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A Survey on Smart Homes for Aging in Place

Toward solutions to the specific needs of the elderly

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Advances in engineering and health science have brought a significant improvement in health care and increased life expectancy. As a result, there has been a substantial growth in the number of older adults around the globe, and that number is rising. According to a United Nations report, between 2015 and 2030, the number of adults over the age of 60 is projected to grow by 56%, with the total reaching nearly 2.1 billion by the year 2050 [1]. Because of this, the cost of traditional health care continues to grow proportionally. Additionally, a significant portion of the elderly have multiple, simultaneous chronic conditions and require specialized geriatric care. However, the required number of geriatricians to provide essential care for the existing population is four times lower than the actual number of practitioners, and the demand-supply gap continues to grow [2]. All of these factors have created new challenges in providing suitable and affordable care for the elderly to live independently, more commonly known as *aging in place*.

Prioritizing proactive care

The driving goal is to keep individuals, especially the elderly, healthy at home through proactive care, while also facilitating remote reactive care when needed rather than requiring frequent visits to the doctor. Proactive care can minimize the physical and mental stress associated with regular hospitalization for the elderly and significantly reduce the financial burden for both patients and the health-care system. Both proactive and remote reactive care can be enabled through continuous, holistic monitoring of the user's health status, daily activities, and behavioral patterns with multimodal sensors in a naturalistic environment. The simultaneous application of both proactive and reactive care, in turn, can promote the use of diagnostic testing to avoid adverse medical outcomes and alleviate the burden on the user as well as the health-care system. In this regard, homes equipped with sensors and smart systems, also known as *smart homes*, designed for the benefit of the aging residents will enable both short-term monitoring for remote reactive care (e.g., monitoring cardiac activity in

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response to newly prescribed medication) and long-term monitoring for proactive care (e.g., tracking adherence to prescribed exercise routines or suggesting lifestyle modifications based on observed behavioral trends of the user).

By using wearable and environmental sensors, wireless sensor networks, and sensing devices that can monitor critical health parameters, we will be able to gather physiological and behavioral data continuously. The key lies in building intelligent, efficient algorithms that can provide valuable insights from daily patterns, e.g., from the changes in a user's gait patterns or eating habits. The new algorithms could also enable predictions of future irregularities, allowing us to turn these predictions into actionable information impacting the quality of life and care delivery, while offering opportunities for adaptive interventions and personalized medicine.

In this article, we present several noteworthy investigations in the field of smart homes and assisted living applications and categorize the important research areas. In particular, we discuss the required technology support including 1) sensors and connectivity solutions, 2) signal processing and data analytics that operate on sensor data and extract actionable information, and 3) information delivery and visualization paradigms that provide the actionable information to the end-users and stakeholders. We will provide in-depth analysis of the challenges and discuss the benefits of smart home technology for aging in place.

While there have been some previous surveys done on smart homes, these surveys are either limited in their scope or fail to provide research direction or opportunities. For example, one recent survey focuses on smart home technologies for activity recognition and its impact on health care in general [3], while another focused on the technology readiness and the effectiveness of existing smart home technologies to address some of the complex health issues faced by older adults but does not provide any guidelines for future researchers [4]. Unlike these previous surveys, this work focuses on the key challenges associated with aging in place for the elderly, considers diverse application drivers, and presents a clear outline of the most important research areas and opportunities for future work.

Application case studies: Major smart home projects for aging in place

In general, smart home projects for aging in place mainly focus on monitoring the health and well-being of elderly persons through sensors tagged on the habitat (doors, walls, ceiling, and so on), sensors in/on household objects (small appliances, beds, couches, and others), or sensors worn by the users (i.e., wearable devices). Monitoring the daily activities and behavioral patterns of a dweller in a smart home environment can be a key factor for facilitating aging in place. Daily activities can include basic efforts like walking, sleeping, personal grooming, toilet usage, self feeding, and so on or instrumental tasks such as food preparation, cleaning, the use of communication tools (e.g., telephones), and watching TV, along with others. Professionals in health care use the term *activities of daily living* (*ADL*) to refer to the daily activities that a person normally performs, and it can be used to define functional capacity, especially that of an elderly person.

