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# MOBILE TECHNOLOGY for ADAPTIVE AGING

PROCEEDINGS OF A WORKSHOP

Board on Behavioral, Cognitive and Sensory Sciences

Division of Behavioral and Social Sciences and Education

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## Preface

In 2004, the National Academies of Sciences, Engineering, and Medicine held a workshop on Technology for Adaptive Aging. Since that meeting, technology has evolved dramatically; in particular, mobile technologies have become more pervasive in U.S. society and a mainstream part of most peoples' lives. Such changes provide new opportunities for research on technology and aging. The National Academies Board on Behavioral, Cognitive, and Sensory Sciences was contracted by the National Institute on Aging (NIA) to convene a workshop in December 2019 to review research on mobile technologies and aging, and to highlight promising avenues for further research through a discussion about and compilation of six commissioned papers focused around mobile technology and adaptive aging. In particular, the NIA was interested in how mobile technologies could be used to support people in their everyday lives to help them live successful lives as they aged. A committee was appointed by the National Academies in April 2019.

### WORKSHOP PLANNING

Committee members first met in May 2019 with representatives from the National Academies and the National Institute on Aging to learn of the specific format and guidelines for the workshop, as well as specific NIA interest areas. A list of six topic areas for the workshop that were of interest to the NIA was produced at this meeting. The committee selected the authors for six commissioned papers to be presented at the workshop in December.



## THE WORKSHOP

The workshop was held on December 11 and 12, 2019 (see Appendix A for the workshop agenda). The primary objective of this meeting was to engage in meaningful discussions about how mobile technology can be employed to enhance the lives of older adults. An author from each of the six teams presented an overview of his or her commissioned paper, with discussion after each presentation. The workshop also included a panel of industry experts. The industry experts gave short overviews of their organizations and use of mobile technologies to advance aging, again followed by discussion. The committee intended that the workshop presentations and discussion, and the subsequent publication of the commissioned papers, would generate ideas for future research that could help NIA set an agenda in this area of study. This volume is the collection of the papers.

In the workshop's first presentation, Jessica Vitak stressed that privacy, security, and trust must be taken into account when designing studies that use mobile technologies, and also when analyzing data that are collected from various mobile devices. She noted the importance of digital literacy for study participants as well as researchers. Vitak also emphasized the challenges of using mobile devices in research, and the importance of finding ways to successfully navigate issues associated with mobile devices.

Karen Fingerma discussed the potential that information and communication technologies (ICTs) have to foster or support social relations among older adults. She emphasized the importance of social relations for survival, noting that both those who are isolated and those who are lonely have greater mortality. Fingerma reviewed various studies showing the beneficial effects of ICTs on social relations for older adults, and also noted research showing that technology does not necessarily substitute for in-person human social ties. Fingerma suggested one possible path forward is to focus efforts on individuals who do not use ICTs. She observed that another key question is whether ICTs should be used to complement existing ties or to help generate new ties for older adults. Another line of inquiry in this area indicated by Fingerma is access and design; she observed that ICTs can be very frustrating for individuals with cognitive impairment.

Diane Cook discussed ways in which sensor technology might promote aging in place, but also identified a range of opportunities to expand research using data gathered via sensors. These include enhancing diversity in samples; developing new and innovative technologies that adapt as people change; scaling up findings from smaller projects to see if they are reproducible in different and larger groups, and if impacts persist over time; decreasing costs of new technologies; and determining whether people continue to use devices after the research period ends. Cook also

discussed related challenges, such as identifying behavioral markers from raw sensor data, protecting user privacy, and ensuring that the technology is accessible to users.

Neil Charness focused on use and limitations of mobile technologies for interventions. One of the key issues Charness raised was the need for mobile monitoring systems to be tailored to participants in order to be successful. To advance research in this area, Charness suggests possible paths forward: avoiding small and unrepresentative older adult samples; ensuring adequate control groups to demonstrate efficacy; and including long-term assessment. Achieving these, however, will necessitate long-term funding for large, multisite studies. He also noted the need for better partnerships between academic researchers and industry to enhance usability, scalability, and deployment of mobile monitoring systems.

Elizabeth Murnane presented an overview of her commissioned paper that surveyed ways to gather data with sensors and mobile technologies. Murnane highlighted the importance of ensuring usability of devices among older adults. She noted that this includes interface elements (e.g., large touch targets, fonts, and screen sizes, as well as high contrast, simple interfaces, low manipulability, and enhanced and adaptive volume control) and interaction modalities that are more intuitive and natural. Minimizing information overload and delivering cognitively legible feedback are also important when using sensors and mobile technologies to attempt to change behavior. Murnane also noted the need for more common-format, interoperability, and reusable mHealth platforms.

In his presentation, Alvin Rajkomar noted that it is possible to use sensors to collect data from a lot of people, and while there is great potential in this volume, a variety of challenges affect generalizability of the studies being done. In addition, other types of data are typically needed besides sensor data in order to make predictions. Unless data are collected from various sources (types of sensors, groups, and places), there may be selection biases present, which could bias the machine-learning outcomes. However, he made the point that humans are equally or perhaps more biased than artificial intelligence.

We would like to acknowledge the contributions of those who were invited to participate in the industry panel, including Scott Moody, K4Connect; Jim Harper, SondeHealth; and Kyle Rakow, AARP. The National Academies staff facilitated all aspects of the committee's work. Special thanks go to Molly Checksfield, the study director, who facilitated the work prior, during, and after the workshop. She took over from Sujeeta Bhatt, who staffed the effort until September 2019. Jacqueline Cole handled the logistics for the committee and its invited guests at vari-

ous stages of the project. Barbara Wanchisen, BBCSS board director, and Adrienne Stith Butler, associate board director, provided guidance to the committee throughout its work.

Shelia Cotten, *Chair*  
Steering Committee for the Workshop on  
Mobile Technology for Adaptive Aging

## Acknowledgments

This Proceedings of a Workshop was reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the National Academies of Sciences, Engineering, and Medicine in making each published proceedings as sound as possible and to ensure that it meets the institutional standards for quality, objectivity, evidence, and responsiveness to the charge. The review comments and draft manuscript remain confidential to protect the integrity of the process.

We thank the following individuals for their review of this proceedings: Joseph Ali, Bloomberg School of Public Health, Johns Hopkins University; Lisa Huber, School of Public Health and the School of Education, Indiana University; Tracy L. Mitzner, Engineering Psychology and Cognitive Aging Program, Georgia Institute of Technology; Marilyn J. Rantz, Sinclair School of Nursing, University of Missouri; Blain Reeder, Sinclair School of Nursing, University of Missouri; and Eleni Stroulia, Department of Computing Science, University of Alberta.

Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse the content of the proceedings nor did they see the final draft before its release. The review of this proceedings was overseen by Kirsten Sampson Snyder, Division of Behavioral and Social Sciences and Education. She was responsible for making certain that an independent examination of this proceedings was carried out in accordance with standards of the National Academies and that all review comments were carefully considered. Responsibility for the final content rests entirely with the rapporteur and the National Academies.



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# 1

## Trust, Privacy and Security, and Accessibility Considerations When Conducting Mobile Technologies Research With Older Adults

*Jessica Vitak and Katie Shilton<sup>1</sup>*

### INTRODUCTION AND OVERVIEW

Information and communication technologies (ICTs)—including smartphones, tablets, and other mobile devices—provide a number of important social, emotional, and tangible resources to older adults. Aging is associated with increased social isolation and a subsequent decline in emotional well-being; ICTs may provide a social lifeline to those living in retirement communities or far from family (e.g., Brewer and Jones, 2015; Cotten et al., 2017; Gatto and Tak, 2008). ICTs can help older adults become more cognitively engaged through games, information seeking, and other activities (Koo and Vizer, 2019; Lu et al., 2017). As physical health and mobility decline, use of mobile devices provides older adults with more freedom by removing the geographical constraints associated with many normal activities, including grocery shopping, banking, and accessing medical records (Kötteritzsch and Weyers, 2016; Winstead et al., 2013). Finally, mobile devices can help caregivers and medical staff provide better care through monitoring and data collection (Kang et al., 2010; Kuerbis et al., 2017).

While older adults generally lag behind the general population in adopting new technologies, they represent an increasingly large proportion of users. In 2019, 91 percent of American adults age 65+ owned a mobile phone and 53 percent owned a smartphone (Pew Internet, 2019). Companies are increasingly designing and marketing mobile technologies

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toward older adults to help them age in place, stay connected with family and friends, and maintain a sense of independence. Likewise, existing technologies like wearables (e.g., fitness trackers) and personal digital assistants (e.g., Amazon Echo, Google Home) can be particularly helpful to older adults as they seek to maintain their health and live on their own (e.g., Nath et al., 2018).

Mobile technologies also provide researchers with a wide range of tools and methods for doing research with older adults. Sensors, mobile apps, digital assistants, and other technologies can collect passive and active data from users to improve care, provide assistance, and enhance their quality of life, and researchers have used such technologies to develop mobile health interventions for a wide range of physical and emotional health outcomes (Joe and Demiris, 2013). These devices can also help offset problems of accuracy and recall in data collection by providing “just-in-time” data collection through text messages, apps, and other mobile tools (Heron and Smyth, 2010).

At the same time, the use of mobile technologies by older adults introduces challenging privacy and security risks. The privacy and security of mobile data are complex topics. Mobile devices gather a broad spectrum of data about their users, ranging from in-application activity to communications to movement and location data generated by sensors in the phone, and those data are collected in ways that are not always clear to end users. For example, many applications on smartphones—including GPS/navigation, ride services, and fitness tracking—require location data to function, and many consumers will therefore opt-in to (or decline to opt-out of) widespread location tracking by their device. Location data can provide an exact accounting of where a person is located at any given time and are generally considered highly sensitive (Boshell, 2019). Beyond location data, people use their phones to generate and share sensitive data, including emails, text messages, and financial transactions, which could pose privacy and security risks.

Furthermore, the sensitive data generated by mobile devices are shared with a wider ecosystem that includes device manufacturers, telecommunication companies, and application companies, as well as third-party data brokers (Shilton, 2009). Although recent legislation in Europe and California provides individuals specific rights over their data, understanding those access and control rights is challenging—and which companies and researchers must adhere to the new regulations is still being fought over in the courts. And while application developers frequently give users choices about the privacy and security of their data, these choices can be cognitively and logistically difficult to navigate (Kelley et al., 2012; Madden, 2012).

Researchers collecting and/or analyzing data from mobile devices, particularly those working with older adults, must account for a wide range

of physical and cognitive abilities and tailor study design and participant protections to account for that variance. As Farage and colleagues (2012) note, designing for older adults should focus on simplicity, flexibility, and ease of use. In the case of mobile devices, this means considering how the size of the device and any text-based displays may create additional barriers to adoption and use and offering multiple formats for presenting and collecting data. Second, older adults are frequently less experienced users of mobile and digital technologies, and experience with these technologies is correlated with both trust in the systems as well as understanding of the privacy and security risks. Research suggests that older adults are more likely to experience fear or distrust of technology (Knowles and Hanson, 2018); this may lead to a lack of engagement or nonparticipation from some older adults (Waycott et al., 2016). Other research suggests older adults may engage in impression-management strategies during the research process to counter stereotypes about older adults' knowledge of technology or to provide socially desirable responses (Franz et al., 2018).

Because of the general risks to privacy and security from mobile devices, the specialized risks of research using mobile data streams, and the particular challenges of doing research with older adults, researchers at this intersection have an obligation to carefully consider their study design, paying particular attention to data collection, analysis, sharing, and storage policies. The relationship between these challenges is highlighted in Figure 1-1.

