheimer’s disease [58-61]. We have reviewed techniques to assess both walking speed and number of steps in the section on Physical Function as this variable relates to both cognitive function and physical ability. Briefly, walking speed can be assessed using wrist-worn devices such as wrist-worn or body worn accelerometers [21-23], GPS-based devices [25, 62] and in-home sensor platforms [20, 31, 61]. Using such systems, it has been demonstrated that walking speed as well as variability in walking speed is an indicator of cognitive decline [61, 63].

Medication Adherence

Medication taking is a routine part of daily life for most elderly [64]. It is a prototypical everyday cognition task as adhering to a medication regimen involves a number of cognitive capacities including executive function (organization, planning); and prospective memory, among other functions [65]. Impairment in these functions may be reflected in poor medication adherence [66]. Thus, tracking medication taking routines forms a means of assessing cognitive function over long periods of time in a person’s familiar home environment.

Unobtrusive, passive techniques for tracking medication adherence are vital to using this daily activity to assess cognition. Self-reporting of medication has been found to be unreliable, with an accuracy of only 43% [67]. One approach for continuous monitoring of medication taking behavior is to use common pillboxes that have been instrumented to electronically report when compartments for each day of the week are opened [68]. This approach has the advantage of being relatively inexpensive and familiar to many older adults. An example of such a device, called the "MedTracker" that tracks this important behavior is shown in Figure 1. In a study using the MedTracker, independently living older adults were divided in two groups: one with high cognitive function and the other with low cognitive function. Members of the low cognitive function group had significantly worse adherence to a twice daily vitamin regime when compared to the high cognitive function group, indicating that medication adherence is related to cognitive function [69]. An example of data collected from the MedTrackers is shown in Figure 2. In this figure, we have plotted the medication taking events as recorded from MedTrackers in two different participant homes. Each participant takes their medications from the device twice a day, and the colors represent the clustering of each medication event into either the morning cluster or the evening cluster. As can be seen, the participant in Figure 2a has high adherence and high consistency in the time of day medications are taken. In contrast, the participant in Figure 2b frequently skips medications and is inconsistent in the time of day they take their medications.

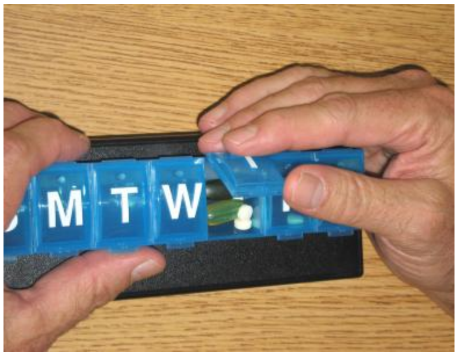

Figure 1: MedTracker pillbox

Other methods of tracking medication are being developed commercially using sensor-tagged pills that send a signal after ingestion to a patch worn by the person. These systems, unlike electronic pillboxes, more closely ensure that the medication is ingested since opening the compartment of the pillbox only provides inference that the medication was removed from the box and does not guarantee that a pill was swallowed. However, the widespread use of a tagged pill system would require all available pills to be tagged before the approach could be practically applied widely among population studies. Finally, it is important to realize that regardless of method of tracking implemented in a cohort or population study, medication

