Sensors in Support of Aging-in-Place: The Good, the Bad, and the Opportunities

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Abstract

Growth in wireless sensor and machine learning have reshaped the technology landscape. The maturing of these technologies is well-timed, because an aging population needs sensor-based technologies to support their increasing health needs. In this paper, we examine the state of the science in sensor technologies and their ability to promote successful aging. We review recent developments in sensor design and behavior marker discovery as well as their roles in automating health assessment and intervention. In addition to highlighting technology progress, we also discuss significant challenges that researchers and designers are facing. The tremendous demand for sensor solutions to adaptive aging also introduces opportunities for unprecedented research breakthroughs. Both innovation and user needs must be considered as we transition technologies from infancy to widespread use.

1. Introduction

We are experiencing a dramatic and unprecedented shift in national and global demographics. Soon, a quarter of our population will be age 65+, and unique healthcare challenges will accompany this age wave. Because people are living longer, chronic illness rates are increasing, and with them, the number of individuals who are unable to function independently. For the first time, older adults will outnumber children, creating a discrepancy between persons needing care and those capable of providing it [1]. While the future of healthcare availability and service quality seems uncertain, the future of healthcare IT is bright, with a projected market growth to $391 billion by 2021 [2].

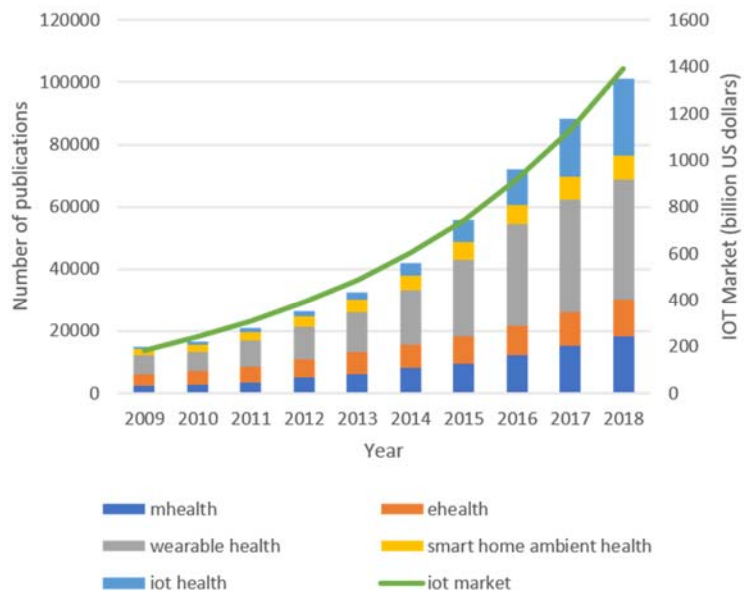

Figure 1. (bars) Number of publications, by year, for sensor-related healthcare topics over the past decade. Numbers are reported by Google Scholar; (line) Size of the global IoT market. Numbers are reported by Statista.

Technology holds a promise to meet some of the coming age wave needs by automating and dramatically scaling health assessment and treatment. This promise is reflected in research and business interest. As Figure 1 illustrates, research activity and market activity related to sensor technology for healthcare have both been steadily growing over the past decade. Because 90% of seniors want to stay in their own homes as they age [3], many look to technology to extend functional independence and improve quality of life. There are many potential benefits of sensor-based technology for promoting successful aging in place. Rather than calling Mom several times a day to check in, family members can discretely view a display that reassures them she is up and carrying about her daily business. Instead of seeing a patient for 30 minutes, care providers can create diagnosis and treatment plans based on a complete behavioral profile generated from continuous monitoring over the previous year. Older adults do not need to worry about taking the right medications in the correct context when smart pill dispensers offer timely reminders. Furthermore, they can rest assured that assistance is on its way if a fall or other accident does happen.

To exploit the promise of aging-in-place support that is offered by smart sensor platforms, we need to determine what progress has been made in this field and what are essential next steps. In this paper, we look at the state of the science in smart sensor-based health monitoring, assessment, and intervention for aging in place. We start by comparing the capabilities of popular sensor platforms and types of information that can be gleaned from these sensors. Based on this starting point, we then investigate the variety and maturity of sensor-based technologies that have been developed for adaptive aging. Finally, we discuss barriers and opportunities that arise as we move this field forward.

2. Sensors and Behavior Markers

Sensors provide information on a vast variety of physiological and behavioral features. In recent years these sensors have become low cost, wireless, integrated into larger packages, and deployable in real-world settings. Sensors differ in type, purpose, output signal, and technical infrastructure. Table 1 lists sensors that are commonly used for ubiquitous healthcare because they provide moment-by-moment human behavior markers, in situ. Here, we discuss the potential use cases for sensor data as well as the pros and cons for alternative sensor types.

Table I. Common types of sensors employed for health monitoring and assistance.

Category	Sensors
Ambient	passive infrared (PIR) motion, magnet / contact switch, temperature, light, humidity, vibration, pressure, power usage, electric device usage, water usage, RFID
Wearable	accelerometer, gyroscope, magnetometer, compass, phone, text, app, battery, location
Environment	frequented locations with type, outdoor walkability score, indoor and outdoor air quality, temperature, light levels, sound levels, number of residents, environment clutter
Physiological	ECG, EEG, EMG, respiration, pulse, galvanic skin response, skin temperature, cortisol level, blood pressure, blood oxygen saturation
High-dimensional	camera, microphone array
Digital traces	web browser, purchases, social media

Ambient sensors are attached to a physical environment. These sensors passively provide data [4]. Thus, individuals do not need to interact with the sensor or change their behavior in any manner. Because they are not associated with a single person, these sensors generate data that reflect the actions of everyone in the space together with external environment influences. While these sensors are inexpensive and do not quickly drain their batteries, the information they provide is often coarse in granularity. As a result, sophisticated software is required to understand behavior patterns and health states from these data.