To guide this process of recognizing and responding to the specific challenges of conducting mobile device research with older adults, this chapter first reviews general privacy and security risks in the mobile data ecosystem. It then narrows its scope to the ways those general risks intersect with research among older adults, and maps best practices throughout the research life cycle to address these barriers. The paper also discusses the benefits and barriers to academic–corporate research partnerships in this space.

## PRIVACY AND SECURITY CHALLENGES IN THE MOBILE ECOSYSTEM

The unique privacy and security challenges of the mobile ecosystem have been extensively detailed in previous work (Boyles et al., 2012; Christin et al., 2011; Decker, 2008; Future of Privacy Forum, 2012; Greene and Shilton, 2017; Harris, 2013), and researchers should be aware of these challenges before asking older adults to engage in mobile device research.

First, mobile devices collect extremely intimate data, making them very useful for research but challenging for privacy and security. Data collected from mobile devices might document who a user contacts via voice or text, how frequently, and the content of those messages; a variety of leisure activities ranging from shopping to games to reading; and the location of a

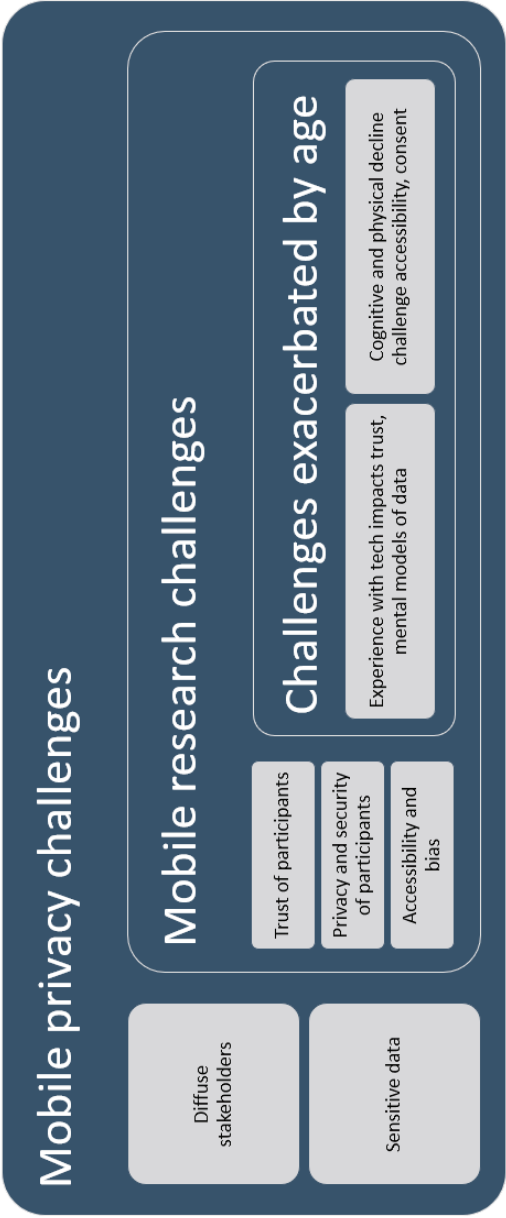


FIGURE 1-1 Nested ethical challenges of conducting mobile research with older adults.

user's home and work, as well as any other stops they make along the way. Mobile phones and wearables can intuit sleep and wake times, document searches for symptoms or concerns, and record social media activity. In most cases, the data are synced with external servers automatically, requiring no input from the user; while this improves user experience, people may easily forget—or not realize—the digital traces they share with companies throughout each day.

Next, both privacy and security of mobile data are complicated by the sheer number of data stakeholders in the mobile ecosystem. Application developers—who might range from individuals to academic researchers to huge corporations—make choices about what data to collect, how long to keep them, and how well to secure them. They may also decide to monetize user data by selling them to third-party data brokers or advertising companies. These decisions are subject to soft regulation from application marketplaces (Greene and Shilton, 2017), which generally require that users be notified of—and consent to—data collection (a minimum bar for privacy). Similar data may also be collected by device manufacturers and telecommunications companies in addition to application developers. While consumers in Europe and California have increasing rights to both the visibility of their data and restrictions on their sharing—and the U.S. Congress has been debating new privacy legislation throughout 2019—these laws are quite new (and in the case of U.S. federal legislation, still in draft form), and enforcing compliance will remain an ongoing hurdle for the foreseeable future.

Until consumer legislation is strengthened, enforced, and universally applied, researchers should be aware that asking older adults to increase data collection on mobile devices may put data in the hands of unknown third parties, ranging from telecommunications companies to shadowy data brokers. Careful mobile application design can mitigate some, but not all, of these concerns. See work by the Center for Democracy and Technology (2011) and the Future of Privacy Forum (2012) for detailed recommendations on creating privacy policies and disclosures, ensuring accessibility of content, notifying end users about changes in data collection practices, sharing data with outside parties, and more.

### **Challenges for Mobile Data Research with Older Adults**

U.S. researchers doing mobile device research with older adults have an obligation to fully inform participants of the implications of research participation, protect participants from the risks of participation, and ensure equitable access to research (Federal Register, 2017). Similar obligations apply to researchers in Canada, the UK, Australia, and the EU. However, characteristics of the research population intersect with the general chal-

lenges of mobile privacy and mobile device use in ways that particularly challenge informed consent, risk, and equity.

Privacy is frequently defined in both legal and commercial sectors as individual control over personal data (Solove, 2010). However, empirical and legal research increasingly challenges this definition (Nissenbaum, 2009; Martin and Nissenbaum, 2016). This research emphasizes privacy as the *appropriate* use of data within a given social or societal context, where appropriateness is governed by established values and social norms of a context.

We argue that avoiding a definition of privacy focused on individual control over data is particularly important for mobile data research with older adults. Ensuring privacy by asking participants to make complex decisions about the uses of their data introduces high cognitive and logistical overhead to a project and places the burden for privacy protection on participants rather than researchers. This is inappropriate for any research but particularly for research with older adults. Because older adults are frequently less experienced users of mobile devices, they may have incomplete mental models of what mobile data can be used to infer, who might access that information, and what the real risks of engaging in mobile data research might be.

According to a national study of American adults by Pew Internet (Auxier et al., 2019), the majority of Americans report having little to no knowledge about what companies or the government do with data they collect; furthermore, Americans generally feel they lack control over who can collect personal data. Compared to younger adults, older Americans report feeling less in control over their location data, search terms, online purchases, browsing behaviors, text messages, and social media posts (Auxier et al., 2019). At the same time, older adults are much less likely to believe their online and mobile activities are tracked than younger adults, which may lead them to make less-informed decisions about sharing personal data (Auxier et al., 2019).

These challenges of experience and understanding may impact older adults' trust in the research process and willingness to participate. In addition, age-related cognitive and physical decline may impact both the accessibility of research projects for participation and participants' ability to meaningfully consent to complex, granular data collection. The following sections discuss challenges to informed consent and trust, privacy and security risks, and accessibility and bias, and suggest best practices to mitigate concerns in each area.

### Addressing Challenges to Informed Consent and Trust

Trust is a critical component in any research setting, but it becomes even more important in situations where there may be knowledge or power

gaps, such as when one is conducting technology-based research with older adults. For example, Serrano and colleagues (2016) looked at the use of mobile devices for collecting health data and found that older adults were less willing to share data through mobile devices; more broadly, study participants were less willing to share sensitive health data over mobile devices compared to nondigital methods. Research also indicates that distrust in big data research is an even larger issue among marginalized communities; in a large study in the United States, Madden et al. (2017) found that older Americans with lower levels of income and education expressed greater concerns about information (and physical) privacy and security. Similarly, communities already targeted for increased surveillance (e.g., foreign-born Latinxs in the U.S.) recognize that participation in pervasive tracking could put them at greater risk.

A careful informed consent process is critical to building trust with mobile research participants. With improvements in mobile data collection and analysis techniques, researchers and ethics review boards are debating best practices for obtaining informed consent (see, for example, Vitak et al., 2016, 2017). In the U.S., new guidance from the Office for Human Research Protections emphasizes the allowability of electronic consents (eConsent) but has specified that it may not be appropriate for populations who “have difficulty navigating or using electronic systems because of, for example, a lack of familiarity with electronic systems, poor eyesight, or impaired motor skills.” (U.S. Department of Health and Human Services et al., 2016, p. 4). Informed consent—whether paper based or electronically mediated—is further complicated because a large amount of data is being collected in the background by sensors, mobile phones, and application programming interfaces. This raises questions about both breadth and duration of data being collected, as well as whether participants can fully understand the inferences that can be made from granular data, and the resultant risks such data pose. While popular press accounts (e.g., Valentino-DeVries et al., 2018) are gradually educating consumers about the risks of device use and data collection, older adults with less technology experience may still find such inferences surprising.

An additional challenge is determining when informed consent to *existing* data use is needed at all. Studies that scrape content from social media platforms or online communities, or those that use data already collected by commercial mobile applications, raise questions about whether secondary consent for research is needed. Research by Vitak and colleagues (2016, 2017) highlights disagreements among the research community over whether informed consent for such projects is feasible, as well as variations in how institutional review boards in the U.S. evaluate research using large datasets.

## Best Practices for Obtaining Meaningful Informed Consent

Guaranteeing meaningful informed consent for older adults is not a simple matter. The first challenge is to maximize older participants' comprehension of the study's procedure, risks, and benefits. Research with adults has shown that comprehension of standard informed consent processes is frequently low (Nishimura et al., 2013), and older adults are less likely to fully understand data collection practices involving mobile devices (Choi and DiNitto, 2013; Schreurs et al., 2017). Overly technical descriptions of data collection and analysis procedures are especially problematic for older adults because research has consistently shown that they lag behind the general population in digital literacy and skills and may lack the support network to assist them in developing those skills (e.g., Schreurs et al., 2017; Wagner et al., 2010).

There are several options for maximizing comprehension during the informed consent process of any study. In order to ensure that participation includes older adults with cognitive impairments, researchers should develop study materials to allow proxies to assist participants in completing the study, interact with participants across multiple sessions, and provide clear benefits for participation (Bonnie, 1997). When possible, consent should be conducted in person, and the document should be readable—both in document design and complexity of text. Relying on mobile consent procedures introduces additional risks that older adults may not be able to easily navigate documents or read and comprehend materials and should be avoided. Researchers might consider providing examples of the data they are collecting and clearly listing the sorts of inferences they plan to draw. Researchers should also consider analogies that can help inexperienced mobile device users to build better mental models of how the devices collect data and what the data can reveal about participants. Offering alternate versions of the consent document, including audio and/or video versions of the consent information, may be useful for participants with vision or other disabilities.

In addition to having formal consent documentation, researchers may want to create a second document that provides a straightforward list of risks and benefits to participation, as well as options for discontinuing participation or having their data removed from the dataset. Even if content is written at an appropriate reading level, older adults may need additional time to read through study materials and may have questions for researchers (Alt-White, 1995). In some cases, researchers should carefully consider whether a potential participant has the cognitive capacity to make decisions regarding participation (Kim et al., 2001); in cases where a proxy is used, researchers should still try to obtain assent from the participant.

## Best Practices for Building Trust with Research Participants

There are several ways to build trust in mobile data research beyond the informed consent process. First, we encourage investigators to reflect on questions of data ownership. Data ownership is a complex legal and social issue. Currently, technology users have little legal ownership over data produced by platforms and technologies due to terms of service contracts that give ownership to companies; we advocate a different model for researchers. Researchers should consider writing consent documents so that older adults understand themselves to be the primary guardians of their data. For older adults who may struggle to feel empowered in their technology use, framing their data as an asset they control and contribute can increase their sense of ownership in the research.

Researchers can also improve the trust of older participants in their project by focusing on the utility of mobile research for this demographic. Research shows that older adults may perceive newer technologies as unnecessary and are less likely to take the effort to learn about them (Lee and Coughlin, 2015; Turner et al., 2007). By engaging participants in discussions of why mobile devices are a uniquely useful and effective research tool, researchers can build participant trust and engagement in the process.