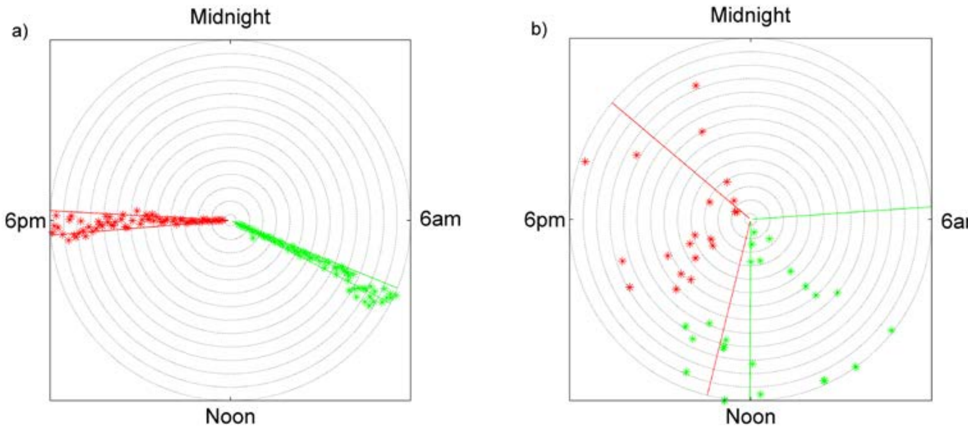

Figure 2: Circular plots of medication taking patterns from two individuals over the same 3 month period. The data are plotted as a 24 hour clock, with midnight at the top and noon at the bottom. The solid black circles mark one week boundaries. Both participants reported taking medication at two separate times, and the two colors represent the clustering of each medication event into one of these two times. The corresponding bounding lines represent the interquartile range of the spread of the data. A clear regularity in medication taking can be seen in plot (a) whereas in plot (b), the participant is considerably more sporadic at taking their medication and frequently forgets to open the pillbox at all for an entire day.

regimens change frequently. Thus effective collection of this kind of data requires additional up-to-date information regarding the schedules and actual medications taken.

Computer Use

Using a computer and navigating the internet are cognitively challenging tasks, requiring multiple cognitive capacities including attention, working memory and executive function. Assessing how older adults interact with computers can offer new insights into their cognitive function. Computer use, as noted, is increasing among the older population, with over 50% of seniors using the internet [70]. Aspects of computer use that can be monitored include time spent on the computer or in specific tasks, time to complete web-based surveys, terms searched for in search engines such as Google, and facility with a computer mouse and keyboard. Although many formal cognitive tasks or tests may be presented through the computer interface, these are not reviewed here. Interested readers may refer to Wild et al [71], Woo [72], and Zygouris [73] for reviews of computer-based cognitive testing.

The overall way an individual interacts with the computer may be related to cognitive function. In addition to monitoring behaviors while completing a web based survey, software can be installed on computers to track higher level computer behaviors such as applications used and websites visited. Using such software, we found computer use patterns among those with mild cognitive impairment (MCI) differed from age-matched cognitively intact older adults [74]. The MCI participants tended to use the computer less often and for shorter periods of time. They also reported less confidence and more anxiety about working with the computer [75]. Computer games have also been designed for the purpose of cognitive assessment [76]. Thus, it may be possible that those individuals with cognitive impairment will spend less time in cognitively engaging activities such as games than cognitively intact individuals. This aspect of computer use will be discussed further under Socialization below. Other aspects of computer behavior that may relate to cognitive function include online banking, social interactions, and the terms searched for on the Internet. These methodologies require important consideration with regard to privacy and security to manage effectively over time.

Web-based surveys have already been successfully incorporated into the HRS [47] to collect information about HRS participants. In addition to obtaining important participant content via the computer, survey-taking habits while providing this information may be useful to capture as well. In our own research using a weekly health form with 100 older adults, we found that respondents who had MCI started their survey later in the day and took longer to complete the survey than those without such impairment [77]. This may be due to the cognitive challenges associated with reading and understanding the questions or with moving the mouse from one question to the next. It may also be that those with cognitive impairment spent more time formulating descriptions of items they endorsed, for example describing the trip they went on in the last week. Other work has found older adults with MCI spend a higher percent of time in a conversation talking than cognitively intact older adults [78]. This may carry over into survey responses as well.

Beyond answers provided to a survey, a participant’s interaction with a computer keyboard and mouse can be assessed [79, 80]. Again in our own research on older adults who completed an internet-based weekly health form, MCI was found to be associated with making fewer mouse movements which were also less efficient than the mouse movements made by those without cognitive impairment [79]. Motor speed is an indicator of cognitive function and has been commonly assessed using finger-tapping tasks. Typing speed has been found to be a suitable analogue of finger tapping which can be captured by assessing the speed of typing a double letter [81]. Measuring typing speed (or other functional computer input tasks) has several advantages because the information is collected at more regular intervals outside a clinic or study visit. The data can be collected at a higher frequency and reflects a more natural task than finger tapping. Further, one may combine assessment approaches: surveys that might be regularly delivered (such as the weekly health and activity survey discussed above) to capture important self-report data can also be used as an opportunity to assess keyboard and mouse behaviors while the individual is completing the survey.