In contrast with ambient sensors, wearable sensors both require much more user attention and provide much larger data. Individuals who collect data from mobile phones, smartwatches, or other wearable sensors need to consider proper sensor placement [5]. These sensors must be frequently charged because the battery drains quickly, especially if collected information is communicated offsite or location services are employed [6]. On the other hand, mobile devices offer a compact mechanism for bundling many sensors together. Frequently, these devices either directly collect physiological information or offer attachments that monitor these readings. These sensors provide personalized information in large volumes that offer tremendous insight into movement and behavior patterns. Consider a smartwatch that collects sensor readings at a rate of 50Hz. This device will generate over 4 million readings each day. While the resulting data are a treasure trove for data analysis, they quickly exceed the storage capacity of a mobile device.

Other input devices that provide high-granularity data are cameras and microphone arrays. These sources offer perhaps the richest information and attract a great deal of research on activity recognition and analysis [7]. Video and audio data are valuable for fall detection, speech-based health assistance, and analysis of group activities [8]. At the same time, they pose some of the most significant challenges. These data are so voluminous that they prevent on-site storage and real-time analysis. They are sensitive to environmental factors, because lighting and ambient sound conditions can obscure the information. Perhaps most dauntingly, the perceived (or actual) privacy risk thwarts user acceptance of the technology, particularly in their own homes [9], [10]. An unlimited number of external information sources can also be analyzed to understand a person's health state and behavior patterns. People leave digital traces when they use the Internet to browse, shop, and tweet. The digital exhaust contributes to creating personal behavior markers. Due to the computational and privacy hurdles faced by these information sources, we restrict our state-of-the-science focus to the role of ambient and wearable sensors in health monitoring and assistance, particularly for older adults.

From raw sensor data, digital behavior markers can be gleaned. Mapping raw data onto health scores and identifying emergencies from raw data is extremely difficult. More often, features are extracted based on expert design or through automated feature learning methods such as autoencoders, independent component analysis, and clustering [11], [12]. Over the last few years, researchers have made great strides in identifying and validating these digital phenotypes [13]. Table 2 summarizes some of these phenotypes, or behavioral markers, that are particularly relevant for monitoring and assisting older adults.

Table II. Behavioral markers that are extracted from sensor data.

Category	**Features**
Mobility	step count, walking speed, daily distance covered, number and duration of times in one spot, number walking bouts, activity level
Exercise	number, duration, movement types, intensity, location
Sleep	number and duration of daily sleep bouts, sleep times, sleep locations, sleep fitfulness, sleep interruptions, sleep apnea
Activity	number, duration, and location of basic and instrumental activities of daily living
Environment	frequented locations with type, outdoor walkability score, indoor and outdoor air quality, temperature, light levels, sound levels, number of residents, environment clutter
Devices	types of device interactions, medication frequency, use of compensatory devices
Socialization	number and duration of incoming/outgoing phone calls, text messages, missed calls, address book, calendar, time out of home, number and duration of visitors, activity before and after calls
Circadian and diurnal rhythm	complexity of daily routine, number of daily activities, minimum and maximum inactivity times, daily variance in activity and mobility parameters, periodogram-derived circadian rhythm

Perhaps the most prevalent behavior metric is movement type and intensity. An accumulating body of research indicates that engaging in preventative health brain aging behaviors may slow cognitive and physical decline as well as promote brain neuroplasticity [14], [15]. Furthermore, an estimated 10-25% improvement in modifiable risk factors could prevent up to 3 million cases of Alzheimer's disease worldwide [16]. At the forefront of these healthy behaviors is exercise, which demonstrably improves cognition and mood while slowing signs of aging [17], [18]. In the home, motion sensors trigger a reading when movement is sensed in their field of view. Software estimates mobility levels and walking speed by tracking motion from one sensor to the next. On a mobile device, accelerometers quantify changes in speed and even support gait cycle estimation. Based on this information, walking speed, duration, and step counts can be estimated. Although these sensors can be fooled by other types of movements [19], they provide a baseline of movement behavior against which each person can measure changes.

Sleep is also a strong indicator of health in older adults [20]. Not only does poor sleep correlate with many adverse health outcomes, but sleep quality itself is an indicator of aging and health [21]. Ambient and motion sensors, together with specialized bed sensors, provide a host of sleep quality indicators. Total sleep time, sleep efficiency, and deep sleep can be sensed from movement and respiration. When location information is added, unusual sleep locations (e.g., in a living room chair rather than in bed) can be detected.

One of the most common features that is learned from sensor data is an activity label. Activities provide a vocabulary to express human behavior. Human activity recognition is a popular research topic [22]–[25]. Although much of the current work uses sensors to recognize activities in scripted settings, the same methods can be refined to label activities as they occur. Wearable sensors have traditionally be employed to recognize movement-based activities (e.g., sit, stand, walk, climb, lie down), while ambient sensors typically label basic and instrumental activities of daily living (e.g., work, exercise, relax, cook, eat, entertain, sleep). Once these labels are generated, information about the timing, regularity, location, and duration of routine activities can be incorporated into a personalized phenotype.

When additional sources of information are added to the mix, the number of behavior features that can be extracted is virtually unbounded. Sensors can now determine the use of water and electrical devices, monitor medication access, and detect interaction with items that offer compensatory aid [26]–[28].

Figure 2. The sensor-based process to support adaptive aging. Sensors generate readings, from which behavior markers are extracted. Machine learning techniques map behavior markers onto assessment categories, which form a basis for automated intervention.

Online sources can be tapped to assess the air quality, temperature, and walkability of a geographic area. Similarly, a person's computer usage leaves traces that indicate socialization habits. A vital behavior marker that confounds researchers is nutrition monitoring. While researchers have succeeded in detecting eating movements [29], they typically require users to specify the type of food being consumed, which results in a decline in technology use over time [30].