Next, we suggest investigators think of consent for older adults as an ongoing informational process, rather than a single occurrence. Because older adults may struggle with incomplete mental models of how data are collected, stored, and analyzed, researchers should look for ways to make sure that participants understand (1) data flows and (2) research process and goals *throughout the study*. This might include the use of large icons or pop-up reminders on the mobile device interface to indicate ongoing data tracking; providing a dashboard for participants to view some or all of their collected data; or providing regular project communications and updates tailored to the research population. In one example of this, Barron and colleagues (2004) describe testing a smartphone app that encouraged physical activity; in their study, they ran three rounds of data collection, making adjustments to the app's interface after each round of data collection based on feedback from older adult participants. Researchers should also consider ways to give older participants control over data collection, including the ability to turn collection on and off, or to delete data before sharing it with researchers.

We also encourage investigators to consider more participatory forms of research. Citizen science techniques for engaging participants throughout the research process can include opportunities to co-design activities for data collection apps, focus groups to engage participants in setting research goals and developing research questions, and opportunities for individuals to analyze their own data and see their data compared to those of others in



the study (Pandya, 2012). These techniques are particularly effective with older populations, who may have more time available to participate in co-research activities, and who can particularly benefit from the technology literacy such engagement sessions can provide.

Finally, researchers can build trust with participant populations by behaving in a trustworthy manner with participants' data. We suggest adhering to *privacy by design* as a project goal. Privacy by design is an orientation toward research and technology development that emphasizes privacy as built into every element of a technology or protocol (Cavoukian, 2012). Ensuring that privacy is embedded into study design and any technologies developed for the study is a multistep process, which we describe in more detail in the next section.

### Addressing Privacy and Security Risks in Mobile Research with Older Adults

Practicing data privacy and security by design in mobile data research with older adults involves attention to protecting participants' data at each stage of the data life cycle: collection, storage, analysis, and deletion. We encourage researchers to craft a *data management plan* (Michener, 2015) to proactively spot privacy and security issues in their own projects and make plans to counter the issues. A data management plan for managing the data of older adults will likely not vary greatly from those for other adults; the technical means of securing sensitive data are similar across populations. However, because of the differences in expertise between researchers and older adults discussed earlier, researchers using mobile data about older adults have an increased duty of care for participant privacy and security.

Two major issues to consider during data collection are data minimization and dealing with personally identifiable information (PII). Data minimization is collecting only what is needed to answer the project's research questions. A key strategy for minimizing data collection is careful reflection on meaningful indicators. For example, is collecting a participant's location needed for an exercise-monitoring project if accelerometer data are collected? Collecting the bare minimum of data needed to satisfy a project's research questions minimizes the amount of data that could be exposed in a leak, used for reidentification, or shared by third parties. Researchers should also consider performing data processing on the mobile device when possible, sending only aggregated data or models to project servers. For example, instead of collecting all location data from older adults, researchers might consider using the mobile device to process GPS readings into "time at home" and "time away from home" and keeping only those aggregate characteristics while discarding the GPS trace. Collecting and sharing a minimal set of data can reassure older adults who may treat expansive data collection with suspicion or confusion.

Next, reflect upon what data a project will collect that could be considered PII. In a world of big data and linkable datasets, “personally identifiable” has become a broader term than names or Social Security numbers. For example, individuals might be identifiable through their location traces, particularly those who spend large amounts of time at an identifiable home or institutional address. Individuals may also be identifiable through aggregation of several data types; for example, Sweeney (2000) showed that combining gender, birthday, and zip code is often enough to identify someone. Even deidentified data are subject to reidentification attacks when they are combined with publicly available datasets (Narayanan and Shmatikov, 2008). Researchers should realize that few people—and especially older adults—fully realize the extent of reidentifiability of mobile data. Even if investigators have taken pains to minimize the amount of PII collected, they should not rely upon deidentification of mobile data as the main privacy or security safeguard, and they should not make inflated promises of confidentiality or anonymity to project participants.

Considerations for data storage can impact the data’s security. Best practices for all populations, but particularly vulnerable populations such as older adults, include encrypting data in storage on both devices and project servers, and limiting researcher access to those data. Projects should also consider access restrictions and storage protections for the application on participants’ mobile devices. Storage protections, such as passwords or lock codes on mobile devices, have tradeoffs for research among older adults. Secure passwords become more difficult to use as memory declines with age (Kowtko, 2014). Likewise, biometric identifiers, such as fingerprint unlocking available on smartphones, are easy to use but may have higher rates of failure among older adults (Kowtko, 2014). A recent study found pattern-based authentication techniques to be most usable among older adults (Grindrod et al., 2018).

Privacy measures can also be taken during data analysis. Most researchers already take steps to protect individuals in a dataset, commonly by reporting results in the aggregate. With the increased push by federal agencies and others to share data more widely—which supports a number of important research goals around replication and advancing science—new challenges arise to protecting individuals within a dataset. Researchers have consistently shown that standard deidentification techniques, such as removing sensitive variables from a dataset, do not effectively prevent reidentification of individuals (see Ohm, 2009, for a review). Furthermore, as more variables are removed from a given dataset, its utility decreases, making this process a less-than-optimal solution for advancing research. The current state of the art in technical privacy solutions is known as *differential privacy*, a technique that “ensures that the removal or addition of a single database item does not (substantially) affect the outcome of any analysis”

(Dwork, 2011). Differential privacy is especially useful for protecting datasets that will be shared more widely because it allows for robust analyses without putting individuals at risk of reidentification. See Cheruvu (2018) for a high-level overview of how differential privacy works.

Finally, researchers should plan for how data will be deleted at the end of a study. This includes managing deletion of data stored on participants' devices as well as any data on servers or in the cloud. If complete deletion is difficult or impossible due to the number of intermediaries who have stored the data, this limitation should be clearly specified to participants during the consent process. Researchers should also consider whether they will allow participants to actively delete data (or request data deletion) during the study itself. Older adults may need particular guidance on user interfaces for deleting data or requesting data deletion.

### **Addressing Challenges of Bias in Research With Older Adults**

For researchers using mobile devices and mobile data collection, concerns extend beyond the privacy and security risks of mobile data. Study design reliant on mobile technology may also introduce issues of accessibility and bias. In this section, we discuss challenges to accessibility and bias in studies with older adults and mobile technologies.

It is important that researchers carefully evaluate their study design and materials for biases and stereotyping. When studying technology adoption and use, stereotypes abound regarding older adults' aptitude for, use of, and attitudes toward ICTs. Wandke and colleagues (2012) identified six myths regarding older adults and technology use, including the belief that older adults are not interested in using ICTs and view them as useless, as well as the belief that older adults lack the physical and cognitive capabilities to use ICTs. These types of assumptions could negatively bias sampling (e.g., avoiding adults 80+ or in nursing homes), protocol materials (e.g., not asking participants about certain technologies, not having them directly interact with ICTs), or interpretation of findings (e.g., making generalizations about all older adults).

It is also important for the study design to minimize any effect that stereotypes held by older adults regarding ICTs may have on their participation. Older adults may be hesitant to use mobile technologies because of a lack of experience or negative past experiences (see, for example, Comunello et al., 2017). Both attitudes may negatively affect older adults' willingness to participate in research on mobile devices as well as how they interact with technologies, so researchers should consider ways of framing their study and any artifacts that might be used in the study to address these attitudes.

Finally, for researchers using existing data by partnering with mobile companies or platforms, considerations of the representation of older adults

in mobile datasets is an issue. Though the penetration of mobile devices among older individuals is increasing, just over half of U.S. adults 65 and older owned a smartphone in 2019 (Pew Internet, 2019). Almost half of all seniors in the U.S. would be left out of many existing datasets, and those left out of the data may also be marginalized in other ways.

### BEYOND DATA COLLECTION: CONSIDERATIONS FOR ACADEMIC–CORPORATE PARTNERSHIPS

As noted earlier, numerous companies are involved directly or indirectly in developing hardware, software, and other mobile tools for older adults, and the rich data these tools collect could advance our understanding of older adults' relationship with mobile technologies. Therefore, we encourage researchers and companies to focus on collaborations that enable academic researchers access to corporate data that would be difficult—if not impossible—to obtain otherwise. Partnerships with major companies like Apple, Google, and Microsoft could advance research on a wide range of health and wellness outcomes for older adults, improving quality of life both for those aging in place and for caregivers providing assistance as adults age.

That said, we acknowledge that there are significant barriers to researcher–industry collaborations that must be overcome, including corporate concerns about intellectual property and academic concerns about data access restrictions. In the aftermath of controversies that blurred the lines between corporate and academic uses of data, from Facebook's "emotional contagion" study (Selinger and Hartzog, 2016) to the revelations of improper data usage by Cambridge Analytica (Confessore, 2018), companies may be cautious about partnering with external researchers. In addition, companies may hesitate to partner with external researchers because of concerns related to research output, particularly any output likely to be critical of the company itself. Because of this, many companies may only partner with academics they already trust and require corporate sign-off of any data analyses or written reports.

In spite of these challenges, academic–corporate research partnerships are critical because of the quantity and quality of data; these companies have highly granular and longitudinal data that can be used to draw inferences and improve a range of outcomes. Given that a large percentage of the mobile technologies older adults use are targeted directly or indirectly at health and well-being, researchers can use data from mobile apps, wearables, and other devices to directly improve the health of and care for older adults. Furthermore, academic researchers can more narrowly focus on specific research questions and applications of the data that companies may have neither the time, energy, nor expertise to pursue.

The biggest hurdles to overcome in data sharing between companies and academics are ensuring the privacy and security of end-user data and meeting any legal requirements set out in the company's terms of use. The recent breakdown of Facebook's partnership with independent research commission Social Science One—a program that invited researchers to submit proposals to study misinformation and promised to share aggregated data related to elections with funded researchers—highlights how challenging secure data sharing can be at scale (see Alba, 2019, for an overview). In response to concerns about Facebook releasing sensitive personal information of users, the company began applying differential privacy algorithms to the data to ensure usability and privacy; however, as of fall 2019, Facebook and Social Science One have not been able to meet these competing demands. Other research by the Future of Privacy Forum (2017) suggests that while there are signs that companies are more open to academic partnerships, as of now they are largely limited to a small set of elite institutions and researchers. Companies are more likely to support research proposals that support the company's core mission, which may exclude important societal questions that fall outside of those goals.

Models for how corporate-academic partnerships can function do exist, and these could be used to guide future partnerships. Focusing on the role of mobile data in improving older adults' health outcomes, we can look at Apple's HealthKit and ResearchKit<sup>2</sup> as examples of applications that encourage individuals to voluntarily share their data with researchers and thus provide a platform for researchers to securely access and analyze those data. HealthKit is a developer framework embedded in Apple's mobile (iOS) and Watch (watchOS) operating systems that lets users share various types of data from the devices and third-party apps in an easy-to-read format through a dashboard. Individuals who want to participate in research studies can easily share their health data and can control the types of data they share. Apple's ResearchKit allows medical researchers to collect and analyze detailed and granular data from their patients unobtrusively through iPhones. Other organizations and applications have provided similar access to researchers; for example, the online platform PatientsLikeMe has procedures for allowing academic researchers to request access to their data.<sup>3</sup>

Recognizing that access to corporate data is difficult and may not be possible, nonprofits have begun to develop guidelines and frameworks to help researchers in their evaluation of mobile technologies. One example of this PsyberGuide,<sup>4</sup> a nonprofit organization focused on improving mental

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<sup>2</sup>For more information, see: <https://developer.apple.com/healthkit/> and <https://www.apple.com/researchkit/>.