For a number of reasons, computer use monitoring may be a very effective assessment tool for longitudinal studies such as the HRS. Because many seniors increasingly need to use the internet to conduct business or find vital information, a growing variety of participants may be engaged in computer use. As computer use becomes a more routine activity of daily living, it lends itself to being studied continuously for long periods of time. By assessing this behavior longitudinally, it may be possible to detect cognitive changes or trends as they happen. There are challenges to this approach. If computer-based assessments are incorporated into survey studies they will require a secure information technology infrastructure to handle the installation and maintenance of software. In addition, study participants will likely need to be instructed about procedures, and systems will need to be put in place to manage and analyze what will be potentially large amounts of data.

Sleep

Sleep quality is closely linked with cognitive function and monitoring sleep patterns offers important information about the well-being of aging citizens. Normal aging is associated with many changes in sleep patterns such as increasing sleep fragmentation, insomnia and difficulty falling asleep [82]. These changes in sleep patterns affect cognitive performance even in healthy older adults [83]. This is of concern because poor sleep quality is associated with a variety of health concerns, ranging from an increase in falls to cognitive changes [84] and depression [85]. Importantly, inadequate sleep has been shown to be correlated with increasing amyloid beta concentrations which may culminate in Alzheimer's disease [86]. Thus, monitoring sleep may offer a valuable window into the cognitive status of the elderly population.

There are two traditional methods for assessing sleep quality: polysomnography and sleep logs. Historically, objective sleep monitoring has involved polysomnography. In this technique, participants are required to sleep overnight in a sleep lab while being connected to multiple monitors including electrocardiographs (EKG) which measure heart rate, electroencephalographs (EEG) which measure brain waves, and electromyographs (EMG) which measure muscle movements [87]. Using this array of sensors, analysts are able to reliably determine key sleep variables such as the sleep stage (I-IV or REM) and number of arousals. However, the sheer number of electrical leads attached to the participant may interfere with normal sleep patterns. In addition, the equipment and personnel required to operate the sleep lab make this approach expensive. Finally, participants cannot be monitored for more than a few days in a row so analysis of changes in sleep patterns over time is not possible.

Sleep logs and questionnaires are also often used to assess sleep. However, questionnaires have some disadvantages. First, self-reported data is known to be unreliable [88-92]. In a study comparing a two-hour self-reported activity log with activity recorded by in-home sensors, Wild et al. observed that nearly one-quarter of the reports were incompatible with the sensor data [93]. When compared with polysomnography, subjects filling out sleep reports tended to significantly underestimate the number of night awakenings experienced [94]. In addition, maintaining sleep logs and filling out regular questionnaires also can be a burden on study participants and is impractical for long-term data collection. Less obtrusive continuous monitoring of sleep can address many shortcomings of traditional sleep assessment methods. Examples of such monitoring methods include actigraphy, bed-based sensors, and infrared sensors. These methods allow for continuous monitoring of sleep in the home environment over long periods of time.

Actigraphy uses accelerometers or actigraphs, devices generally worn on the wrist or ankle which detect acceleration. These are identical in principle to those used to assess mobility or ambulatory activity discussed above in the section on assessment of physical behaviors. Actigraphy is relatively sensitive in detecting sleep patterns associated with sleep disorders and medical or neurobehavioral disorders [95, 96]. When worn over the long periods of time, actigraphy can be used to gain information about a subject’s circadian rhythms [97], which may change with age. In addition, while many methods for detecting sleep in the home only work if a participant is sleeping in the bed alone, actigraphy can work for any number of persons sleeping together, and for sleep occurring in any room of the home. This is ideal for older adults who may regularly sleep in the living room, for example. While an inexpensive option, actigraphy does have some disadvantages. It requires the participant to remember to wear the device every night which may be problematic among older adults, especially those with cognitive or memory impairment. Actigraphy also only detects movement by the limb on which the device is worn which may be an inaccurate indicator for some people. While there is a growing market of body worn devices that include an accelerometer which enables the opportunity to infer nighttime behaviors and sleep, the validation of these devices is currently limited in aging populations.