Several studies have investigated systems based on habitat sensor networks and household object sensor networks for monitoring ADL. Suryadevara et al. propose an activity detection system consisting of a wireless sensor network, which has the objective of wellness detection [5]. The sensor network consists of current sensors placed at power outlets to detect the use of electrical appliances, flexible pressure sensors to detect activity around nonelectrical objects (e.g., beds and sofas), and a Zigbee-based mesh network protocol for connectivity. Through the use of a conditional probabilistic model, this method achieves an overall accuracy of 94% in detecting and forecasting daily activities. Another study that leverages wireless sensor networks for recognizing ADL was conducted by Ghayvat et al. [6]; it also uses a Zigbee mesh topology for the network. Their system employs power outlet sensors for monitoring the use of electrical and electronic devices, pressure and contact sensing, passive infrared (PIR)-based movement sensing, and temperature-monitoring units, all connected through Zigbee-based radio-frequency (RF) modules. This particular investigation also reports on the interference and attenuation issues of the wireless network when implemented in a smart home. A common factor between these two investigations, besides ADL recognition, is the use of parameters called *wellness indices* or *wellness functions* to quantify the well-being of an elderly person. Both studies leverage the measurement of active versus inactive time intervals of different appliances to estimate wellness.

Fleury et al. propose a support vector machine (SVM)-based ADL recognition mechanism leveraging a variety of sensors including wide-angle webcams, microphones, and contact sensors to detect the opening and closing of doors, infrared (IR) sensors to detect the presence of a subject in a room, and wearable motion sensors (i.e., three-axis accelerometer and magnetometer) [7]. The authors suggest tagging the habitat with sensors rather than objects to simplify the design and implementation. This work considers seven basic ADL (including eating, sleeping, toilet usage, and so on) and uses multiclass SVMs to classify them, with accuracies ranging from 97.8% to 64.3% depending on the activity.

While the prior studies reported impressive accuracy levels for detecting ADL, these systems have been designed with static requirements and do not consider the possible variations in the application and usage of the system and variations in the environment. The detection and system architecture requirements may vary from one application to another, and it is important to maintain the concept of adaptability and tuning of the accuracy, sensitivity and the specificity requirements of the ADL detection. This typically translates to tuning of system architecture, sensors, and the optimization process, accordingly. Additionally, the output of the ADL recognition may need to be represented in various forms, including deterministic and probabilistic, which is not present in the proposed case studies.

Moving away from detection of ADL, Kim et al. proposed an alternative method of inferring the well-being of an elderly person using location information [8]. Their method incorporated an RF identification (RFID)-based indoor tracking system that used location information in association with the durations of stay in different locations of the home to infer information such as movement patterns, and the frequency of certain location-specific activities (e.g., using the toilet or sleeping in the bedroom) to estimate the well-being of an elderly dweller.

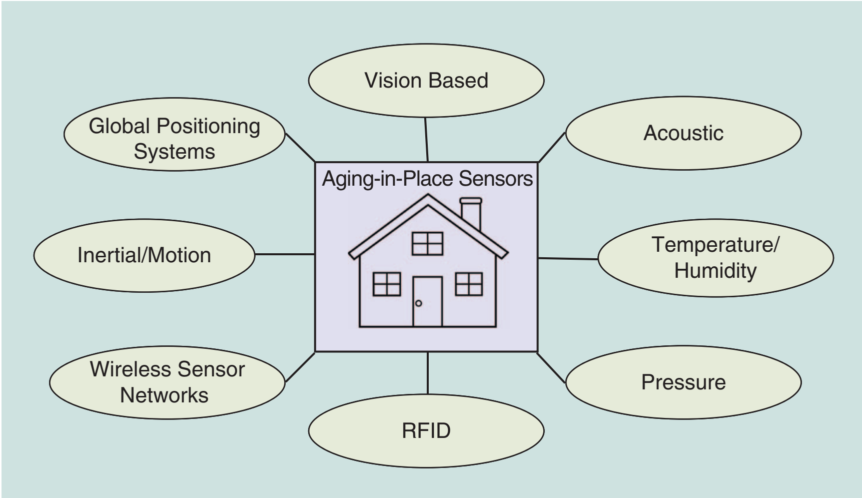

FIGURE 1. The common sensors that are used to support aging in place.