All of these behavior markers represent one level of information on top of raw sensor data. On their own, the markers have been linked with health indicators and can be used to automate prevention and treatment plans. However, the markers are most effective when they are examined in combination and over time. The amount of time that is spent outside the home by itself may not provide an indicator of health, social anxiety, or loneliness, but day-to-day variability and trends paint a more vivid picture [31]. Similarly, automatically identifying circadian and diurnal rhythms [32], [33] is essential for all of the behavior markers by themselves and in combination.

3. Automated Assessment

One particular need which technology can help address is the need to assess a person's health and functional performance. Assessing the ability of an individual's physical state and their ability to be functionally independent supports family planning, creation of an appropriate treatment plan, and evaluation of intervention strategies. Technology offers many potential improvements to assessment Because many technology-based tests can be administered without a clinician present, they can be utilized by people living in rural settings without imposing time and location constraints [34]. Performing assessments in a patient's everyday environment is more representative of the person's capabilities [35].

Additionally, collected sensor data can identify novel correlations that were unanticipated but are meaningful. As Figure 2 illustrates, automated assessment relies on large sensor data and corresponding behavior markers. Here, we review recent studies and findings that automate assessment of factors contributing to aging in place, including motor functioning, cognition, mood, and functional independence.

Motor function. Throughout the field, wearable sensors are typically used to analyze ambulation and gestures. Thus, they naturally support motor function assessment. A key aspect of motor function is gait, and sensors placed within shoes pick up on multiple elements of gait, including walking patterns and stride [36], [37]. Researchers have used these patterns to diagnosis movement-related conditions including insensible feet, Parkinson's disease, Huntington's disease, Amyotrophic Lateral Sclerosis, peripheral neuropathy, frailty, diabetic feet, injury recovery, and fall risk [38], [39]. In addition to analyzing movement patterns, these sensor technologies can also detect wandering and learn behavior precursors [40] and monitor time/distance traveled outside the home during rehabilitation [41].

Mood. Because sensors can be seamlessly woven into everyday life, they support timely assessment in ecologically valid settings. Moods can change quickly, and at unexpected times, so they need to be detected in-the-moment. Researchers have successfully identified mood at smaller sample sizes. For example, Boukhecbha et al. [31] predicted social anxiety based on visited location types as well as fine-grained behavior features that were extracted before and after texting and phone conversations. Similarly, Quiroz et al. [42], as well as Mehrotra and Musolesi [43] inferred emotion from movement and heart rate data. Quiroz, et al. were able to predict happy, sad, or neutral states using accelerometer data. Mehrotra and Musolesi inferred levels of activeness, happiness, and stress, each on a Likert 1..5 scale. Instead of analyzing accelerometer readings, these researchers collected GPS data and extracted markers, such as number and duration of places visited throughout the day, to output predictions. Using ambient sensors, Aicha et al. [44] and Austin et al. [45] found a correlation between self-reported feelings of loneliness and sensor-detected minimal socialization.

Cognition. Researchers have hypothesized that changes in cognition correlate with behavior changes. With the maturing of sensor technology, we now can validate the hypothesis and automate assessment and analysis of cognitive function. Because assessment tests designed with ecological validity are more effective than laboratory tests at predicting everyday functioning, researchers have designed studies to link behavior and cognition in home settings. Initially, many of these studies were performed in a simulated home environment with scripted activities, yet significant correlation was found with traditional neuropsychological test scores [46]–[48]. More recently, study participants were allowed to perform their typical uninterrupted routines at homes while sensors monitored their behavior. Behavior parameters over time were found to correlate with diverse health parameters including fall risk functional performance, cognitive function, motor function, and dyskinesia “on” states. Cook et al. validated their technology for 84 older adults, although the study was based on scripted activities [47]. Other groups have tested these methods in actual homes over multiple months, although the sample size 1-2 homes [49]–[51]. Traditional assessment scores have occasionally been predicted from behavioral markers observed over months or years [52], [53]. In many of these cases, walking speed and activity regularity were reliable indicators of cognitive health. However, Hellmers et al. [54] and Akl et al. [55] found that time spent in areas of the home and daily variation in room occupancy were strong predictors of mild cognitive impairment. Similarly, Petersen et al. [56] discovered a link between time out of the home and cognitive health.

Functional independence. Very few efforts have been made thus far to automate functional performance assessment in everyday settings using sensor technology. Validating functional performance is challenging. In partnership with an occupational therapist, Robben et al. [57] were able to link daily variability in room occupancy with AMPS and Kat-15 scores. However, automated detection of compensatory use has not yet been explored. Similarly, automatic scoring of a person’s activities based on sensor-observed consistency, efficiency, and completeness has not yet been designed.

4. Prevention and Intervention

Sensor technology is better suited to observing behavior and health state than to taking preventative or therapeutic actions. However, key intervention technologies have been designed using captured sensor data. Because sensors can detect activities such as taking medications, a natural intervention is to issue prompts (via a mobile device) for medication adherence. Sensor-driven automated prompts are ideal because they are less reliant on patients to program reminder times and contents, reducing user burden and increasing technology adoption. Additionally, studies have shown that prompting individuals based on context is more effective than timing-based prompts [58]. Clearly, a prompt to take medication at a person's standard dinner time of 6:30pm will be unsuccessful if dinner is delayed until 7:00pm. Similarly, if the person is away from the medication dispenser or busy with an unrelated activity, the prompt may not even be heard, let alone be productive. The link between recognizing activity context and providing timely reminders was further investigated by Minor et al. [59]. Their app forecasted the next expected time for a key activity (e.g., take medicine), then issued a prompt if the activity was not initiated at the predicted time.