<sup>3</sup>For more information, see: <https://www.patientslikeme.com/research/faq#qr3>.

<sup>4</sup>For more information, see: <https://psyberguide.org>.

health outcomes; it says its goal is to “provide accurate and reliable information free of preference, bias, or endorsement.” PsyberGuide evaluates mental health apps’ usability, credibility, and privacy practices and can help researchers make decisions about what mobile apps to use in their research. Other nonprofits like the Future of Privacy Forum can help researchers forge new relationships with companies and help companies navigate the privacy risks associated with data sharing.

## CONCLUSION

Performing research with older adults using mobile technologies places researchers and participants at a nexus of complex ethical issues. General concerns about the privacy, security, and accessibility of the mobile data ecosystem are exacerbated by the duty of care researchers owe to participants and the complex challenges of aging. In this chapter, we have highlighted a number of issues researchers should consider when conducting research in this space. Our suggestions focus on ensuring accessibility and access for participants with a wide range of potential physical and cognitive limitations, reducing potential bias in research, and building trust throughout the research process. We provide specific suggestions for protecting participant data during and after data collection and communicating procedures effectively to older adults throughout the process. We advocate for researchers to embrace “nontraditional” research methods, such as employing citizen science methods of data collection to both empower older adults and provide them with more control over their data. Finally, we encourage researchers to continue to develop relationships with companies and other organizations that can enable collection and analysis of richer datasets and provide more meaningful insights into the core research questions guiding this research community.

## REFERENCES

- Alba, D. (2019, September 29). Ahead of 2020, Facebook falls short on plan to share data on disinformation. *The New York Times*. Available: <https://www.nytimes.com/2019/09/29/technology/facebook-disinformation.html>.
- Alt-White, A.C. (1995). Obtaining “informed” consent from the elderly. *Western Journal of Nursing Research*, 17, 700–705. <https://doi.org/10.1177/019394599501700610>.
- Auxier, B., Rainie, L., Anderson, M., Perrin, A., Kumar, M., & Turner, E. (2019). *Americans and privacy: Concerned, confused and feeling lack of control over their personal information*. Washington, DC: Pew Internet Project. Available: <https://www.pewresearch.org/internet/2019/11/15/americans-and-privacy-concerned-confused-and-feeling-lack-of-control-over-their-personal-information/>.
- Barron, J.S., Duffey, P.L., Byrd, L.J., Campbell, R., & Ferrucci, L. (2004). Informed consent for research participation in frail older persons. *Aging Clinical and Experimental Research*, 16, 79–85. <https://doi.org/10.1007/BF03324536>.

- Bonnie, R.J. (1997). Research with cognitively impaired subjects: Unfinished business in the regulation of human research. *Archives of General Psychiatry*, 54, 105–111.
- Boshell, P.M. (2019, March 25). The power of place: Geolocation tracking and privacy. *Business Law Today*. Available: <https://businesslawtoday.org/2019/03/power-place-geolocation-tracking-privacy/>.
- Boyles, J.L., Smith, A., & Madden, M. (2012). *Privacy and data management on mobile devices*. Washington, DC: Pew Internet & American Life Project. Available: <http://www.pewinternet.org/Reports/2012/Mobile-Privacy.aspx>.
- Brewer, R.N., & Jones, J. (2015). Pinteresce: Exploring reminiscence as an incentive to digital reciprocity for older adults. *Proceedings of the 18th ACM Conference Companion on Computer Supported Cooperative Work & Social Computing* (pp. 243–246). New York: ACM. <https://doi.org/10.1145/2685553.2699017>.
- Cavoukian, A. (2012). *Operationalizing privacy by design: A guide to implementing strong privacy practices*. Office of the Privacy Commissioner of Canada, Ontario, Canada. Available: <http://www.privacybydesign.ca/index.php/paper/operationalizing-privacy-by-design-a-guide-to-implementing-strong-privacy-practices>.
- Center for Democracy and Technology. (2011). *Best practices for mobile applications developers*. Available: <http://www.cdt.org/blogs/2112best-practices-mobile-applications-developers>.
- Chervu, R. (2018, November 19). A high-level introduction to differential privacy. *Towards Data Science* (blog). Available: <https://towardsdatascience.com/a-high-level-introduction-to-differential-privacy-edd20e6adc3b>.
- Choi, N.G., & DiNitto, D.M. (2013). The digital divide among low-income homebound older adults: Internet use patterns, eHealth literacy, and attitudes toward computer/Internet use. *Journal of Medical Internet Research*, 15(5), e93. <https://doi.org/10.2196/jmir.2645>.
- Christin, D., Reinhardt, A., Kanhere, S.S., & Hollick, M. (2011). A survey on privacy in mobile participatory sensing applications. *Journal of Systems and Software* 84, 1928–1946. <https://doi.org/10.1016/j.jss.2011.06.073>.
- Comunello, F., Fernández Ardèvol, M., Mulargia, S., & Belotti, F. (2017). Women, youth and everything else: Age-based and gendered stereotypes in relation to digital technology among elderly Italian mobile phone users. *Media, Culture & Society*, 39, 798–815. <https://doi.org/10.1177/0163443716674363>.
- Confessore, N. (2018, April 4). Cambridge Analytica and Facebook: The scandal and the fallout so far. *The New York Times*. Available: <https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html>.
- Cotten, S.R., Yost, E., Berkowsky, R., Winstead, V., & Anderson, W. (2017). *Designing technology training for older adults in continuing care retirement communities*. Boca Raton, FL: CRC Press.
- Davidson, J.L., & Jensen, C. (2013). Participatory design with older adults: An analysis of creativity in the design of mobile healthcare applications. *Proceedings of the 9th ACM Conference on Creativity & Cognition* (pp. 114–123). New York: ACM. <https://doi.org/10.1145/2466627.2466652>.
- Decker, M. (2008). Location privacy—an overview. *Proceedings of the 2008 7th International Conference on Mobile Business* (pp. 221–230). IEEE Computer Society Press. <https://doi.org/10.1109/ICMB.2008.14>.
- Dwork, C. (2011). Differential privacy. In H.C.A. van Tilborg & S. Jajodia (eds.), *Encyclopedia of Cryptography and Security* (second ed., pp. 338–340). Springer.
- Farage, M.A., Miller, K.W., Ajayi, F., & Hutchins, D. (2012). Design principles to accommodate older adults. *Global Journal of Health Science*, 4, 2–25. <https://doi.org/10.5539/gjhs.v4n2p2>.
- Federal Register. (2017, January 19). Rules and regulations. *Federal Register*, 82(12), 7149–7274.



- Franz, R.L., Baecker, R., & Truong, K.N. (2018). "I knew that, I was just testing you": Understanding older adults' impression management tactics during usability studies. *ACM Transactions on Accessible Computing (TACCESS)*, 11(3), 1–23. <https://doi.org/10.1145/3226115>.
- Future of Privacy Forum. (2017). *Understanding corporate data sharing decisions: Practices, challenges, and opportunities for sharing corporate data with researchers*. Available: <https://fpf.org/2017/11/14/understanding-corporate-data-sharing-decisions-practices-challenges-and-opportunities-for-sharing-corporate-data-with-researchers/>.
- Future of Privacy Forum and Center for Democracy and Technology. (2012). *Best practice for mobile application developers*. Available: [http://www.futureofprivacy.org/wp-content/uploads/Best-Practices-for-Mobile-App-Developers\\_Final.pdf](http://www.futureofprivacy.org/wp-content/uploads/Best-Practices-for-Mobile-App-Developers_Final.pdf).
- Gatto, S.L., & Tak, S.H. (2008). Computer, internet, and e-mail use among older adults: Benefits and barriers. *Educational Gerontology*, 34, 800–811. <https://doi.org/10.1080/0360127080243697>.
- Greene, D., & Shilton, K. (2017). Platform privacies: Governance, collaboration, and the different meanings of "privacy" in iOS and android development. *New Media & Society*. <https://doi.org/10.1177/1461444817702397>.
- Grindrod, K., Khan, H., Hengartner, U., Ong, S., Logan, A.G., Vogel, D., Gebotys, R., & Yang, J. (2018). Evaluating authentication options for mobile health applications in younger and older adults. *PLOS ONE*, 13(1), 1–16. <https://doi.org/10.1371/journal.pone.0189048>.
- Hallinan, B., Brubaker, J.R., & Fiesler, C. (2019). Unexpected expectations: Public reaction to the Facebook emotional contagion study. *New Media & Society*. <https://doi.org/10.1177/1461444819876944>.
- Harris, K.D. (2013). *Privacy on the go: Recommendations for the mobile ecosystem*. Sacramento, CA: California Department of Justice.
- Heron, K.E., & Smyth, J.M. (2010). Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. *British Journal of Health Psychology*, 15, 1–39. <https://doi.org/10.1348/135910709X466063>.
- Joe, J., & Demiris, G. (2013). Older adults and mobile phones for health: A review. *Journal of Biomedical Informatics*, 46, 947–954. <https://doi.org/10.1016/j.jbi.2013.06.008>.
- Kang, H.G., Mahoney, D.F., Hoenig, H., Hirth, V.A., Bonato, P., Hajjar, I., Lipsitz, L.A., & Center for Integration of Medicine and Innovative Technology Working Group on Advanced Approaches to Physiologic Monitoring for the Aged. (2010). In situ monitoring of health in older adults: Technologies and issues. *Journal of the American Geriatrics Society*, 58, 1579–1586. <https://doi.org/10.1111/j.1532-5415.2010.02959.x>.
- Kelley, P.G., Consolvo, S., Cranor, L.F., Jung, J., Sadeh, N., & Wetherall, D. (2012). A conundrum of permissions: Installing applications on an android smartphone. In J. Blyth, S. Dietrich & L.J. Camp (Eds.), *Financial cryptography and data security, lecture notes in computer science* (pp. 68–79). Berlin, Heidelberg: Springer.
- Kim, S.Y., Caine, E.D., Currier, G.W., Leibovici, A., & Ryan, J.M. (2001). Assessing the competence of persons with Alzheimer's disease in providing informed consent for participation in research. *The American Journal of Psychiatry*, 158, 712–717. <https://doi.org/10.1176/appi.ajp.158.5.712>.
- Knowles, B., & Hanson, V.L. (2018). Older adults' deployment of "distrust." *ACM Transactions on Computer-Human Interaction (TOCHI)*, 25(4), 1–25. <https://doi.org/10.1145/3196490>.
- Koo, B.M., & Vizer, L.M. (2019). Mobile technology for cognitive assessment of older adults: A scoping review. *Innovation in Aging*, 3(1), 1–14. <https://doi.org/10.1093/geroni/igy038>.