While most investigations in smart home technology consider only a single user, this is not necessarily the case in a real home environment. Moreover, recognizing multiple users could enable detection of social interactions associated with wellness. The recognition of ADL in a multiuser setting is challenging due to two additional requirements: 1) identifying each of the dwellers and 2) accommodating a more complex set of activities involving multiple persons. Wang et al. presented a multiuser activity recognition system in a smart home setting using wearable audio sensors, actimetry sensors (e.g., accelerometer, temperature, humidity, and light), and RFID tags [9]. This system achieved a maximum accuracy of 98.59% in detecting single-user activities and 95.91% in detecting multiuser activities. While these results are admirable, one shortcoming is that the single- and multiuser activities are predefined and distinct; this may not be the case in a real-world scenario where these two different types of activities can overlap. Another system by Mokhtari et al., which uses PIR-based occupancy sensors and ultrasound arrays, performs human identification among multiple users and reports 100% accuracy [10]. This system, which uses Bluetooth Low Energy for connectivity and has been designed with energy efficiency in mind, recognizes different users based on their height and detects movement direction and speed to monitor a user. One shortcoming of this system is that the height difference between each of the users has to be at least 4 cm for the algorithms to operate with an acceptable level of accuracy.

An open question is a uniform, generalizable, and quantifiable description of the well-being of an older adult. While two of the studies mentioned in this section presented wellness indices, they each had different definitions for the term; the research community for this application space could benefit from a more standardized definition of this wellness index to appropriately assess the effectiveness of smart home systems in estimating wellness. A standardized definition can also help determine ADL of relevance, which in turn can dictate the number and type of sensors used in the smart home. One approach that has been previously explored to bridge this gap is to establish relationships between recognized ADL and clinically established mobility and cognitive tests such as Timed Up and Go and Repeatable Battery for the Assessment of Neuropsychological Status [11]. Additionally, there are opportunities to create such generalizable or disorder-specific wellness indices, potentially customized to individuals by comparing the observed trends to each user's baselines, thus offering insights for improvement and progress.

Sensors and connectivity paradigms

Sensors are crucial for measuring data from individuals and environments. These sensors can be discrete (e.g., contact switches) or continuous (e.g., physiological sensors) observing devices [3]. Figure 1 presents an overview of various sensor types that have been used with the diverse range of complex monitoring and automation tasks for aging in place.

It is rarely the case that a single sensor type is sufficient for quantifying the health and well-being of a person; therefore, multiple sensors are often combined to achieve specific goals. For the same target phenomenon, different sensors have their own observations with different levels of noise and reliability. In a survey on fall detection and activity recognition in elderly care by Abbate et al. [12], the authors highlight the use of vision-based sensors and environmental and/or wearable sensors such as inertial sensors for fall detection in a home setting. Vision-based sensors are reliable and can depend on sophisticated image-recognition algorithms; however, it is costly and time consuming to install these cameras, and there are significant privacy concerns associated with this modality. Environmental sensors, such as IR or pressure sensors placed on household objects, offer a cheaper alternative that preserves privacy; yet they are limited to sensing only the specific spaces/objects on which they are placed. Wearable sensors, such as an inertial sensor on an ankle strap, are user centric and allow ubiquitous, unrestricted monitoring at low cost, unlike vision and environmental sensors. Nevertheless, data from wearable sensors can be challenging to interpret due to noise from motion artifacts, misleading data due to improperly worn sensors, or missing data due to sensors occasionally not being worn at all. There is an opportunity to develop generalizable sensor selection techniques that consider the complementary nature of the sensors in the context of the end-application requirement.