Not only can sensor data inform intervention design, but they can also provide a valuable means to understand treatment adherence. As an example, Fallahzadeh et al. [60] captured sensor-derived contextual descriptions of instances when subjects followed a medication regimen and when they skipped a treatment dose. They found, for example, that individuals who linked their medication schedule with another routine activity (e.g., waking up, dinner) had higher adherence rates. These findings can help validate intervention theories and automate prompt timings for automated interventions.

While prompts represent a primary sensor-driven intervention in current technologies, a few investigations have considered additional automated assistance for older adults. One example is automatically contacting a care provider if a health event or significant anomaly is detected. While anomaly detection from sensor data is a heavily-studied topic [61], detection of primarily irrelevant abnormalities is quite common. In the case of smart home data, anomalies can be reported due to sensor noise, an unexpected visitor, or a power outage. If the care provider receives too many alerts, they will be ignored. A recent project uses a clinician-in-the-loop approach to address this issue [62]. By providing a small number of clinically-relevant anomaly examples, this algorithm found a much higher percentage of anomalies that were related to health events such as falls, nocturia, depression, and weakness.

One area that has not received much investigation is home automation assistance. Some researchers have automated smart homes based on anticipated actions and needs [63], [64]. However, these capabilities have not tested for usability by older adults. Given the observation that older adults are enjoying assistants such as Alexa and Google Home, and are learning to use these devices faster than in the past [65], this is an opportunity that can be explored by researchers and entrepreneurs.

5. Barriers and Opportunities

There has been a flurry of activity in the space of pervasive computing and machine learning-driven analysis of human behavior data. These advances set the stage for tremendous technological support of aging in place. However, there are still significant challenges that need to be addressed before the promise becomes a reality. Primary barriers to wide-spread use include study reproducibility, technology scaling, user privacy, and technology adoption. While there are significant hurdles to overcome in these areas, the challenges also present rich opportunities for researchers to tackle fascinating problems.

5.1. Scale and reproducibility

Many breakthroughs have been made in health-assistive technologies. However, most sensor-based health monitoring and assistance studies have not focused on result reproducibility or generalizability. Engineering fields focus primarily on innovation. Devoting time and resources to designing new technology diverts them away from ensuring study reproducibility. In the assessment and intervention studies we reviewed, the median sample size was 17 subjects. Additionally, only a handful of studies collected data continuously for multiple days, let alone months or years. While some researchers focus on particular population groups, the vast majority of studies use a convenience sample. Including diverse populations has not been a priority when showing “proof of concept” for a new technology. However, this step is critical to ensure that these important technologies are usable and achieve reliable results for all older adults. Large diverse populations are also needed to address issues of bias and fairness when training machine learning models [66].

Admittedly, difficulties in validating sensor-driven healthcare thwart attempts at scalability and reproducibility. First, ground truth is frequently inaccessible and erroneous. Whether the technology is generating value for activity, behavior markers, or health state, accurate labels are necessary to validate the technology. However, while sensor data can observe humans continuously, clinicians cannot. Traditionally, self-report is gathered when clinician data is unavailable. However, these are often error-prone because the retrospective details of past experiences and health states cannot be consistently recalled. Recent work in designing apps for Ecological Momentary Assessment (EMA), or experience sampling, can help by collecting information on health events, current activities, and self-reported functioning “in the moment” [67], [68].

Second, sensor-driven health technologies are a sophisticated assortment of components, each of which represents a new, dynamic breakthrough. Each part introduces a potential for failure and thus must be validated separately. As a result, many technologies are tested in a laboratory or heavily-controlled setting, rather than “in the wild.” Using sensor technologies in actual deployments requires handling issues including sensor noise, missing data, and system failure. If data are available, then they need to be preprocessed to filter patterns of interest. Even if clean and segmented data are available, researchers have to contend with one of the most complex, dynamic types of processes: human behavior and its relationship to health. Problems with any one of these steps can propagate error downstream and jeopardize the reliability of the assistive technology. For this reason, many commercially-available packages perform a subset of the pieces described in this paper. Furthermore, commercial products are often driven by expert-crafted rules, to ensure their consistency and trustworthiness. Novel, machine learning-driven methods will need to be scaled and validated before they can be safely transferred to the marketplace.

Third, sensor-driven healthcare needs to scale to multiple types of sensors, data sources, and population demographics. Researchers have found that there is no single “silver bullet” sensor source that provides all of the necessary insight to a person's health and functional independence. As a result, methods including data fusion [69], transfer learning [70], and domain adaptation [71] will be essential. Using these procedures, sensors in a smart home can "train" a smartwatch on how to recognize classes of behaviors. Once the individual leaves home, the smartwatch can continue observing behavior where the home left off and can update the home's models when it returns. The house can then take up the task while the watch is charging. Similarly, these algorithmic methods can assist in adapting data and learned models to new devices, new behavior categories, and new population groups.

5.3 Privacy and security

Because data acquisition and analysis form the backbone of sensor-supported aging in place, older adult's privacy now increasingly depends on the ability to keep others from extracting or inferring sensitive information from data. Companies are eager to obtain medical information. Some employers dispense rewards or penalties based on fitness data; others assess consumers' health risks to increase insurance rates.

Most older adults doubt that their personal information is being kept private and feel that online safety is low [65]. These worries are warranted. Even after data is scrubbed of obvious identifying markers, observed behavior data are still linked to an individual, that person's medical data, and a host of other sensitive information. Maintaining anonymity has typically consisted of removing key identifiers such as a person's name, address, social security number, and other unique identifiers. However, the recent proliferation of high-dimensional datasets introduces the possibility of piecing together a person's complete profile from seemingly disparate and anonymized pieces of information [72]. This ability has been confirmed by several projects in which sensitive medical data was identified from seemly-obscure pieces of information [73], [74].