- Kötteritzsch, A., & Weyers, B. (2016). Assistive technologies for older adults in urban areas: A literature review. *Cognitive Computation*, 8, 299–317. <https://doi.org/10.1007/s12559-015-9355-7>.
- Kowtko, M.A. (2014). Biometric authentication for older adults. *IEEE Long Island Systems, Applications and Technology (LISAT) Conference* (pp. 1–6).
- Kuerbis, A., Mulliken, A., Muench, F., Moore, A.A., & Gardner, D. (2017). Older adults and mobile technology: Factors that enhance and inhibit utilization in the context of behavioral health. *Mental Health and Addiction Research*, 2(2). <https://doi.org/10.15761/MHAR.1000136>.
- Lindsay, S., Jackson, D., Schofield, G., & Olivier, P. (2012). Engaging older people using participatory design. *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1199–1208). New York: ACM. <https://doi.org/10.1145/2207676.2208570>.
- Lee, C., & Coughlin, J.F. (2015). PERSPECTIVE: Older adults' adoption of technology: An integrated approach to identifying determinants and barriers. *Journal of Product Innovation Management*, 32, 747–759. <https://doi.org/10.1111/jpim.12176>.
- Lu, M.H., Lin, W., & Yueh, H.P. (2017). Development and evaluation of a cognitive training game for older people: A design-based approach. *Frontiers in Psychology*, 8 (Article No. 1837), 1–15. <https://doi.org/10.3389/fpsyg.2017.01837>.
- Madden, M. (2012). *Privacy management on social media sites*. Washington, DC: Pew Internet Project. Available: <http://www.pewinternet.org/2012/02/24/privacy-management-on-social-media-sites>.
- Madden, M., Gilman, M., Levy, K., & Marwick, A. (2017). Privacy, poverty, and big data: A matrix of vulnerabilities for poor Americans. *Washington University Law Review*, 95, 53–125.
- Martin, D. (2007). Bureaucratizing ethics: Institutional review boards and participatory research. *ACME: An International E-Journal for Critical Geographies* 6, 319–328.
- Martin, K., & Nissenbaum, H. (2016). Measuring privacy: An empirical test using context to expose confounding variables. *Columbia Science and Technology Law Review*, 18, 176–218.
- Michener, W.K. (2015). Ten simple rules for creating a good data management plan. *PLoS Computational Biology*, 11(10), e1004525. <https://doi.org/10.1371/journal.pcbi.1004525>.
- Narayanan, A., & Shmatikov, V. (2008). Robust de-anonymization of large sparse datasets. *Proceedings of the 2008 IEEE Symposium on Security and Privacy* (pp. 111–125). Oakland, CA: IEEE. <https://doi.org/10.1109/SP.2008.33>.
- Nath, R.K., Bajpai, R., & Thapliyal, H. (2018). IoT based indoor location detection system for smart home environment. *Proceedings of the 2018 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1–3). <https://doi.org/10.1109/ICCE.2018.8326225>.
- Nishimura, A., Carey, J., Erwin, P.J., Tilburt, J.C., Hassan Murad, M., & McCormick, J.B. (2013). Improving understanding in the research informed consent process: a systematic review of 54 interventions tested in randomized control trials. *BMC Medical Ethics* 14, 28. <https://doi.org/10.1186/1472-6939-14-28>.
- Nissenbaum, H. (2009). *Privacy in context: Technology, policy, and the integrity of social life*. Stanford, CA: Stanford Law Books.
- Ohm, P. (2009). Broken promises of privacy: Responding to the surprising failure of anonymization. *UCLA Law Review*, 57, 1701–1778.
- Pandya, R.E. (2012). A framework for engaging diverse communities in citizen science in the U.S. *Frontiers in Ecology and the Environment*, 10, 314–317. <https://doi.org/10.1890/120007>.
- Pew Internet Project. (2019). Mobile Fact Sheet. Available: <https://www.pewresearch.org/internet/fact-sheet/mobile/>.

- Schreurs, K., Quan-Haase, A., & Martin, K. (2017). Problematizing the digital literacy paradox in the context of older adults' ICT use: Aging, media discourse, and self-determination. *Canadian Journal of Communication*, 42, 359–377. <https://doi.org/10.22230/cjc.2017v42n2a3130>.
- Selinger, E., & Hartzog, W. (2016). Facebook's emotional contagion study and the ethical problem of co-opted identity in mediated environments where users lack control. *Research Ethics*, 12, 35–43. <https://doi.org/10.1177/1747016115579531>.
- Serrano, K.J., Yu, M., Riley, W.T., Patel, V., Hughes, P., Marchesini, K., & Atienza, A.A. (2016). Willingness to exchange health information via mobile devices: Findings from a population-based survey. *The Annals of Family Medicine*, 14, 34–40. <https://doi.org/10.1370/afm.1888>.
- Shilton, K. (2009). Four billion little brothers?: Privacy, mobile phones, and ubiquitous data collection. *Communications of the ACM*, 52, 48–53. <https://doi.org/10.1145/1592761.1592778>.
- Solove, D.J. (2010). *Understanding privacy*. Harvard University Press.
- Sweeney, L. (2000). *Uniqueness of simple demographics in the U.S. population* (Technical Report No. LIDAP-WP4). Pittsburgh, PA: Carnegie Mellon University, School of Computer Science, Data Privacy Laboratory.
- Turner, P., Turner, S., & Van De Walle, G. (2007). How older people account for their experiences with interactive technology. *Behaviour & Information Technology*, 26, 287–296. <https://doi.org/10.1080/01449290601173499>.
- U.S. Department of Health and Human Services et al. (2016). *Use of electronic informed consent: Questions and answers. Guidance for institutional review boards, investigators, and sponsors*. Available: <https://www.fda.gov/media/116850/download>.
- Valentino-DeVries, J., Singer, N., Keller, M.H., & Krolik, A. (2018, December 10). Your apps know where you were last night, and they're not keeping it secret. *The New York Times*. Available: <https://www.nytimes.com/interactive/2018/12/10/business/location-data-privacy-apps.html>.
- Vitak, J., Shilton, K., & Ashktorab, Z. (2016). Beyond the Belmont principles: Ethical challenges, practices, and beliefs in the online data research community. *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW)*, (pp. 941–953). New York: ACM. <https://doi.org/10.1145/2818048.2820078>.
- Vitak, J., Proferes, N., Shilton, K., & Ashktorab, Z. (2017). Ethics regulation in social computing research: Examining the role of Institutional Review Boards. *Journal of Empirical Research on Human Research Ethics*, 12, 372–382. <https://doi.org/10.1177/1556264617725200>.
- Wagner, N., Hassanein, K., & Head, M. (2010). Computer use by older adults: A multi-disciplinary review. *Computers in Human Behavior*, 26, 870–882. <https://doi.org/10.1016/j.chb.2010.03.029>.
- Wandke, H., Sengpiel, M., & Sönksen, M. (2012). Myths about older people's use of information and communication technology. *Gerontology*, 58, 564–570.
- Waycott, J., Vetere, F., Pedell, S., Morgans, A., Ozanne, E., & Kulik, L. (2016). Not for me: Older adults choosing not to participate in a social isolation intervention. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, (pp. 745–757). New York: ACM. <https://doi.org/10.1145/2858036.2858458>.
- Winstead, V., Anderson, W.A., Yost, E.A., Cotten, S.R., Warr, A., & Berkowsky, R.W. (2013). You can teach an old dog new tricks: A qualitative analysis of how residents of senior living communities may use the web to overcome spatial and social barriers. *Journal of Applied Gerontology*, 32, 540–560, 2013. <https://doi.org/10.1177/0733464811431824>.



## 2

# Mobile Monitoring and Intervention (MMI) Technology for Adaptive Aging

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## INTRODUCTION AND OVERVIEW

Mobile monitoring and intervention (MMI) technology offers a promising way to provide interventions tailored to individuals and their current context. Ideally, the system would be capable of monitoring relevant aspects of physiology and behavior, making intelligent predictions about when and how to intervene, and then delivering timely interventions. This chapter outlines critical issues to consider for MMI, including whom to target, what measures to target, where to monitor and intervene, when to monitor and intervene, and how to monitor and intervene. We also discuss attitudinal barriers for aging adults and the challenge of promoting adherence to MMI systems.

We review recent studies, most employing smartphones with small, unrepresentative samples that include monitoring and prediction, though not intervention. Although there are many commercial apps for smartphones aimed at supporting health, they have unknown efficacy and generally are not well designed for aging adults, failing to consider changing needs for the young-old, middle-old, and old-old age groups. We find that MMI technology for aging adults is in its infancy, with few good examples showing efficacy or cost effectiveness. To move such technology toward maturity we

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suggest supporting studies that can enroll larger, more representative samples, and that can track system performance over an extended period (years) to assess efficacy for managing chronic conditions. Such studies might benefit from cooperation between federal agencies such as the National Institute on Aging (NIA) and the National Science Foundation (NSF) and might consider making use of existing longitudinal panels.

## FRAMEWORKS FOR MONITORING AND INTERVENTION FOR ADAPTIVE AGING

Our aim is to provide frameworks and recommendations for research on MMI systems by relying on recent (2015+) studies and reviews that assess efficacy for promoting adaptive aging. We focus primarily on studies of aging adults. We define mobile technology as devices that are wearable (e.g., internally: cardiac pacemaker; externally: smartwatches) or portable (e.g., smartphones, tablets that can fit in clothing or in accessories such as purses). In this chapter, we first introduce a framework for identifying the challenges for deploying MMI systems, then discuss attitudinal constraints on adoption. We then discuss frameworks for MMI, focusing on measurement, prediction, and intervention. We evaluate existing mobile apps and how they might promote adherence for diverse aging populations. This chapter ends with a discussion of how the RE-AIM framework can guide the development of MMI systems and closes by outlining potential research priorities.

Sensor-based monitoring technology, both fixed and mobile, offers advantages and disadvantages for intervening to promote improved well-being for our aging population. Unlike early “one-size-fits-all” interventions in behavioral clinical trials (e.g., Ball et al., 2002), sensor-guided interventions can generate tailored actions (e.g., Lustria et al., 2013). Usually fixed-location sensor systems (e.g., smart home sensor arrays) have the disadvantage that the user must be in a fixed location, though it is possible to envision blended fixed and wearable systems (Skubic et al., 2014). A significant advantage of MMI is that the system can move with the person. A smartwatch monitoring movement can prompt an immobile wearer to move after a lengthy interval of sitting no matter where they are (home, senior center). A significant disadvantage for MMI is that users must continually wear or carry devices on their person and keep them charged (Reeder and David, 2016).

Table 2-1 lists some of the challenges that arise when making the decision to deploy MMI technology.

Some questions relate to the ethics of MMI—that is, whether (“why” and “what”) and under what circumstances (“where” and “when”) MMI might be initiated. The unit of analysis is important (“who”), usually taken to be the monitored person, such as an older adult living alone. But that

**TABLE 2-1** Challenges in Mobile Monitoring and Intervention (MMI) Research and Practice

| Challenge        | Example Responses                                                                            | Constraints to Consider                                                                       |
|------------------|----------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| Why Monitor      | Prevent harm, promote well-being                                                             | Ethical, legal, self-determination for lifestyle, societal resources                          |
| Whom to Monitor  | Aging adult                                                                                  | Co-dependent dyads, caregiving teams                                                          |
| What to Monitor  | Physiological (e.g., blood pressure), psychological (e.g., cognition, well-being) indicators | Reactivity, lifestyle constraints                                                             |
| Where to Monitor | Home, work, everywhere                                                                       | Privacy, legal                                                                                |
| When to Monitor  | Continuous, intermittent intervals, self-chosen intervals                                    | Privacy, data transmission bandwidth, storage, data security                                  |
| How to Monitor   | Sensors, probe questions (e.g., ecological momentary assessment) for person, for proxy       | Power source, device, person and network capability and availability/reliability and security |

unit of analysis may miss the person–family and person–community contexts for MMI (see the chapter by Fingerma et al.), in line with the finding that caring for family members is a primary human social motivation (Ko et al., 2019). Limiting consideration to the older adult (and family) may also miss the issue of bystander capture: people being monitored who did not consent to being monitored.<sup>3</sup> The methodology for monitoring (“how”) is dealt with in other chapters in this volume.