Functional monitoring is also particularly important in smart homes to support aging in place for the elderly. Research supports the notion that a variety of factors, including physical and intellectual activity, social engagement, and nutrition, all contribute to optimizing cognitive health in the aging population [13]. To enable the monitoring of mental health, a combination of different sensing modalities is imperative, such as using PIR or inertial sensors for physical activity monitoring, acoustic sensors for social monitoring, and vision-based sensors for nutrition assessment. In addition to functional monitoring, physiological monitoring is also of particular importance toward achieving the goal of aging in place. This can include the detection of emergency situations such as falls using wireless networks [12], continuous monitoring of existing chronic conditions, e.g., dementia or cardiac health [14], and monitoring of sleep health using motion sensors [15]. Wood et al. presented a wireless sensor network system called *AlarmNet*, which integrates environmental, physiological, and activity sensors in a single architecture [16]. The AlarmNet system is unique because it enables improved power conservation by anticipating which sensors should be active and which should be disabled by analyzing the behavioral pattern of the user. Additionally, the system is designed with flexibility, which allows for the integration of new sensors and ad hoc deployment into existing structures.

Sensor selection and ease of deployment are a critical challenges in the design of smart homes for aging in place. The types and number of sensors to be deployed should not become a burden for the user. Human factors, such as ease of use even with declining levels of function and cognition, must be taken into consideration when designing and deploying the sensors [17]. Some key factors that contribute to technology acceptance, particularly among older adults, include perceived usefulness and ease of use, as well as personal characteristics, e.g., functional ability [18]. In noncritical cases, it is unlikely that older adults will be inclined to keep up with constantly changing technology developments in the form of new wearables and environmental technology to be deployed in the home. Therefore, there is an opportunity to leverage existing sensors that were designed for a different purpose for a new sensing paradigm that can, for example, evaluate mobility, social engagement, and loneliness [19]. Additionally, minimizing the number of sensors required would ease communication bandwidth, energy efficiency, costs, and user acceptance concerns. For example, wireless sensor networks can be used not only for daily activity monitoring but also for monitoring sociability and detecting emergencies. To facilitate this, sensors provide the recorded data as well as a quality measure for the data, e.g., a wrist-worn heart-rate monitor can not only detect the heart rate but also the confidence in the heart rate observations and the quality associated with the data, which could be impacted by motion artifacts and can be measured by motion sensors.

The connectivity among different sensors can be realized using wireless sensor networks comprising Bluetooth, RF, Zigbee, RFID, ONE-NET, Wi-Fi and so on and even wired connections like serial communication, Multimedia over Coax Alliance, and Ethernet to create a smart environment. However, challenges exist with numerous communication protocols that are often incompatible at various networking layers, and the existence of varying throughput requirements on sensor outputs and data increases communication complexity [20]. Communication among several high- and low-end sensor nodes has to be established while taking into consideration constraints of the sensor nodes in question. There is currently no unified software interface to collect data from sensors, and this makes it challenging to interface existing sensor data streams with new software since the requirements and specifications are often incompatible. This presents an opportunity for the development of a unified and standard software interface for sensors.

With the growing number of sensors and interconnected systems for aging in place, the requirements for privacy of personal data and secured end-to-end connections become critical. Security can be enforced on two levels: device-level security includes hardware encryption and access control in stand-alone devices, while network- and system-level security include encryption of network traffic, source blocking, and authentication.

Smart home technologies use a diverse range of communication techniques, and the use of Internet protocol connectivity provides the bridge among these devices [21]. However, the use of Internet communication brings the challenge of dealing with cybertheft, data manipulation, unauthorized access, and other such undesirable events. Organizations like the Internet Engineering Task Force continue to work toward the standardization of security in data exchange protocols and enhancing Datagram Transport Layer Security [21]. One investigation of network security by Sivaraman et al. proposes augmentation of network-level security measurements with device-level protection and implements a prototype consisting of a third-party architecture and associated application programming interfaces [22]. The authors also report the security vulnerability of some commercial Internet of Things products and evaluate their implemented software-defined network platforms' protection efficacy.

A number of cryptography methods are used in a variety of security scenarios. RFID-based authorization schemes are seeing increased use, and elliptic curve cryptography is a popular technique used in health-care environments. In their review of several recent works on elliptic-curve-cryptography-based RFID schemes, He et al. considered computation and communication costs as well as several security requirements to compare performances [23]. The authors report that very few works satisfy all security requirements while keeping the cost in an acceptable range. Thus, the establishment of secure protocols for communication among devices subject to the application requirements remains an important research opportunity to realize smart homes for aging in place.