The risk of re-identification is heightened when collected information is linked to ubiquitous, location-tracking mobile devices [75]. Last year, analysts found that a commercial fitness app led to the revelation of remote military outpost locations [76]. De Montjoye et al. [75] found that location data does not need to be continuous and fine-grained to perform re-identification. They theoretically determined that four spatio-temporal points are enough to uniquely identify 95% of the population. Mobility traces were deemed unique even at 1/10 of the available resolution, highlighting the fact that coarse granularity will not protect anonymity.

Even without explicit location information, sensitive features can be re-identified. Wu et al. [77] achieved a human identification rate of 98% from gait data for 4,007 subjects. Similarly, Na et al. [78] analyzed accelerometer data collected during walking periods for seven days as part of the National Health and Nutrition Examination Survey (NHANES). These researchers used random forest and SVM learning algorithms to re-identify demographic and physical activity data for 14,451 subjects. Rocher et al. [79] further challenge the release-and-forget approach to anonymizing and sharing datasets. Based on an analysis of populations within five publicly available data sets, they determine that 99.98% of Americans could be re-identified using 15 demographic attributes.

Fortunately, the increasing awareness of digital exposure has sparked a similar rise in research to maintain the privacy of sensitive information. Privacy-preserving data mining methods are being proposed to combat the corresponding expansion of data exploitation methods [80]. Instead of releasing collected data, for example, synthetic data can be released that exhibits the same properties as collected data but obfuscates features of any one person [71], [81], [82]. Further developing and utilizing these methods can help overcome the dangers associated with collecting sensor data for health assistance.

5.4 Technology adoption

Once technology is robust and secure, an important final step is for older adults to embrace it. Again, several factors must be considered to improve technology adoption for this demographic. One factor is the cost of technology. In 2017, the reported median annual income for older adults in the US was $24,224 [83]. This income is far less than the amount that most need to meet with their day-to-day living expenses, particular since annual healthcare costs for individuals with chronic conditions is up to $13,230. As a result, expensive smartwatches or smart homes will not be a high-priority expenditure. Unless external agencies support sensor technology costs or prices dramatically reduce, the demographic that needs the support the most will be the least likely to be able to purchase it.

A second factor is addressing the desire for older adults to utilize health-assistive technology. While older adults realize that health and wellness tech should be of significant interest, they prefer to invest time and resources on tech that entertains, connects, and informs. Most older adults feel that sensor-based technologies are novelties [84]. They shy away from such mechanisms unless they are singled out by their physician or a family member as needing something to monitor them. At that point, being surrounded by such technology heightens awareness of their health status. As a result, health-related technology often elicits a negative response, while communication technology gets a positive response. Technology developers can be sensitive to this perspective. Sensor technology can serve dual purposes. In addition to monitoring activities, it can provide news coverage, connect older adults with friends, and entertain. Assistive technology should look stylish. It should also allow seniors to bring new capabilities into their home (e.g., control ambient music through voice commands, turn on lights when someone walks at night) as well as protect their well-being.

Finally, researchers must ensure that sensor-based health technology is safe and straightforward to use. Many health-assistive apps require user effort to set up alerts and keep logs [85]. Additionally, individuals with cognitive limitations will require extended teaching time, and use of technologies may be forgotten if not habituated [86], [87]. Technology must take advantage of participatory design, in which feedback from older adults and care providers informs each step of the design process. Software interfaces and assistive devices need to include contrasting colors and large fonts, as well as consider communication difficulties due to hearing loss, when supporting older adults [88]. Through partnership with end-users, researchers can create sensor systems that will support, not undermine, health and functional independence [89]. By additionally creating machine learning models that are interpretable, users will be more accepting of technology. At the same time, clinicians will be informed about insights that can shape their own practices.

6. Conclusions

Sensors and machine learning together provide essential tools that can revolutionize aging-in-place. Ubiquitous ambient and mobile sensors collect large amounts of continuous data. By processing these data, machine learning techniques extract behavioral markers and map behavior features to clinical assessment scores, providing automated assessment of physical, mental, and emotional health. Additionally, these insights provide a basis for designing interventions that support older adults and their functional independence.

Sensor-based methods are becoming increasingly reliable for unobtrusively monitoring behavior and measuring human factors that are related to cognitive and physical health status. Despite plentiful success stories, however, there still remain numerous challenges to face in providing technology strategies for adaptive aging. Technology changes quickly, but health-assistive hardware and software needs to be validating on large, diverse populations to ensure its reliability. Because these sensor data reflect daily lives, collecting and analyzing them in the cloud can introduce privacy and security risks. Even once these issues are addressed, systems must be appealing and usable by older adults for the technologies to be adopted. By addressing these remaining issues now, the technology will be ready to support our aging population when help is most needed.

References

[1] J. Iriondo and J. Jordan, "Older people projected to outnumber children for first time in U.S. history," *United States Census Bureau*, 2018. [Online]. Available: https://www.census.gov/newsroom/press-releases/2018/cb18-41-population-projections.html.

[2] S. Singh, "Healthcare IT Market," *MarketsandMarkets*, 2019. [Online]. Available: https://www.marketsandmarkets.com/PressReleases/healthcare-it-market.asp.

[3] D. Arigoni, "Preparing for an aging population," *AARP*, 2018. [Online]. Available: https://www.aarp.org/livable-communities/about/info-2018/aarp-livable-communities-preparing-for-an-aging-nation.html.

[4] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *J. Neuroeng. Rehabil.*, vol. 9, no. 21, 2012.

[5] Y. Chen, J. Wang, M. Huang, and H. Yu, "Cross-position activity recognition with stratified transfer learning," *Pervasive Mob. Comput.*, vol. 57, no. 1–13, 2019.

[6] P. Josue *et al.*, "Toward ultra-low-power remote health monitoring: An optimal and adaptive compressed sensing framework for activity recognition," *IEEE Trans. Mob. Comput.*, vol. 18, no. 3, pp. 658–673, 2019.

[7] B. Ghanem *et al.*, "ActivityNet large-scale activity recognition challenge 2018," 2018. [Online]. Available: http://activity-net.org/challenges/2018/index.html.