Bed-based sensors are devices such as bed mats and load cells which detect movement in bed. Bed mat designs use thin pneumatic cushions or pressure mats to detect changes in pressure across the cushion or mat [98]. By detecting changes in pressure, these systems may reliably detect motion (and thus may be able to infer total sleep time), but are of variable sensitivity to more specific aspects of sleep behavior such as sleep quality or sleep stage [99]. Bed mat systems may be disturbed by changing of bed linens and could be affected by differences in mattress and bed designs. Also, for the bed mat to record sleep, the participant must sleep on top of it. Thus, for those who may regularly fall asleep in the living room, this approach would not be effective. Load cells are another bed-based sensor used to measure sleep unobtrusively [100]. Load cells are typically installed under each leg of a bed to detect movement in the bed. When compared with polysomnography, the load cells had a sensitivity to movements of 97.5% [101]. Load cell data can also be used to classify sleep and wakefulness during the night with a sensitivity of 0.80 and specificity of 0.81 [102]. Similar to pressure mats, this method does not provide detailed information about sleep posture or night-time activities and sleep estimates can be affected by differences in bed design or mattress style.

Infrared motion sensors provide another unobtrusive method of studying night time behaviors [103, 104]. By placing sensors in each room of a participant’s home, it is possible to track an individual’s movement throughout the home. Using this sensor platform, we developed a rule-based system that tracks the movement throughout the home and determines key variables such as time in and out of bed at night from the interaction of the sensors throughout the home. Using this system, we validated the accuracy of sleep time calculated from the firing of these sensors by comparing it with the sleep time detected by bed mats placed under the bed. We found the estimates of sleep time from the rule-based sensor system correlated highly with the estimates from the bed bats, with correlation coefficients of 0.99 for bed time and 0.96 for rising time [103]. Of course, the system assumes that the participant sleeps in the bedroom (not other rooms) and thus may provide inaccurate estimates of total sleep time for any participant who regularly sleeps in other rooms of the house. Further, because the system relies on data from all sensors in the house, it requires that all other sensors in the home are installed and functioning properly to generate accurate estimates of total sleep time. Despite these shortcomings, this approach has the unique advantage that nighttime behavior can be tracked throughout the home. Thus, it is possible to determine other nighttime behaviors aside from total sleep time such as number of bathroom visits. Because bathroom visits may increase as a function of certain diseases such as urinary tract infections [105], tracking this behavior may be highly important in older adults.

At this time, the best option for continuous sleep or night-time behavior monitoring in large scale studies such as the HRS may be actigraphy due to its low cost and relatively reliable measurements. However, this assumes that challenges of any wearable are accounted for such as comfort level, form factor, need for charging, and access to the Internet or cellular systems for data upload. Reminders may have to be designed to assist the study participants in remembering to wear the devices and to charge them when necessary.

3. Social Behaviors and Function

Individuals who are more socially active - those who participate in a high frequency of social activities - generally exhibit numerous positive health effects from this activity including higher self-rated health [106], lower all-cause mortality [107-109], and decreased risk of cognitive decline [110-112]. Further, those who *perceive* more support from others exhibit similar positive health effects [113-115]. This may be in part because the social network encourages members to engage in positive health behaviors [116, 117] while providing support or resources when issues arise [118]. In addition, the social network may provide purpose and meaning to the members, which increases life satisfaction [119]. Thus, socialization and the social network are critical aspects of behavior to monitor. In the long term, by continuously assessing social network and *changes* in social network over time, it would be possible to understand the complex relationship between the social network and health. For example, Christakis et al. have developed longitudinal models looking at the spread of variables such as loneliness [120], obesity [121], and smoking behavior [116] through the social network. Continuous monitoring of the social network using telephone data could enable such studies in the older adult population as well - a population where self-report may not be as reliable due to cognitive changes. Such data may also enable the prediction of future onset of loneliness or other negative health outcomes. For example, using data from the Cardiovascular Health Study, we demonstrated that deviations in the level of social isolation were linked to reports of loneliness [122]. Other studies have discovered that changes in the social network, especially losses of social network members, are tied to future health changes [123, 124].