Signal processing and data analytics

Signal processing and data analytics in the context of a smart home signify the effective fusion of data from multiple heterogeneous sensors, knowledge extraction, and production of actionable information (see Figure 2). Signal processing is required to process noisy signals to observe fine-grained information over short time periods, such as the response to blood pressure medication over several minutes/hours. In contrast, data analytics can provide more coarse-grained information over several weeks/months after recognizing long-term trends and potentially making predictions and providing feedback to stimulate behavioral changes. Moreover, in a smart home environment with a multitude of sensors tracking the user's location and activity, these approaches can exploit the knowledge of context to improve estimates.

Many different signal processing techniques have been implemented for the purpose of monitoring the health and well-being of occupants in smart homes. Zheng et al. used a self-adaptive neural network called *Growing Self-Organizing Maps* (*GSOM*) for human activity detection in a smart home environment [24]. Starting with an initial network composed of four neurons on a two-dimensional (2-D) grid, the GSOM network adapted during training to determine the winning neuron for each input data and updated the associated weight vectors. One drawback of this approach is that several parameters of the network need to be determined in advance through heuristic trial and error; hence, there is scope here to augment this approach with other machine-learning techniques. Apart from traditional learning methods such as the SVM, some recent machine-learning methods such as temporal neural networks, the hierarchical hidden semi-Markov model, and intertransaction association rule have been used for activity recognition in smart homes and assisted living spaces. Another machine-learning approach is to strategically combine knowledge from various sensors to validate the extracted knowledge and minimize false alarms in emergency detection. Tabar et al. combined wearable accelerometers based on a threshold-based method to detect sudden movements of the user [25]. These sudden events triggered an environmental camera within the space to perform position estimation using simultaneous visual observations and vision-based reasoning. These multisensor learning approaches dovetail well with the requirement for multiple heterogeneous sensors, as described in the previous section.

One challenge is to design algorithms in such a way that the required number of sensors for a given application is optimized [16]. Relying on too few sensors increases the likelihood of the algorithm producing false alarms, which is undesirable, especially in the case of emergency-aware applications. Conversely, an algorithm that relies on too many sensors increases complexity, causing energy and resource consumption for the target smart home system to rise.

Adaptive learning models like GSOM allow the learned algorithms to change and improve with the constantly changing physical environment [24]. For example, a two-occupant home can temporarily become a one-occupant home due to illness, travel, or a change in schedule, and sensors may be added or removed from the network arbitrarily. Therefore, fixed-learning models pose a challenge and can quickly become obsolete. Additionally, the framework should accommodate customizable models for different users; training for specific users will likely focus the accuracy of the learned model on the information that each individual provides, as opposed to expecting a generalized single model to fit a diverse, heterogeneous population. Therefore, an opportunity exists to automatically establish customizable learning models. Given the dynamic nature of the sensor network, transfer learning becomes an important opportunity, i.e., effectively transferring the user behavior and parameters learned through one set of sensors in one environment to another set of sensors in a new environment.

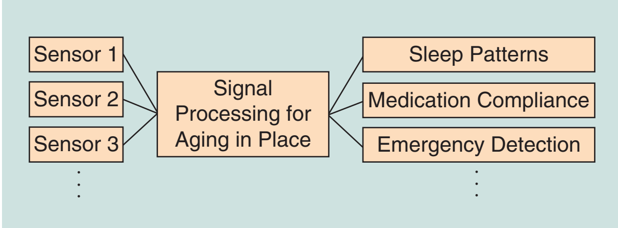

FIGURE 2. The objective of signal processing for aging in place.

Furthermore, large amounts of unlabeled data sets from in-home settings already exist; therefore, a research opportunity lies in improving automatic or semiautomatic labeling techniques of unknown or new data streams. Manual labeling of large volumes of data is not feasible or realistic, so algorithms that can label new data sets from the extracted knowledge gained from a small training set are highly attractive and desired.