Underlying many of the questions is consideration of privacy: whether older adults wish to be monitored and if so, what aspects of their behavior/physiology should be allowed, and how monitoring should occur. A population-representative survey of Americans found that older adult cohorts are more aware than younger cohorts about government monitoring but are less likely to view as “very sensitive” contents of email, text messages, and health information, and equivalently less sensitive about their Social Security number (Madden, 2014). Older cohorts are also less likely

<sup>3</sup>An example from one of our monitoring studies (Evans et al., 2016) is a worker who came into a telehealth-equipped home that was monitoring a heart failure patient. He stepped on a wireless weight scale and triggered an alert because of the increased weight over the patient’s baseline.

than younger adults to take appropriate measures to protect their privacy online, such as asking to have information removed, or anonymizing postings (Madden, 2014). A similar population-representative survey showed that older cohorts on Facebook are less likely to change their Facebook privacy settings: 33 percent of those age 65 and older have changed privacy settings compared to 64 percent of those age 18–29 years (Perrin, 2018). A year following entry into a study of unobtrusive monitoring (ISAAC), nondemented older adult volunteers and older adults with mild cognitive impairment (MCI) showed more concerns with privacy (concern that their information could be exploited) than at entry (Boise et al., 2013). However, 72 percent of participants still showed acceptance of monitoring.

If everyone valued privacy more than any potential gains from monitoring, there would be no basis for developing systems that might provide other benefits, such as prolonging independence or preventing harm. A survey of a diverse sample of aging American adults (45 years and older), showed a willingness (particularly among those with disabilities) to trade off privacy in favor of maintaining independence even for rather intrusive monitoring options, such as cameras (Beach et al., 2009). Still, in terms of sharing information from monitored activities, participants indicated they were more willing to do this with family members and health care providers than with researchers and least willing for insurance companies or government. There appears to be some generalizability across populations. In a representative Swiss survey, 57 percent of those age 50 and older who tracked health data (28% of the sample) were willing to share data with researchers (Seifert, 2018). Such willingness to share data provides constraints on how MMI systems might be designed.

In summary, privacy concerns need to be addressed to encourage aging adults to adopt and use MMI systems. Adoption of “Fair Information Practices” such as the eight principles in the OECD Privacy Framework (2013) is one approach. Another related approach is to provide people with granular control over release of captured information (Caine and Hanania, 2013).

### Age and Technology Attitudes

Attitudes toward health monitoring technologies differ across age groups such that older adults tend to be more accepting than younger adults (Beach et al., 2009). Also, they tend to be primarily concerned about self-efficacy, or perceived ability to use the system (Lv et al., 2012).

Although older age had been associated with greater openness to adoption of health monitoring technology, when accounting for disability status, the effects of old age on openness are much smaller than those of disability status (Beach et al., 2009). If, therefore, the imminent threat of losing health or independence is one of the main motivating forces behind adoption of

health monitoring technology in old age, then preventive interventions for older adults may prove to be the most difficult to stage, as they would be met with the most hesitation. Without an obvious and apparent cause for concern, older adults may be reluctant to accept a new technology-based intervention, even though they remain at higher risk of health decline.

A variety of technology adoption models and variants, such as the Technology Acceptance Model (TAM: Davis, 1989), Universal Theory and Acceptance and Use of Technology (UTAUT: Venkatesh, Thong, and Yu, 2012), and the Senior Technology Acceptance Model (STAM: Chen and Chan, 2014), propose that adoption and use of technology depend on the trade-offs between benefits (e.g., perceived usefulness) and costs (e.g., perceived ease of use) as represented in such models (Charness and Boot, 2009). With respect to predicting concerns and actions by people for security and safety online, the protection motivation theory (Tsai et al., 2016) is also a useful framework.

One recent technology adoption model relevant to MMI is the smart wearable acceptance model (Li et al., 2019), which incorporates additional factors such as compatibility with existing electronics, perceived stigma, device performance (e.g., reliability), and health status. Challenges for compatibility with existing electronics might arise, for example, when trying to switch a user from their preferred smartphone to one with a different operating system. Given that older adults learn at about half the rate of younger adults (Charness et al., 2001), asking them to learn a new operating system may result in poor enrollment in, and adherence to, an MMI system.

### Intervention Framework

If we assume that older adults, who normatively have a variety of chronic conditions and impairments (Buttorff, Ruder, and Bauman, 2017), are willing to be monitored, and that systems can be devised that provide for adaptive interventions, what type of interventions are people likely to accept? One proposed hierarchy is “PRAS”—prevention, rehabilitation, augmentation, substitution—(Charness, 2019), which suggests that if prevention is insufficient and an impairment develops, people will prefer rehabilitation first, then augmentation to current capabilities (assistive devices, such as walkers, hearing aids), and lastly substitution (e.g., prosthetics that replace a failed function, such as pacemakers, cochlear implants).

### STATE OF THE SCIENCE FOR MEASUREMENT, PREDICTION, AND INTERVENTION USING MOBILE SYSTEMS

It is worth noting that any MMI system (a good example of a classical information processing system: Newell and Simon, 1972) will have multiple



components, including sensors, processors, algorithms to interpret sensor data, transceivers (transmitters and receivers), and data storage capabilities (see chapter by Cook). If intervention capabilities are built in, the system will have actuator components that can alert or communicate with the recipient (usually visual, auditory, and haptic output capabilities). A growing platform for monitoring health is the smartphone, which helped initiate the field of mobile health, or mHealth (see chapter by Murnane and Choudhury).

We did not locate any studies of MMI systems that incorporate the full chain of measurement, prediction, and just-in-time intervention for anyone, let alone older adults. A model system illustrating the full chain would be a cardiac pacemaker device. It monitors heart electrical activity, decides that it is irregular, and generates just-in-time pulses to regularize heartbeat). In the absence of studies looking at the full chain, we examine issues around each of the components, discussed next.

### Measurement

Much of the literature concerning measurement capabilities of MMI technologies that we uncovered consists of feasibility pilot projects aimed at developing MMI technology systems. Many of these programs do not test such technologies with older adults, probably because of concerns with safety during simulated fall testing (studies that ask people to simulate the range of fall types) and for convenience of development (e.g., use of a student dormitory for Radio-frequency identification [RFID] tag testing). These problems can be seen in a recent review of wearable sensors and Internet of Things (IoT) monitoring for older adults (Baig et al., 2019). The review by Baig and colleagues indicates the range of target behaviors for measurement (the “what” question in Table 1). Those authors found 14 studies (from 12 projects) between 2015 and 2019 that met inclusion criteria from an initial set of 327 studies. Seven had a focus on fall detection using wrist-worn devices or RFID tags. Others concerned monitoring Activities of Daily Living (ADLs) using smartwatches, smartphones, and smart insoles. Other studies reviewed used smart home environments with passive sensors to monitor ADL and Instrumental Activities of Daily Living (IADL) activity. Lastly, geriatric depression and dementia detection (through classifying “forget” events with front door openings) were the goals of two of the studies.

Based on examining some of the studies in that review, we suggest that future measurement system development for MMI systems include older adults in both the development and testing phases, though this may prove problematic for fall simulation studies.

### Prediction

A largely untapped research area is prediction/inference using mobile technology for older adults. By fusing data across time from multiple sensors and including data from active monitoring components, such as ecological momentary assessment (EMA) surveys, inferences can be made about behavior patterns (Harari et al., 2016).

By fusing data intelligently, systems can generate “mood sensors.” One study invited people to respond to EMA prompts about current mood (Sandstrom et al., 2017) and used phone sensors to determine where they were or directly queried their location with an EMA probe. That study relied on the general public (Android smartphone users) downloading an app ( $n = 12,310$ ) and, given age-related technology adoption lag, enrolled a sample where at least 78 percent of those who reported a birth year were below the age of 45, a young to middle-aged sample.

More sophisticated inferences have been drawn through modeling, using various classifier algorithms and deep learning on data sets that contain large amounts of temporally tagged personal data in order to forecast depressive affect in young and middle-aged adults (Suhara, Xu, and Pentland, 2017) and loneliness in older adults (Sanchez et al., 2015). However, having to use a supervised machine learning procedure (see chapter by Rajkomar) somewhat limits the scalability of the approach, because of the need to have a human in the loop to label/classify patterns.

### Intervention

Behavioral research studies we reviewed that use mobile device data typically do not intervene based on building up behavioral prediction models of study participants. Intervention is a logical next step. Perhaps because of lack of federal regulation, commercial enterprises have already entered the intervention space. Facebook experimentally manipulated mood for hundreds of thousands of its members by changing the information that a user saw in their news feed (Kramer, Guillory, and Hancock, 2014).

Nonetheless, once a model has been validated—for instance, that depressive affect has been detected and that it is predicted to worsen in a few days (e.g., Suhara et al., 2017)—it would make sense to provide referrals to professionals, or as research and technology advance, instantiate validated interventions, particularly to head off conditions that are potentially life-threatening. One such example is a model that predicts that a suicide or homicide attempt is likely, and intervenes accordingly by providing immediate access to a therapist. Suicides show a sharp increase at older ages for men, and older cohorts have also experienced some of

the largest suicide increases between 1999 and 2017 (e.g., > 50% for age 45–64; Hedegaard et al., 2018).

Another behavioral domain where prediction and intervention might be valuable for older adults is falls, given that about 29 percent of older adults reported experiencing a fall in the past year, and about 37 percent of those falls were serious enough to require medical treatment (Bergen, Stevens, and Burns, 2016). Balance and gait can be monitored and risk of falling assessed and detected (e.g., for fixed sensor systems: Rantz et al., 2015). If predicted risk rises above some threshold, the system could prompt the monitored person to seek help, or possibly, could provide validated rehabilitation exercises.

Loneliness and social isolation might present another such domain for MMI. About 20 percent of adults in the U.S. (16% of those age 65 and older) and in the U.K. report significant loneliness (DiJulio et al., 2018), with death of a loved one and health problems given as the top two reasons for loneliness. If a trend that indicates significant loneliness is detected, interventions might be offered via a software suite that aims to improve social connectivity, such as in the PRISM clinical trial (Czaja et al., 2017).

Another area for MMI is the management of chronic conditions. About 81 percent of those age 65 and older have multiple chronic conditions (Buttorff et al., 2017). Total population prevalence was about 60 percent for one or more such conditions in the U.S. A study of heart failure (Evans et al., 2016) is an example of where smart monitoring (examining data to detect deviations from baseline for blood pressure, weight, heart-failure questionnaire items) was used to generate text messages to home health nurses who contacted participants.

MMI might also provide help in managing medication schedules. The greater the number of chronic conditions, the greater the number of prescriptions (Buttorff et al., 2017), possibly leading to complicated medication schedules, though medication adherence is sometimes better in older adults than middle-aged ones (Park et al., 1999). Monitoring (e.g., smart caps for bottled prescriptions) and intervention (prompts to the target person) can be used to help people with medication adherence problems to take medications as prescribed, with prompting more successful ( $d = .5$ ) than not prompting ( $d = .2$ ; Conn et al., 2016).

Finally, supporting those with cognitive impairments due to normal aging and disease (e.g., mild cognitive impairment, dementia) may provide for greater independence and mitigate caregiver burden. If a significant trend of increasing cognitive impairment were detected through long-term individual monitoring, a prompt to seek professional care could be provided. Possibly, short-term interventions to assist people with dementia and their caregivers with everyday tasks could be organized by using Quality of Life Technology interventions such as virtual coaches (e.g., Schulz, 2012).

A recent study showed promise in using mobile monitoring to differentiate MCI and mild dementia from normal aging (Chen et al., 2019).

### IS THERE AN APP FOR THAT?

Google and Apple online stores feature hundreds of thousands of applications (apps) aimed at addressing nearly all aspects of health and disease, many with the goals of supporting MMI, including apps to help monitor and manage medication adherence, weight, nutrition, physical fitness, blood pressure, diabetes, sleep, and mood. Some apps track these activities and variables through self-report or sensors within the smartphone itself, while others rely on external sensors, including smartwatches, fitness trackers, telehealth devices, and web-cameras.