[8] N. Lu, Y. Wu, L. Feng, and J. Song, “Deep learning for fall detection: Three-dimensional CNN combined with LSTM on video dinematic data,” *IEEE J. Biomed. Heal. Informatics*, vol. 23, no. 1, pp. 314–323, 2018.

[9] R. Marvin, “Privacy tops list of consumer smart home concerns,” *PC Mag.*, 2019.

[10] N. Apthorpe, D. Reisman, and N. Feamster, “A smart home is no castle: Privacy vulnerabilities of encrypted IoT traffic,” in *Workshop on Data and Algorithmic Transparency*, 2016.

[11] Y. Bengio, A. Courville, and P. Vincent, “Representation learning: A review and new perspectives,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, 2013.

[12] A. Coates, A. Karpathy, and A. Y. Ng, “Emergence of object-selective features in unsupervised feature learning,” in *International Conference on Neural Information Processing Systems*, 2012, pp. 1–9.

[13] J.-P. Onnela and S. L. Rauch, “Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health,” *Neuropsychopharmacology*, vol. 41, no. 7, pp. 1691–1696, 2016.

[14] A. S. Buchman, P. A. Boyle, L. Yu, R. C. Shah, R. S. Wilson, and D. A. Bennett, “Total daily physical activity and the risk of AD and cognitive decline in older adults,” *Neurology*, vol. 78, pp. 1323–1329, 2012.

[15] C. Phillips, “Lifestyle modulators of neuroplasticity: How physical activity, mental engagement, and diet promote cognitive health during aging,” *Neural Plast.*, p. 3589271, 2017.

[16] D. E. Barnes and K. Yaffe, “The projected effect of risk factor reduction on Alzheimer’s disease prevalence,” *Lancet Neurol.*, vol. 10, no. 9, pp. 819–828, 2011.

[17] M. W. Voss *et al.*, “Acute exercise effects predict training change in cognition and connectivity,” *Med. Sci. Sports Exerc.*, 2019.

[18] N. A. Duggal, R. D. Pollock, N. R. Lazarus, S. Harridge, and J. M. Lord, “Major features of immunesenescence, including reduced thymic output, are ameliorated by high levels of physical activity in adulthood,” *Aging Cell*, vol. 17, no. 2, 2018.

[19] P. Alinia, C. Cain, R. Fallahzadeh, A. Shahrokni, D. J. Cook, and H. Ghasemzadeh, “How accurate is your activity tracker? A comparative study of step counts in low-intensity physical activities,” *J. Med. Internet Res.*, 2017.

[20] D. L. Mohr, M. Zhang, and S. M. Schueller, “Personal sensing: Understanding mental health using ubiquitous sensors and machine learning,” *Annu. Rev. Clin. Psychol.*, 2017.

[21] J. Li, M. V Vitiello, and N. S. Gooneratne, “Sleep in normal aging,” *Sleep Med. Clin.*, vol. 13, no. 1, pp. 1–11, 2018.

[22] A. Bulling, U. Blanke, and B. Schiele, “A tutorial on human activity recognition using body-worn inertial sensors,” *ACM Comput. Surv.*, vol. 46, no. 3, pp. 107–140, 2014.

[23] P. Bharti, D. De, S. Chellappan, and S. K. Das, “HuMAn: Complex activity recognition with multi-modal multi-positional body sensing,” *IEEE Trans. Mob. Comput.*, vol. 18, no. 4, pp. 857–870, 2019.

[24] M.-C. Kwon, H. You, J. Kim, and S. Choi, “Classification of various daily activities using convolution neural network and smartwatch,” in *IEEE International Conference on Big Data*, 2018.

[25] D. J. Cook, N. C. Krishnan, and P. Rashidi, “Activity discovery and activity recognition: A new partnership,” *IEEE Trans. Cybern.*, vol. 43, no. 3, 2013.

[26] S. Gupta, M. S. Reynolds, and S. N. Patel, “ElectriSense: Single-point sensing using EMI for electrical event detection and classification in the home,” in *ACM International Conference on Ubiquitous Computing*, 2010, pp. 139–148.

[27] E. Larson, J. Froehlich, T. Campbell, C. Haggerty, J. Fogarty, and S. N. Patel, “Disaggregated water sensing from a single, pressure-based sensor,” *Pervasive Mob. Comput.*, vol. 8, pp. 82–102, 2012.

[28] M. Aldeer, M. Javanmard, and R. P. Martin, “A review of medication adherence monitoring technologies,” *Appl. Syst. Innov.*, vol. 1, no. 14, 2018.

[29] N. Hezarjaribi, S. Mazrouee, S. Hemati, N. Chaytor, M. Perrigue, and H. Ghasemzadeh, “Human-

in-the-loop learning for personalized diet monitoring from unstructured mobile data," *ACM Trans. Interact. Intell. Syst.*, 2019.

[30] M. C. Carter, V. J. Burley, C. Nykjaer, and J. E. Cade, "Adherence to a smartphone application for weight loss compared to website and paper diary: pilot randomized controlled trial," *J. Med. Internet Res.*, vol. 15, no. 4, 2013.

[31] M. Boukhechba, Y. Huang, P. Chow, K. Fua, B. A. Teachman, and L. E. Barnes, "Monitoring social anxiety from mobility and communication patterns," *ACM Int. Jt. Conf. Pervasive Ubiquitous Comput.*, pp. 749–753, 2017.

[32] S. Abdullah, M. Matthews, E. L. Murnane, G. Gay, and T. Choudhury, "Towards circadian computing: 'Early to bed and early to rise' makes some of us unhealthy and sleep deprived," in *ACM Conference on Ubiquitous Computing*, 2014.

[33] S. Robben, A. N. Aicha, and B. Krose, "Measuring regularity in daily behavior for the purpose of detecting Alzheimer," in *EAI International Conference on Pervasive Computing Technologies for Healthcare*, 2016, pp. 97–100.