A smart home collecting data about a user continuously and persistently via multiple sensors represents a valuable base for longitudinal studies. Evaluations of the performance of certain physical activities can be used to predict health conditions in the older population, while meaningful change detection over time is crucial for proactive health care. Active intervention to help users mold their habits and activities can be the key to proactive health care, as opposed to reactively attending to adverse events after they happen.

However, it is often difficult for users themselves to observe the subtle changes over time because chronic syndromes often progress very slowly and short-term observations may be quite noisy. Thus, an intelligent home-based system is required for continuous, longitudinal, and unobtrusive assessment of the life pattern changes of dwelling older adults. Moreover, by observing the changes over time, an algorithm can predict future trends and possibly avoid undesirable outcomes. In smart home environments, sensor data have been widely used for longitudinal and continuous study concerning daily activities, sleep patterns, gait velocity, and loneliness, among others.

Unusual routines of residents are identified by tracking their mobility and recognizing their daily activities (e.g., sleeping, grooming, and eating) based on the collected sensor data, resulting in an interesting observation on the statistically significant correlation between the changes of daily activities (e.g., mobility scores) and the changes in a clinical measure of global cognitive health [26].

Sleep patterns, a special case of daily activities, convey information critical for assessing human wellness. Mihailidis et al. focused on studying sleep patterns and proposed an approach to measure sleep hygiene of elders over a six-month period [15] in which both acute and slow changes in the sleep patterns are successfully identified. Considering the potential for gait velocity to predict morbidity and mortality, Hagler et al. estimated walking speed from noisy time and location data collected by a sensor line of restricted-view PIR motion detectors [27]. For the approaches presented in both of these works, there is still an open research opportunity to validate the measured trends with known clinical measures to ensure the recorded long-term data are beneficial. Besides the aforementioned unusual physical behavior, mental aspects such as loneliness are also closely related to increased morbidity and mortality, which may lead to decreased sleep quality and increased risk of cognitive decline [19]. Nevertheless, assessing loneliness in older adults is challenging due to the negative desirability bias associated with being lonely. To circumvent this problem, Austin et al. propose a system to measure loneliness by assessing in-home behavior using wireless motion sensors, contact sensors, and phone monitors [19].

One important challenge that these kinds of long-term studies face is the lack of a gold-standard ground truth for the target parameters. It is extremely difficult to track the true health condition of an older adult for long periods continuously without unduly inconveniencing the user. It is also a challenge to remain impervious to occasional external factors that can compromise the integrity of the data, such as motion artifacts or improperly worn sensors. This makes it even harder to validate the results from any new proposed analytical techniques and push the boundaries of longitudinal studies.

For information retrieval and mining of large-scale data, state-of-the-art database techniques should be employed to optimize the structure of data storage and accelerate the process of information retrieval. Cloud storage must also be taken into consideration for storing very-large-scale data, as long as the privacy and security issues of cloud storage can be addressed successfully. There are research opportunities here to develop feasible and scalable data organization and mining techniques. This also ties into data delivery, wherein the health-care provider must be able to quickly and easily access the required subset of user information from a large data set.

Information delivery paradigms and visualization

Given the human-centered nature of smart homes, information delivery to the user must remain seamless and effective. In smart home environments, the raw data collected via different sensors are overwhelming and may require domain-specific knowledge, which will introduce challenges in terms of data interpretability. Older adults with potentially diminished cognitive ability and scarce domain knowledge will be challenged to understand the overwhelming quantity of data. Moreover, the information delivery system may need to provide information not only to the care recipients but also to their caregivers, clinicians, and family members. This necessitates novel summarization techniques that leverage advanced algorithms to convert raw data into relevant, customizable, and comprehensible summaries for the different viewers. This provides the care recipients with insight into their health conditions and the caregivers the information to make knowledgeable clinical decisions.

An information delivery system typically consists of two components: algorithms for summarizing the information and an interface for information delivery. Data summarization is an important component, as the vast amounts of raw data from sensors need to be synthesized and formatted in such a way that the user can quickly and intuitively grasp actionable information. Summarization tools should provide sufficiently relevant information to the caregivers while considering the health conditions of the care recipients. These tools should not only work with large amounts of heterogeneous data and leverage machine-learning techniques but also remain cognizant of the clinical utility of the information delivered.