The relationship between socialization and health is especially important in the elderly population. Normal life changes in old age including retirement, the death of friends or family members, decreased health, and an increased probability of living alone make this population particularly vulnerable to social isolation and feelings of loneliness. Unfortunately, social isolation and loneliness are both accompanied by serious negative health outcomes including increased morbidity and mortality similar to that of smoking [108], increased risk of cognitive decline [125, 126], and poor sleep quality [127, 128]. Currently, the HRS study assesses an individual’s level of social isolation and loneliness using surveys such as the 4-item UCLA Loneliness Survey [129]. However, as noted previously this assessment protocol may be subject to desirability bias [130, 131], memory problems [132], and under or over estimation [133]. Thus, continuous assessment of social behaviors may be increasingly important, especially among older adults. While it is not possible to continuously assess all aspects of socialization, at least not without major privacy concerns and data collection challenges, there are several key aspects of social behavior that can be assessed largely unobtrusively, non-invasively, and continuously.

Time Out of Home

The total amount of time spent outside the home has been demonstrated to be associated with both loneliness and social isolation [28, 134]. Out-of-home behavior has also been linked to cognitive wellbeing [25, 135]. Historically, researchers have used surveys such as the time use survey and the life space questionnaire to query activity such as the total hours spent outside the home, the number of places visited while out, or activities performed inside and outside the home [136-139]. To overcome the biases associated with self-report, techniques have been developed to monitor this social variable using an in-home sensor platform which includes motion sensors in each room of the home in addition to contact sensors on the doors of the home [134]. By monitoring the total time spent outside the home longitudinally over the course of one year, it was demonstrated that time spent outside the home is linked not only to cognitive and physical ability, but also to emotional state, demographic variables, and the weather [28]. This system has the advantage of requiring very little effort on the part of the participant. That is, participants are not required to carry or wear a device (something that can easily be forgotten), but may instead go about their usual routine. In addition, the sensors are non-invasive as they do not take pictures or provide any identifying information about the participants. This approach has been reported to be well received with high acceptance rates among older adults [140].

Other approaches monitor time out-of-home with GPS sensors [25]. Because GPS sensors not only monitor the total amount of time spent outside the home but also the specific places visited and routes chosen, they are especially useful at tracking social activities. By overlaying a map of the area with the GPS data from each participant, it is possible to infer the *types* of activities that are performed while outside the home. This may also enable researchers to understand how far older adults travel to access resources, an especially interesting question as research has demonstrated that older adults' perception of the availability of resources may affect their life satisfaction, wellbeing and overall health [141]. The neighborhood environment has also been linked to the rate of cognitive decline, where more walkable or resource-rich neighborhoods are associated with a slower rate of decline [142, 143]. Previous studies using GPS for out-of-home monitoring required all subjects to wear and charge a GPS watch [25]. This technique may be perceived as cumbersome as it requires participants to remember to carry the device with them - a device they did not need to remember before enrolling in the study. Thus, the future of GPS-based monitoring would involve installing the GPS software on a device participants already regularly carry with them, for example a mobile phone or a smartwatch. Some research groups already use GPS cell phone applications to continually monitor the locations visited by their research participants [144, 145]. However, currently, this approach rapidly drains the device's battery, and may cause acceptance problems if participants have to regularly charge their phones or watches frequently during the day. A less battery draining system might instead rely on WiFi signals to pinpoint location outside the home. This approach would trade battery life for precision, but may still be suitable for continuous, longitudinal location monitoring in areas where WiFi networks are available.

Finally, it should be mentioned that there are some monitoring scenarios that provide partial out-of-home activity assessment that involve monitoring driving behavior. This approach relies on the installation of a telematics sensor in the participants' automobile data port (present in cars sold in the US since 1996). Commercially available systems (e.g., Automatic (San Francisco, CA, USA) or Dash (New York, NY, USA)) provide a means to tap into the data port of a car and transmit all data collected to a phone via Bluetooth. Data collected include real-time speed, route driven, and number of stops. Over 35 million people ages 65 or older drive in the US; this approach would enable real-time monitoring of locations and out of home activities visited via automobile for those who do drive, or for those who are regularly driven by others in a consistent car.