Two critical general issues include the safety and efficacy of interventions. (For other ways of evaluating apps on dimensions such as engagement, functionality, aesthetics, information quality, and subjective quality, see Choi et al., 2018.) Do these apps really benefit the user by improving their health and well-being, and if so, are these improvements long-lasting? And are there any potential negative consequences of use (e.g., risk of harm)? Unfortunately, there is not a large, high-quality evidence base to review, especially when it comes to long-term health outcomes. Further, the large and rapidly increasing number of health apps prevents regulatory agencies from thoroughly evaluating these issues for many technology-based interventions.

In the United States, the Food and Drug Administration (FDA) regulates medical devices. Recent guidance released by the FDA clarifies that health apps that fall under the category of medical device may be regulated only in cases in which there exists a potential risk to the user's safety should the app not work as intended (FDA, 2019). An app that uses gamification to motivate the engagement in physical therapy might fall under the definition of a medical device, but the risk of malfunction is unlikely to result in serious harm to the user. In contrast, an app that makes use of a mobile device's camera to image a skin lesion, and then uses an AI algorithm to make a classification of whether the lesion is dangerous, would be an example of a health app that the FDA would regulate. Should the algorithm be ineffective, the user can be harmed (e.g., cost of missing cancerous lesion or stress induced by a false alarm). Based on this guidance, many health apps are not FDA regulated, meaning that their efficacy is uncertain, and there is little incentive for app developers to conduct efficacy trials.

Specific to the issue of older adults, health apps (and peripheral devices associated with them) for the most part are not developed and designed considering the needs, preferences, and abilities of older adults. This can be seen in human factors evaluations of existing health-related apps. Morey

and colleagues (2019) reviewed popular apps with the aim of supporting medication adherence and managing heart failure. Expert evaluation uncovered deficiencies that would make these apps challenging for older adults to use, including small and hard-to-see buttons, difficult-to-navigate menus, confusing terminology, and other usability problems. Similar issues were identified in evaluating pain management apps (Bhattarai, Newton-John, and Phillips, 2017). Usability challenges have been noted in user testing as well (e.g., Wildenbos et al., 2019). Many studies have identified difficulties using hardware and software among older adults experiencing normative age-related changes in perception and cognition. Design guidelines do exist for how to reduce these challenges (Czaja et al., 2019). However, such challenges are likely to be greater for older adults experiencing cognitive impairment (e.g., MCI and dementia).

### Reminder Efficacy

MMI technology has the potential to greatly benefit the success of interventions at home and in the community by promoting adherence to healthy behaviors. Across a variety of domains, including pharmacological, behavioral, exercise, and nutrition interventions, adherence can be quite poor, resulting in a gap between the potential and actual benefit of a treatment. For example, 50 percent of individuals prescribed a medication for chronic conditions do not take that medication as prescribed (Brown and Bussell, 2011). MMI technology can serve two potential roles: 1) it can monitor whether a behavior (e.g., medication bottle was opened) has occurred, and 2) it can provide reminders to engage in behaviors (e.g., taking a medication at a certain time).

There is a long history of study of methods to improve adherence, for example, to health-related behaviors, and this has resulted in the publication of several systematic reviews. Although these reviews often focus on a broad age range, they are informative with respect to anticipating important issues older adults may face. With respect to medication management, Nieuwlaat et al. (2014) conducted a comprehensive review of general methods to improve adherence, and this was followed by a specific review of all adherence interventions that were mediated by technology (Mistry et al., 2015). Technology-based reminders included various telephone, text messaging, and software-based reminders, and remote monitoring included the use of telehealth devices and electronic drug monitoring. In general (for technology and nontechnology-based adherence interventions), this 2014 Cochrane report arrived at the pessimistic assessment: “Even the most effective interventions did not lead to large improvements in adherence or clinical outcomes” (p. 2). For a variety of reasons, one might expect technology-based adherence interventions to be more successful, but this more

focused review concluded that there was limited evidence for effectiveness, and that adherence-promoting technology “will need to improve if clinically important effects are to be realized” (p. e190). Both Nieuwlaet et al. and the Cochrane report noted the poor quality of many studies that have been conducted to date. Additional, high-powered, well-designed studies (with appropriate control group contrasts) are clearly needed. Further, as discussed later, “one-size-fits-all” interventions should be contrasted with personalized, customizable, and adaptive interventions to explore whether these types of interventions provide additional benefit.

Simons et al. (2016) reached similarly pessimistic conclusions about the efficacy of “brain training” cognitive interventions for impact on everyday functioning, for far transfer measures (e.g., driving safety) compared to near transfer ones (improved performance on the training games). Given concerns with sample inclusion/exclusion rules that tend to exclude comorbid older adults (He et al., 2016), small sample sizes, lack of adequate control groups, and lack of long-term assessment, a cautious conclusion is that the Scottish verdict “not proven” best describes the efficacy of MMI systems.

Beyond efficacy, there is also the issue of cost effectiveness. The largest-scale clinical trial (N = 3230 people with diabetes, COPD, or heart failure) conducted by the National Health Service in the U.K. (Steventon et al., 2012) showed that a telehealth intervention for chronic conditions was not cost effective compared to usual treatment (Henderson et al., 2013), primarily because of equipment costs. Technology costs usually diminish over time (a recent exception being the cost of “flagship” smartphones in the past few years), potentially altering that conclusion as technologies become more affordable.

## INTERVENTION STRATEGIES

Traditional intervention strategies often follow a one-size-fits-all approach, with the dose of the intervention identical or similar across individuals and changing infrequently over time. An exercise intervention, for example, might have individuals engage in a walking program in which participants are asked to walk a certain amount of time for a certain number of days each week. Likewise, an individual with hypertension could be prescribed medication at a dose that is adjusted over time based on occasional blood pressure readings. These interventions have the potential, unfortunately, to ignore the varying needs and attributes of the individual and might be insensitive or slow to adapt to the time-varying intervention context.

Just-in-time adaptive interventions (JITAI) represent an exciting new approach that can be implemented through a combination of mobile and sensor-based technologies (Nahum-Shani et al., 2017). JITAI are character-

ized by their ability to monitor the state and the context of the individual and, based on this information, provide the appropriate amount and type of intervention at the right time. For example, when sedentary behavior is detected by a worn accelerometer, an app-based JITAI might suggest that the individual engage in physical activity. Further, the system might suggest a specific activity based on the time and weather conditions. Although there appears to be great promise to the approach (Wang and Miller, 2019), additional higher-powered studies are needed to determine the success of JITAIs over other approaches (Hardeman et al., 2019), and to address the unique issues involved in designing successful JITAIs for older adults.

## LIMITATIONS FOR USE OF MOBILE AND SENSOR TECHNOLOGY IN HEALTH

### Readiness in Aging Populations

When designing a technological intervention, it is important to consider whether the target population is likely to have basic computer experience, or a home broadband connection. In early 2019, only an estimated 53 percent of older adults owned a smartphone (Pew Research Center, 2019), meaning that technologies incorporating the use of a mobile application may not be practical for everyone without significant training for smartphone use. Additionally, older smartphone owners are much less proficient than younger ones (Roque and Boot, 2016). Likewise, although 73 percent of older adults (aged 65+) use the internet, only 59 percent report having a home broadband connection (Pew Research Center, 2019), which is critical for telehealth, mostly done with videoconferencing. Also, only 48 percent of “older-old adults” (aged 75+) use the internet, compared to 78 percent of “younger-old adults” (aged 65–74) (Czaja et al., 2019). Thus, computer and technology literacy are a barrier to adoption, though older adults can significantly benefit from computer literacy interventions, and more specifically, eHealth literacy interventions, resulting in positive changes to health care (Xie, 2011).

### The Challenge of Subgroups with Low Tech Adoption

Not all older adults aged 65 and older share the same knowledge about and access to technology products. We have already seen that more specific age groups can be established within the classification of older adults, and these subgroups have different levels of technology usage. In addition to age, education/income and ethnicity are also important factors.

Across age groups, 56 percent of people with an income lower than \$30,000 have a home internet connection, compared to 92 percent of those



who make over \$75,000. Older adults who have retired may be living with a restricted budget. It is estimated that 9 percent of the older adults in America live below the poverty level (Czaja et al., 2019). Therefore, even those who are willing and cognitively able to adopt new technology and participate in an intervention may not be able to afford to do so. Among older adults, racial minorities are more likely to face the challenges of poverty, as are women and those who live by themselves. Racial minorities and those with lower socioeconomic status are also more likely to rely on a smartphone for internet access, without having a home broadband connection (Pew Research Center, 2019).

Thus, we cannot make broad assumptions about readiness and acceptance of technology. As MMI technology continues to develop, it will be important to consider that older adults may need to adopt an entire infrastructure of technology (e.g., home network, broadband subscription, specific smartphone), and not just that which is necessary for the MMI system itself.

### FUTURE DIRECTIONS FOR MOBILE TECHNOLOGY SUPPORTING ADAPTIVE AGING

Several outcome criteria can be envisioned for assessing effectiveness of MMI systems as they mature, drawing on the RE-AIM framework (Glasgow, Vogt, and Boles, 1999) that was developed in the public health intervention field. RE-AIM criteria include *reach* (the percentage and risk characteristics of persons who receive or are affected by a policy or program), *efficacy* (positive and negative outcomes for the intervention), *adoption* (proportion and representativeness of settings), *implementation* (fidelity of delivery of the program: effectiveness = efficacy × implementation), and *maintenance* (long-term maintenance of behavior change).

Assuming that researchers can demonstrate MMI efficacy with typical, unrepresentative (He et al., 2016) older adult samples through short-duration, high-internal-validity studies (e.g., phase three clinical trials), what challenges would remain? Pragmatic clinical trials (Ford and Norrie, 2016) are a way to evaluate implementation and adoption. Current home monitoring studies and interventions rely on volunteers, and older volunteers are more likely to have higher levels of education and income, as well as better health and social integration, and less likely to be minority than white (Howell, 2010). Further, in our studies (e.g., Evans et al., 2016) lower SES homes and apartments presented challenging environments for deployment of monitoring equipment. Internet access, a necessity for MMI systems, can be costly and difficult to arrange in rural settings. Broadening participation by underserved populations in pragmatic trials is a worthy goal. Also, once a system either receives FDA approval or earns a best clini-



cal practice designation, ensuring that it is affordable and implementable is an important next step.

Even if a system proves to be efficacious and cost effective, often-overlooked features of cutting-edge technology are maintenance and obsolescence. Maintenance can be problematic in part because companies abandon commercial product lines, or go out of business. A good example was a recent RCT pilot study that showed significant improvement in fitness relative to a wait list control for sedentary middle-aged and older adults. It used a Jawbone UP24 monitor (wearable fitness tracker) in conjunction with an iPad app, and a thigh-worn ActivPAL monitor (Lyons et al., 2017). Jawbone discontinued the fitness tracker, so it became an “orphaned” device. To what extent was that specific hardware and software platform necessary for efficacy?

Further, systems based on mobile devices need to contend with additional challenges. U.S. consumers apparently change smartphones about every two years (Ng, 2019) though that period is lengthening, perhaps in response to smartphone cost increases and slowing improvement in functionality. Our suspicion is that aging adults may change phones less frequently, based on evidence that of those age 65 and older, 53 percent own smartphones and 39 percent own nonsmart cellphones compared to ages 18–29, where 96 percent own smartphones and 4 percent own nonsmart cellphones (Pew Research Center, 2019). This would mean that older adults are likely at greater risk for device obsolescence. Mobile operating system changes by Apple (iOS) and Google (Android OS) can “break” applications, so apps must be maintained and updated. Considering lifespans from onset of chronic conditions, a 10- to 20-year MMI program is conceivable. Focusing on technology functions rather than devices (e.g., Skubic et al., 2014) can address obsolescence.

Finally, maintenance, in the RE-AIM sense, assumes that people will continue to use the MMI system over extended periods of time (years) to support positive changes. Chronic conditions, such as hypertension, require vigilance, and as noted earlier, adherence to taking a prescribed medication is very poor in the general population and for older adults. There is little information available about how best to motivate aging adults to adhere to treatments over long-term intervals, especially when payment to participants is unavailable.