Furthermore, considering each care recipient's unique behavior can maximize the usefulness of the output; it is an essential task to design visualization tools that can deliver interpretable information in an accessible manner, especially for older adults with potentially diminished cognitive and sensory capacity. Thus, the paradigms must be thoughtfully designed with multiple pathways of delivery to robustly handle potential sensory impairments. Examples of different information delivery paradigms are shown in Figure 3.

When it comes to communicating the summarized information, the visualization formats can be quite diverse, ranging from a simple health score statistical visualization (e.g., plots and charts) to complicated 2-D or three-dimensional renderings of the complete smart home space. Thomas et al. present a suite of visualization tools called *PyViz* that uses algorithms to track the position of residents and provide an interactive graphical interface through which users can view the smart home system in real time and gain access to historical trends [28]. Chen et al. present a web-based visualization system (CASASviz) that takes this visualization technique one step further with a consumer-centric design [29]. Specifically, CASASviz applies data mining and machine-learning techniques to recognize user behavior patterns and detect unexpected changes that may be indicative of a decline in health status. Moreover, the visualization format of CASASviz can be customized to highlight the events of particular interest via a set of user-defined rules. Although CASASviz is among the earliest efforts to develop human- and consumer-centric visualization tools, research investigations on health visualizations from a consumer perspective remain scarce, especially for older adults. Age-dependent visualization has attracted research interest, taking normal, age-associated changes into consideration, such as deteriorated visual functions and reduced information processing efficiency [30]. For instance, graphical interfaces should remain as succinct as possible since older adults often have difficulties locating target items in a cluttered background. There is a research opportunity to explore intuitive delivery mechanisms beyond traditional displays. Visual information can be depicted in various forms, such as wall projections, smart lights, or even a single light-emitting diode customizable for various applications. Besides visual representation, information can also be delivered in other forms, including audio feedback and vibrotactile feedback.

Consumer-centric and disorder-specific visualization tools remain largely unexplored. Older adults with diverse health conditions and disorders may require more degrees of freedom to customize the information delivery according to their needs and capabilities. They may also want to prioritize viewing information that is relevant to their specific condition. However, the information delivery via current visualization techniques is generally fixed and ad hoc, and thus cannot be tailored to the specific requirements of different groups of older adults.

Finally, one important challenge is to cater to specific needs and display only the information of particular interest excluding redundant information at the right time. The information delivery methods must remain context-aware, which can help circumvent challenges associated with information overload that can ultimately lead to insensitivity to the information presented and negatively impact outcomes.

As previously mentioned, the privacy of personal information is a major concern in the context of smart homes for aging in place. Therefore, in any discussion of user interface and information delivery mechanisms we must also consider the privacy of the user. While there are many sophisticated algorithms and encryption mechanisms, care should be taken to ensure the right balance between protection of data and ease of use for senior citizens as well as any potential caregivers. User interfaces, like the one designed by Sivaraman et al. in which the user can choose between different security and privacy settings for different household devices, might be one of the solutions [22]. However, it can be argued that overzealous protection of information might hamper the overall goal of a health-monitoring smart system if users are not careful about the choices they make. So the challenge is not only to design user-friendly interfaces to protect privacy but also to provide proper privacy awareness among users.

An important research effort is the development of data obfuscation techniques to protect the fundamental privacy