Phone Use

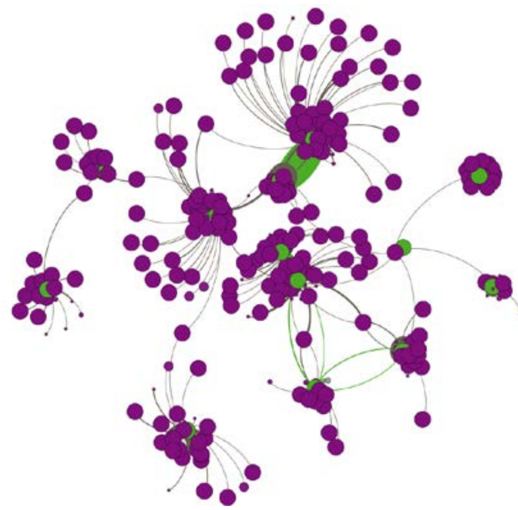

Figure 3: Egocentric social network graph of 12 participants using data from detailed phone logs. Participants are shown as green nodes. All purple nodes represent a contact called by the participant. The thickness of lines between nodes corresponds to the number of calls between the nodes. In addition, nodes are sized by the distance from Portland, OR (smaller nodes mean longer distance).

Telephone use may be a very useful window into social behavior and interaction. Using both in-home phone sensors and call logs from wireless companies, we have demonstrated that the total number of incoming calls is linked to both loneliness [146] and cognitive function [147]. But the total number of calls is not the only social behavior that can be assessed unobtrusively through continuous monitoring of phone use. Because people use the phone to call their social network members, continuous monitoring of the number dialed would enable objective, longitudinal monitoring of various aspects of the social network including its overall size, the frequency of contact with the social network, and relative closeness with network members as shown in Figure 3. In this Figure, we have plotted the egocentric social network of 12 adults whose call logs were collected for a two month period. Each participant is displayed as a green node, and the individuals they regularly call are shown in purple. As can be seen, it is possible to assess both the network size and closeness (in terms of call frequency) of the network members using this monitoring technique.

In our research we have found that currently the older population is mixed in its use of landline and mobile phones. For landline monitoring, we have used in-home phone line sensors (Shenzen Fiho Electronic, Fi3001B) to continuously monitor the landline telephone use of the older adults. These sensors function by plugging into the phone line and recording all signals on the line (but not the content of the calls). Possible signals include ‘on hook’, ‘off hook’, ‘dtmf’ (which records the number dialed) and ‘ring start’. We have used these sensors to continuously track the number of incoming and outgoing phone calls [146]. As older adults are increasingly adopting cell phone and smartphones (albeit slowly), an approach that could be used to monitor mobile phone use is required. One avenue that shows promise is the continuous monitoring of all phone activity through the use of applications that operate in the background such as RescueTime Professional (RescueTime, Seattle WA). RescueTime can be installed on all Android cell phones, and collects all data regarding application usage, text messaging, and call logs. The rich dataset generated can be automatically exported and stored locally for further analysis. Unfortunately, currently no similar application exists for iOS systems or non-smart phones. Thus, for the purposes of implementation in current population survey studies, additional effort is needed to capture this kind of data. This may include partnering with existing cell phone companies and downloading the cell phone data directly from the source. For telephone companies that do not provide ongoing detailed call logs, it may also be possible to download call records for each participant with their consent. That is, the phone companies store call logs and most companies allow users to export the last year of call and text data to .csv. While we have used this latter procedure in our research, the time and effort required to set up each participant with an online account and export the call logs for the past year makes this approach more difficult to scale in large national studies.

Computer Use

While many aspects of computer use may relate to cognitive function [74, 148] as noted above, the computer can also be used as a social medium - sending and receiving email, accessing social networking sites, or chatting with friends online [149]. Indeed, several studies have investigated whether computer training could be used as an intervention for loneliness because the computer, when used correctly, can help reduce loneliness while strengthening relationships [150-152]. Because computer use taps multiple domains of wellbeing, it can be especially valuable to monitor this behavior continuously.

While social aspects of computer use cannot be assessed by monitoring simple physical aspects such as mouse and key movements by themselves (discussed above), computer software installed on the computer can be used to continuously monitor how the computer is being used, e.g. for social or anti-social applications. In our research, we found that using the computer for social purposes was negatively associated with loneliness [153]. Others have also found that the use of the computer is differentially related to health depending on what activity is performed on the computer. For example, using the computer to engage in chat rooms is associated with higher loneliness levels, whereas using the computer to email or engage with established network members is associated with lower loneliness levels [154]. Installing computer use tracking software on the computers of older adults facilitates the ability to understand the relationship between computer behavior and outcomes such as loneliness, social isolation or cognitive function. In addition, in the process of collecting detailed information on the way older adults use the computer and how that changes over time, it may be possible to observe a broader spectrum of the dynamics of social networks and interactions across generations as well as among familiar or more distant relationships.