[34] N. DeYoung and B. V Shenal, "The reliability of the Montreal Cognitive Assessment using telehealth in a rural setting with veterans," *J. Telemed. Telecare*, 2018.

[35] C. Zampieri, A. Salarian, P. Carlson-Kuhta, J. G. Nutt, and F. B. Horak, "Assessing mobility at home in people with early Parkinson's disease using an instrumented Timed Up and Go test," *Parkinsonism Relat. Disord.*, vol. 17, no. 4, pp. 277–280, May 2011.

[36] S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," *Sensors*, vol. 17, no. 1, p. 130, 2017.

[37] L. Fiorini, M. Maselli, and E. Castro, "Feasibility study on the assessment of auditory sustained attention through walking motor parameters in mild cognitive impairments and healthy subjects," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2017, pp. 897–900.

[38] J. C. Ayena, L. D. C. Tchakouté, M. Otis, and B. A. J. Menelas, "An efficient home-based risk of falling assessment test based on smartphone and instrumented insole," in *IEEE International Symposium on Medical Measurements and Applications*, 2015, pp. 416–421.

[39] M. Mancini *et al.*, "Continuous monitoring of turning mobility and its association to falls and cognitive function: A pilot study," *Journals Gerontol. Ser. A Biol. Sci. Med. Sci.*, vol. 71, no. 8, pp. 1102–1108, 2016.

[40] Q. Lin, D. Zhang, L. Chen, H. Ni, and X. Zhou, "Managing elders' wandering behavior using sensors-based solutions: A survey," *Int. J. Gerontol.*, vol. 8, no. 2, pp. 49–55, 2014.

[41] M. K. O'Brien, C. K. Mummidisetty, X. Bo, C. Poellabauer, and A. Jayaraman, "Quantifying community mobility after stroke using mobile phone technology," in *ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2017, pp. 161–164.

[42] J. C. Quiroz, M. H. Yong, and E. Geangu, "Emotion-recognition using smart watch accelerometer data: Preliminary findings," in *ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2017, pp. 805–812.

[43] A. Mehrotra and M. Musolesi, "Designing effective movement digital biomarkers for unobtrusive emotional state mobile monitoring," in *Worskhop on Digital Biomarkers*, 2017, pp. 3–8.

[44] A. N. Aicha, G. Englebienne, and B. Krose, "Unsupervised visit detection in smart homes," *Pervasive Mob. Comput.*, vol. 34, pp. 157–167, 2017.

[45] J. Austin, H. H. Dodge, T. Riley, P. G. Jacobs, S. Thielke, and J. Kaye, "A smart-home system to unobtrusively and continuously assess loneliness in older adults," *IEEE J. Transl. Eng. Heal. Med.*, vol. 4, 2016.

[46] M. A. U. Alam, N. Roy, A. Gangopadhyay, and E. Galik, "A smart segmentation technique towards improved infrequent non-speech gestural activity recognition model," *Pervasive Mob. Comput.*, 2016.

[47] D. J. Cook, M. Schmitter-Edgecombe, and P. Dawadi, "Analyzing activity behavior and movement in a naturalistic environment using smart home techniques," *IEEE J. Biomed. Heal.*

Informatics, vol. 19, no. 6, 2015.
[48] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, “Automated cognitive health assessment using smart home monitoring of complex tasks,” *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 43, no. 6, 2013.
[49] A. N. Aicha, G. Englebienne, and B. Krose, “Continuous gait velocity analysis using ambient sensors in a smart home,” in *Ambient Intelligence*, Springer, 2015, pp. 219–235.
[50] D. Austin, T. L. Hayes, J. Kaye, N. Mattek, and M. Pavel, “Unobtrusive monitoring of the longitudinal evolution of in-home gait velocity data with applications to elder care,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 6495–6498.
[51] N. Darnall *et al.*, “Application of machine learning and numerical analysis to classify tremor in patients affected with essential tremor or Parkinson’s disease,” *Gerontechnology*, vol. 10, no. 4, 2012.
[52] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, “Automated cognitive health assessment from smart home-based behavior data,” *IEEE J. Biomed. Heal. Informatics*, vol. 20, no. 4, 2016.
[53] A. Alberdi Aramendi *et al.*, “Smart home-based prediction of multi-domain symptoms related to Alzheimer’s Disease,” *IEEE J. Biomed. Heal. Informatics*, 2018.
[54] S. Hellmers *et al.*, “Towards a minimized unsupervised technical assessment of physical performance in domestic environments,” in *EAI International Conference on Pervasive Computing Technologies for Healthcare*, 2017, pp. 207–216.
[55] A. Akl, J. Snoek, and A. Mihailidis, “Unobtrusive detection of mild cognitive impairment in older adults through home monitoring,” *IEEE J. Biomed. Heal. Informatics*, vol. 21, no. 2, pp. 339–348, 2017.
[56] J. Petersen, S. Thielke, D. Austin, and J. Kaye, “Phone behaviour and its relationship to loneliness in older adults,” *Aging Ment. Heal.*, 2015.
[57] S. Robben, G. Englebienne, and B. Krose, “Delta features from ambient sensor data are good predictors of change in functional health,” *IEEE J. Biomed. Heal. Informatics*, vol. 21, no. 4, pp. 986–993, 2017.
[58] J. Lundell *et al.*, “Continuous activity monitoring and intelligent contextual prompting to improve medication adherence,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2007, pp. 6286–6289.
[59] B. Minor, J. R. Doppa, and D. J. Cook, “Learning activity predictors from sensor data: Algorithms, evaluation, and applications,” *IEEE Trans. Knowl. Data Eng.*, 2017.
[60] R. Fallahzadeh, B. Minor, L. Evangelista, D. J. Cook, and H. Ghasemzadeh, “Mobile sensing to improve medication adherence,” in *ACM/IEEE International Conference on Information Processing in Sensor Networks*, 2017, pp. 279–280.
[61] U. A. B. U. A. Bakar, H. Ghayvat, S. F. Hasanm, and S. C. Mukhopadhyay, “Activity and anomaly detection in smart home: A survey,” in *Smart Sensors, Measurement and Instrumentation*, Springer International Publishing, 2015, pp. 191–220.
[62] J. Dahmen and D. J. Cook, “Indirectly-supervised anomaly detection of clinically-meaningful health events from smart home data,” *ACM Trans. Intell. Syst. Technol.*, 2019.
[63] M. C. Mozer, “Lessons from an adaptive home,” in *Smart Environments: Technology, Protocols, and Applications*, D. J. Cook and S. K. Das, Eds. Wiley, 2004, pp. 273–298.
[64] K. Gopalratnam and D. J. Cook, “Online sequential prediction via incremental parsing: The Active LeZi Algorithm,” *IEEE Intell. Syst.*, vol. 22, no. 2, 2007.
[65] B. N. Kakulla, “2019 tech and the 50+ survey,” 2019.
[66] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, “A survey on bias and fairness in machine learning,” *arXiv:1908.09635*, 2019. .
[67] J. D. Runyan and E. G. Steinke, “Virtues, ecological momentary assessment/intervention and smartphone technology,” *Front. Psychol.*, vol. 6, p. 481, May 2015.
[68] S. Aminikhanghahi, M. Schmitter-Edgecombe, and D. J. Cook, “Context-aware delivery of