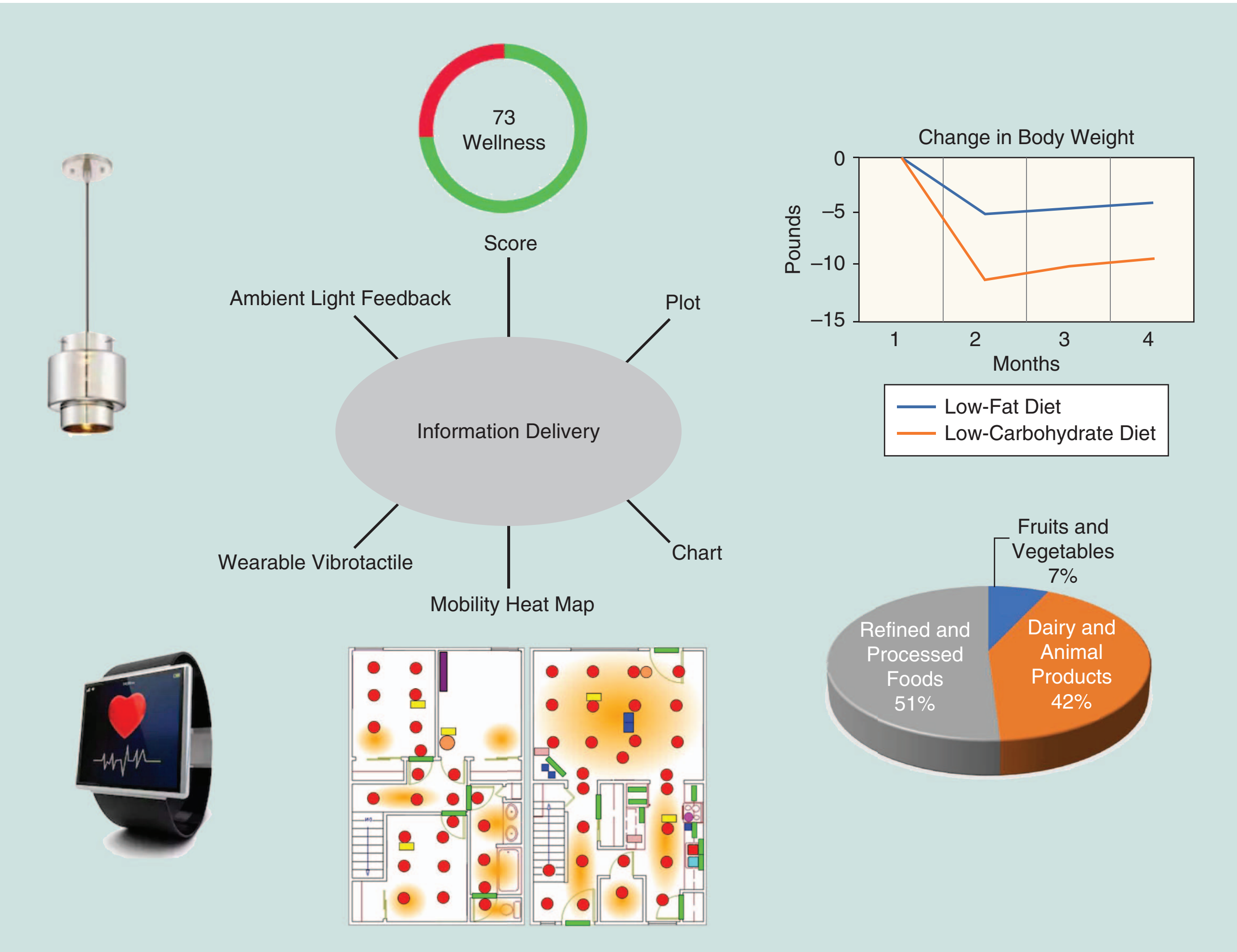

FIGURE 3. Different forms of information delivery. (The mobility heat map is from [29] and used with permission. Ambient light and wearable vibrotactile images courtesy of www.shutterstock.com.)

rights of the user while still providing health-care providers with sufficient actionable data.The use of lightweight authorization and encryption techniques for battery-operated devices is another research opportunity in this regard. Researchers should also consider designing contextual privacy-protection interfaces and devices to improve user discretion while keeping the balance between protection of personal information and the performance of the system in terms of achieving its goals. For example, the privacy-protection mechanism for an online purchase that could be viewed as typical should be different from that used for a transaction that would reveal important information about the user.

Conclusions

In this article, we identified some of the research challenges and opportunities associated with the key aspects of a smart home system with the objective of enabling aging in place. Many of the known problems in the fields of smart home sensing, signal processing, analytics, and visualization require solutions that are cognizant of the specific needs of the elderly. We highlighted several relevant recent works in the area to give the readers a perspective on the current status, while also presenting the necessary future directions of research to realize the vision of aging in place.

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