III. SUMMARY

In this review, we have covered a number of different continuous more real-world monitoring applications ranging from wrist-worn devices which can record health behaviors such as sleep, heart rate and general activity to potentially more comprehensive in-home sensor platforms which can be used to monitor more specific location-based information such as daily hours spent outside the home or total time spent in the bathroom. These latter systems provide an avenue to simultaneously assess multiple domains in the course of a day over long periods of time. A summary of the various continuous monitoring applications and exemplars of behaviors or activities they can detect and assess is shown in **Table 1**. Each assessment strategy has its own advantages and disadvantages. For example, while an infrared sensor network or a similar WiFi-based platform can assess multiple behaviors and does not require any input from the participant, the initial home installation and upkeep required to keep the system functioning and outputting high quality data requires a significant infrastructure to implement and maintain at the large scale that would be required by the HRS. Despite this front end infrastructure need, because of the great potential of this more comprehensive system it is worth considering that in the near future, a sub-sample of the HRS be engaged in this more intensive multi-domain continuous monitoring approach to lead into what will be next generation assessment methods.

Wearable devices (which may be integrated into a more comprehensive system or used as a more ‘stand-alone’ approach) have many attractive aspects to their use. Many current wearable devices can track multiple metrics such as heart rate and walking speed, but require the participant to comply with wearing the device regularly. Further, there is a need to customize the form-factors of these worn devices to meet the needs of a diverse population. A diminutive 85 year old woman is unlikely to readily sport the same watch-design as a husky 65 year old man. In an older adult population, especially one that may be prone to memory problems, the user interface becomes a serious challenge to the concept of continuous assessment with body worn or carried devices. Nevertheless, a substantial subset of participants may increasingly be capable of wearing these devices regularly, providing novel high quality longitudinal data on functional changes, mobility, sleep habits, heart rate variability, and other key health variables in older adults.

One possible approach to more continuous assessment that does not require input from the user is computer software installed on their computer that runs in the background. Because the computer taps multiple aspects of health and wellbeing including social behavior, cognitive function and possibly even sleeplessness (e.g., if people are using their computer in the middle of the night), this continuous data collection strategy is an important potential adjunct to longitudinal assessment. A major consideration however is the large volume of data that may be generated using computer tracking software. In our studies of computer use on personal computers, each subject generated on average 860 kB of data in one month. Adding mouse and keyboard movement dramatically increases the volume of data collected. When looking over numerous years and hundreds or thousands of subjects, this may generate an large volume of data that would require important considerations in terms of the design of servers and databases for data storage and retrieval. Data retrieval and processing could become especially cumbersome and time consuming unless a distributed server was used to distribute the computation time. This technology is rapidly evolving. Big data of today will be “small data” tomorrow. In any event, this technology would enable analysis into unique aspects of specific ways older adults use the computer, how their behavior varies by socioeconomic status or cultural background, how computer use changes through retirement, and the relationship between computer behavior and outcomes of interest such as cognitive function, social isolation or loneliness.

Although land-line phone use may be informative, another personal computer - the smart phone - may also enable more frequent and informative assessment of key behaviors of interest. Studies indicate that smartphone (and related technology likely in the future such as smartwatches) adoption is on the rise among older adults [32], so smartphone applications may become a major, minimally obtrusive monitoring platform of the future. Smartphone applications can track the number of steps per day, locations visited each day (via GPS), time in various applications, and telephone use. These key behaviors may be related to health outcomes such as socialization level, cognitive function, and physical ability. As with any computer software, data size and dynamics may be an issue; any application installed would need to be able to readily output the data wirelessly to a secure database for further processing and analysis.