ecological momentary assessment," *IEEE J. Biomed. Heal. Informatics*, 2019.

[69] P. Tsinganos and A. Skodras, "On the comparison of wearable sensor data fusion to a single sensor machine learning technique in fall detection," *Sensors*, vol. 18, no. 2, 2018.

[70] J. Wang, V. W. Zheng, Y. Chen, and M. Huang, "Deep transfer learning for cross-domain activity recognition," in *International Conference on Crowd Science and Engineering*, 2018, p. 16.

[71] G. Wilson and D. J. Cook, "A survey of unsupervised deep domain adaptation," *ACM Trans. Intell. Syst. Technol.*, 2019.

[72] E. E. Schadt, "The changing privacy landscape in the era of big data," *Mol. Syst. Biol.*, vol. 8, no. 612, pp. 1–3, 2012.

[73] L. Sweeney, "Only you, your doctor, and many others may know," *Technol. Sci.*, vol. 2015092903, 2015.

[74] L. Sweeney and J. S. Yoo, "De-anonymizing South Korean resident registration numbers shared in prescription data," *Technol. Sci.*, vol. 2015092901, 2015.

[75] Y.-A. De Montjoye *et al.*, "On the privacy-conscientious use of mobile phone data," *Nat. Publ. Gr.*, vol. 5, pp. 1–6, 2018.

[76] R. Perez-Pena and M. Rosenberg, "Strava fitness app can reveal military sites, analysts say," *The New York Times*, 29-Jan-2018.

[77] Z. Wu, Y. Huang, L. Wang, X. Wang, and T. Tan, "A comprehensive study on cross-view gait based human identification with deep CNNs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 2, pp. 209–226, 2017.

[78] L. Na, C. Yang, and C.-C. Lo, "Feasibility of reidentifying individuals in large national physical activity data sets from which protected health information has been removed with use of machine learning," *JAMA Netw. Open*, vol. 1, no. 8, p. e186040, 2018.

[79] L. Rocher, J. M. Hendrickx, and Y.-A. de Montjoye, "Estimating the success of re-identifications in incomplete datasets using generative models," *Nat. Commun.*, vol. 10, no. 3069, 2019.

[80] C. Desmet and D. J. Cook, "Recent developments and ongoing challenges for privacy-preserving mining of clinical data," *ACM Trans. Knowl. Discov. Data*, 2019.

[81] N. C. Abay, Y. Zhou, and B. Thuraisingham, "Privacy preserving synthetic data release using deep learning," in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 2018.

[82] B. K. Beaulieu-Jones, W. Yuan, S. G. Finlayson, and Z. S. Wu, "Privacy-preserving distributed deep learning for clinical data," in *Machine Learning for Health Workshop*, 2018.

[83] Pension Rights Center, "Get the facts," 2018. [Online]. Available: http://www.pensionrights.org/.

[84] L. Connect, "2019 technology survey older adults age 55-100," 2019.

[85] J. Y. E. Park, J. Li, A. Howren, N. W. Tsao, and M. De Vera, "Mobile phone apps targeting medication adherence: Quality assessment and content analysis of user reviews," *JMIR Mhealth Uhealth*, vol. 7, no. 1, p. e11919, 2019.

[86] M. C. Greenaway, N. L. Duncan, and G. E. Smith, "The memory support system for mild cognitive impairment: randomized trial of a cognitive rehabilitation intervention," *Geriatr. Psychiatry*, 2013.

[87] M. Schmitter-Edgecombe, S. Pavawalla, J. T. Howard, L. Howell, and A. Rueda, "Dyadic Interventions for Persons with Early-Stage Dementia: A Cognitive Rehabilitative Focus," in *New Directions in Aging Research: Health and Cognition*, R. Bougham, Ed. Nova Science Publishers, 2009.

[88] W. Wittich and J.-P. Gagne, "Perceptual aspects of gerontechnology," in *Gerontechnology: Research, Practice, and Principles in the Field of Technology and Aging*, S. Kwon, Ed. Springer, 2016, pp. 13–34.

[89] R. Ravichandran, S.-W. Sien, S. Patel, J. A. Kientz, and L. R. Pina, "Making sense of sleep sensors: How sleep sensing technologies support and undermine sleep health," in *Conference on Human Factors in Computing Systems*, 2017.