Devices placed in the home that can communicate wirelessly also enable tracking of key health behaviors. For example, an in-home scale can collect weight and heart rate estimates each time the participant steps barefoot on the scale. A medication tracking device can enable the tracking of the regularity of medication taking or allow researchers to study the relationship between health outcomes and medication use controlling for the frequency each participant took their medication. These devices could most easily be deployed in the field if a clinician performs an in-home visit, such as may occur in the smaller study sections of the HRS. It is also possible to mail devices to homes with simple instructions, although one must not overestimate a given participant’s ability to follow seemingly simple set-up directions at home.

Finally, by adding weekly surveys administered via a now familiar communication medium - email - to a routine protocol, it may be possible to gain more detailed information regarding events or activities that are difficult to identify with high certainty such as falling frequency, medication changes, incident pain levels, or even internal psychological states like loneliness. This more regular self-report assessment allows researchers to investigate longitudinal interactions between variables, and to better understand the causal relationships between health and behavior as the gap between measurements would not be so long. While many of the HRS cohort do not currently use a computer, future waves added to the study are more likely to use email and be connected to the internet as trends in computer use continue to rise steadily among both older adults and the population as a whole [32, 70].

As noted, this review is not an exhaustive summary of all the different parameters and behaviors relevant to health that can be assessed continuously. In addition to continuously assessing aspects of the individual and their behavior, it may be possible to monitor key population-wide environmental variables such as air pollution or weather. Multiple studies have linked air pollution to negative health outcomes such as headaches and asthma [155], which may be especially problematic among older adults. Air quality localized in the home can be tracked using a wireless scale such as that discussed under *Weight*. The scale logs the amount of carbon dioxide present in the room the scale is located in. Other approaches allow the incorporation of data from publically available databases from the Environmental Protection Agency which can provide information on air pollution at the zip code level [156] where participants reside.

The weather also affects behavior: on sunny days people are more likely to be happier and have fewer headaches [157, 158]. The weather outside a home affects the movement of older adults inside their home [27] and the number of hours spent outside the home [28]. Thus, continuous tracking of weather in the location each participant is in may help explain some of the variance in scores on measures such as mobility, depression, loneliness, or social isolation. Weather data is already stored in publically available databases such as those made available by the National Climate Data Center [159]. Thus, HRS would need to only log each participant's area code or city of residence to link the daily weather to the participant. The time the sun rises and sets may also be important to log, especially as disorders such as seasonal affective disorder (SAD) have higher prevalence rates in the winter. The sunset and rise times are also publically available through the US Astronomical Applications Department [160] and can be added into models of continuous home-based behavior monitoring.

IV. CONCLUSION

Continuous, unobtrusive or minimally obtrusive assessment platforms offer more objective, ecologically valid data, providing insight at the individual level that was previously impossible to capture. By moving away from reliance on infrequent self-report, the data collected is not biased by recency effects (memories of closer events are stronger) or by the desirability biases that may frequently occur, especially in reports of depression, loneliness or other behaviors that may be perceived as negative. In addition, by increasing the frequency of data capture, a shorter time period (e.g. months or years instead of decades) may be sufficient to uncover the longitudinal relationships between health behaviors and health outcomes. Many devices and technologies exist to provide the objective sensed data and frequent self-reports. Applications range from body-worn devices which can record numerous aspects of health and wellbeing to fully featured in-home sensor platforms or networks which require no feedback or input from the user and can be used to monitor activities and behavior by location. In consideration of applying these techniques, important attention needs to be directed toward the specific health parameters to be monitored, as well as user interfaces and usability, participant adherence, data security, handling, storage and data analysis. At this point in the evolution of clinical research technology it seems prudent for the HRS and similar studies to begin to adopt these methods as part of regular assessment strategies to gain new insights and advance research that will greatly benefit older adults in the future.

Table 1: Overview of the various devices that can be used to continuously track behavior and the relevant behaviors they can assess.

	Physiologic/Physical Function					Cognitive/Intellectual Function				Social Behaviors and Function		
	Weight	Heart Rate	Steps	Pain	Falls	Walking Speed	Medication Adherence	Mouse and Keyboard Use	Sleep	Time Out of Home	Phone Use	Application and Internet Use
Body-worn Device		x	x		x	x			x	x		
Smart Scale	x	x										
Infrared Sensor System						x			x	x		
WiFi Sensor System		x							x			
Smart Pill Box							x					
Momentary Assessments				x	x			x				
Smart Phone Application			x			x			x	x	x	
Computer Software								x				x

V. References

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