A recent study (Scherbina et al., 2019) of 2,783 iPhone users age 18 and older ( $M = 48$  years, a middle-aged sample) used a smartphone app to try to increase physical activity over a four-week period; the app offered four different intervention types for one week each (crossover design) following a one-week baseline period. All conditions increased step count about 10 percent for those who completed at least one intervention; however, that represented 1,075 people only—a 60 percent attrition rate that

does not bode well for long-term adherence. Only 493 people completed all interventions, representing an attrition rate of 83 percent.

### **SUGGESTIONS FOR FUTURE MMI STUDIES AND RESEARCH PRIORITIES**

We agree with earlier conclusions (e.g., Joe and Demiris, 2013) that too many studies are very short term pilot or feasibility studies. It was difficult to locate robust studies demonstrating MMI efficacy using older adult populations. None followed the full chain of measurement, prediction/inference, and just-in-time intervention, so the following could be priority areas.

#### **Potential Research Priorities for MMI Study Design**

- Future studies need to address weaknesses such as small, unrepresentative older adult samples, lack of adequate control groups, and lack of long-term assessment. This may entail funding for a large, multisite study like ACTIVE (Ball et al., 2002).
- Effective MMI systems can be facilitated by partnerships between the research community and industry to enhance usability, scalability, and deployment.
- Given that multimorbidity becomes the norm in old age, MMI studies need to relax exclusion rules to enhance generalizability of results.
- MMI systems should be designed to honor/respect privacy rights.

#### **Potential Research Priorities for MMI Technology Acceptability**

Even if an MMI system can show efficacy and cost effectiveness, its value for enhancing well-being in our aging population will be in jeopardy if it is not adopted and used.

- Studies of adoption and use of MMI systems need extended time frames (e.g., decades) to assess longer-term efficacy and cost effectiveness commensurate with lengthened life spans burdened by later life chronic diseases.
- Studies need to incorporate diverse samples including young-old, middle-old, and old-old users; those with disabilities; and disadvantaged groups to gauge comparative effectiveness of MMI versus home-based sensor technology.
- It would be ideal to tap into existing longitudinal studies, such as National Health and Aging Trends Study (NHATS), Health and Retirement Study (HRS), National Health and Nutrition

Examination Survey (NHANES) to create subsample MMI study opportunities.

- Encourage interdisciplinary MMI teams encompassing engineering, computer science, data science, health, and behavioral science through interagency projects.

## REFERENCES

- Baig, M.M., Affi, S., GholamHosseini, H., & Mirza, F. (2019). A systematic review of wearable sensors and IoT-based monitoring applications for older adults—a focus on ageing population and independent living. *Journal of Medical Systems*, 43(8), 233. <https://doi.org/10.1007/s10916-019-1365-7>.
- Ball, K., Berch, D.B., Helmers, K.F., Jobe, J.B., Leveck, M.D., Marsiske, M., Morris, J.N., Rebok, G.W., Smith, D.M., Tennstedt, S.L., Unverzagt, F.W., & Willis, S.L. (2002). Effects of cognitive training interventions with older adults: A randomized control trial. *Journal of the American Medical Association*, 288(18), 2271–2281. <https://doi.org/10.1001/jama.288.18.2271>.
- Beach, S.R., Schulz, R., Downs, J., Matthews, J., Barron, B., & Seelman, K. (2009). Disability, age, and informational privacy attitudes in quality of life technology applications: Results from a national web survey. *ACM Transactions on Accessible Computing (TACCESS)*, 2(1), 1–21. <http://doi.acm.org/10.1145/1525840.1525846>.
- Bergen, G., Stevens, M.R., & Burns, E.R. (2016). Falls and fall injuries among adults aged ≥65 years—United States, 2014. *Morbidity and Mortality Weekly Report (MMWR)*, 65(37), 993–998. <https://doi.org/10.15585/mmwr.mm6537a2>.
- Bhattarai, P., Newton-John, T.R.O., & Phillips, J.L. (2017). Quality and usability of arthritic pain self-management apps for older adults: A systematic review. *Pain Medicine*, 19(3), 471–484.
- Boise, L., Wild, K., Mattek, N., Ruhl, M., Dodge, H.H., & Kaye, J. (2013). Willingness of older adults to share data and privacy concerns after exposure to unobtrusive in-home monitoring. *Gerontechnology*, 11(3), 428–435. <https://doi.org/10.4017/gt.2013.11.3.001.00>.
- Brown, M.T., & Bussell, J.K. (2011). Medication adherence: WHO cares? *Mayo Clinic Proceedings*, 86(4), 304–314.
- Buttorff, C., Ruder, T., & Bauman, M. (2017). Multiple chronic conditions in the United States. Santa Monica, CA: RAND Corporation, 2017. Available: <https://www.rand.org/pubs/tools/TL221.html>.
- Caine, K., & Hanania, R. (2013). Patients want granular privacy control over health information in electronic medical records. *Journal of the American Medical Informatics Association*, 20(1), 7–15. <https://doi.org/10.1136/amiajnl-2012-001023>.
- Charness, N. (2020). A framework for choosing technology interventions to promote successful longevity: Prevent, rehabilitate, augment, substitute (PRAS). *Gerontology* 66(2), 169–175. <https://doi.org/10.1159/000502141>.
- Charness, N., & Boot, W.R. (2009). Aging and information technology use: Potential and barriers. *Current Directions in Psychological Science*, 18(5), 253–258. <https://doi.org/10.1111/j.1467-8721.2009.01647.x>.
- Charness, N., Kelley, C.L., Bosman, E.A., & Mottram, M. (2001). Word processing training and retraining: Effects of adult age, experience, and interface. *Psychology and Aging*, 16(1), 110–127. <https://doi.org/10.1037/0882-7974.16.1.110>.
- Chen, K., & Chan, A.H.S. (2014). Gerontechnology acceptance by elderly Hong Kong Chinese: A Senior Technology Acceptance Model (STAM). *Ergonomics*, 57(5), 635–652. <https://doi.org/10.1080/00140139.2014.895855>.

- Chen, R., Jankovic, F., Marinsek, N., Foschini, L., Kourtis, L., Signorini, A., Pugh, M., Shen, J., Yaari, R., Maljkovic, V., Sunga, M., Song, H.H., Jung, H.J., Tseng, B., & Trister, A. (2019). Developing measures of cognitive impairment in the real world from consumer-grade multimodal sensor streams. *KDD '19—Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 2145–2155). New York, NY: ACM. <https://doi.org/10.1145/3292500.3330690>.
- Choi, Y.K., Demiris, G., Lin, S-Y., Iribarren, S.J., Landis, C.A., Thompson, H.J., McCurry, S.M., Heitkemper, M.M., & Ward, T.M. (2018). Smartphone applications to support sleep self-management: Review and evaluation. *Journal of Clinical Sleep Medicine*, 14(10), 1783–1790. <http://dx.doi.org/10.5664/jcsm.7396>.
- Conn, V.S., Ruppap, T.M., Enriquez, M., & Cooper, P. (2016). Medication adherence interventions that target subjects with adherence problems: Systematic review and meta-analysis. *Research in Social and Administrative Pharmacy*, 12(2), 218–246.
- Czaja, S.J., Boot, W.R., Charness, N., Rogers, W.A., & Sharit, J. (2017). Improving social support for older adults through technology: Findings from the PRISM randomized control trial. *The Gerontologist*, 58(3), 467–477. <https://doi.org/10.1093/geront/gnw249>.
- Czaja, S.J., Boot, W.R., Charness, N., & Rogers, W.A. (2019). *Designing for older adults: Principles and creative human factors approaches* (3rd ed.). Boca Raton: CRC Press.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13(3), 319–340.
- DiJulio, B., Hamel, L., Muñana, C., & Brodie, M. (2018). *Loneliness and social isolation in the United States, the United Kingdom, and Japan: An international survey*. Henry J Kaiser Family Foundation. Available: <http://files.kff.org/attachment/Report-Loneliness-and-Social-Isolation-in-the-United-States-the-United-Kingdom-and-Japan-An-International-Survey>.
- Evans, J., Papadopoulos, A., Tsien Silvers, C., Charness, N., Boot, W. R., Schlachta-Fairchild, L., & Crump, C. (2016). Remote health monitoring for older adults and those with heart failure: Adherence and system usability. *Telemedicine and e-Health*, 22(6), 480–488. <https://doi.org/10.1089/tmj.2015.0140>.
- Food and Drug Administration (2019). *Policy for device software functions and mobile medical applications*. FDA-2011-D-0530. Available: <https://www.fda.gov/regulatory-information/search-fda-guidance-documents/policy-device-software-functions-and-mobile-medical-applications>.
- Ford, I., & Norrie, J. (2016). Pragmatic trials. *New England Journal of Medicine*, 375(5), 454–463. <https://doi.org/10.1056/NEJMr1510059>.
- Glasgow, R.E., Vogt, T.M., & Boles, S.M. (1999). Evaluating the public health impact of health promotion interventions: The RE-AIM framework. *American Journal of Public Health*, 89(9), 1322–1327.
- Guo, X., Zhang, X., & Sun, Y. (2016). The privacy–personalization paradox in mHealth services acceptance of different age groups. *Electronic Commerce Research and Applications*, 16, 55–65.
- Hardeman, W., Houghton, J., Lane, K., Jones, A., & Naughton, F. (2019). A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity*, 16(1), 31.
- Harari, G.M., Lane, N.D., Wang, R., Crosier, B.S., Campbell, A.T., & Gosling, S.D. (2016). Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. *Perspectives on Psychological Science*, 11(6), 838–854.

- He, Z., Charness, N., Bian, J., & Hogan, W. R. (2016). Assessing the comorbidity gap between clinical studies and elderly patient populations. *Conference Proceedings, 2016 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)* (pp. 136–139). New York, NY: IEEE. <https://doi.org/10.1109/BHI.2016.7455853>
- Hedegaard H., Curtin, S. C., & Warner, M. (2018). Suicide mortality in the United States, 1999–2017. NCHS Data Brief, no 330. Hyattsville, MD: National Center for Health Statistics. 2018. <https://www.cdc.gov/nchs/data/databriefs/db330-h.pdf>.
- Henderson, C., Knapp, M., Fernández, J-L., Beecham, J., Hirani, S. P., Cartwright, M., Rixon, L., Beynon, M., Rogers, A., Bower P, Doll H, Fitzpatrick R, Steventon A, Bardsley M., Hendy J., Newman S.P., & Whole System Demonstrator evaluation team. (2013). Cost effectiveness of telehealth for patients with long term conditions (Whole Systems Demonstrator telehealth questionnaire study): Nested economic evaluation in a pragmatic, cluster randomized controlled trial. *British Medical Journal*, 346, f1035. <https://doi.org/10.1136/bmj.f1035>.
- Joe, J., & Demiris, G. (2013). Older adults and mobile phones for health: A review. *Journal of Biomedical Informatics*, 46, 947–954. <http://dx.doi.org/10.1016/j.jbi.2013.06.008>.
- Ko, A., Pick, C.M., Kwon, J.Y., Barlev, M., Krems, J.A., Varum, M.E.W., Neel, R., Peysha, M., Boonyasiriwat, W., Brandstätter, E., Crispim, A.C., Cruz, J.E., David, D., David, O.A., de Felipe R.P., Fetvadjeiev, V.H., Fischer, R., Galdi, S., Galindo, O., Golovina, G., Gomez-Jacinto, L., Graf, S., Grossmann, I., Gul, P., Hamamura, T., Han, S., Hitokoto, H., Hřebíčková, M., Johnson, J.L., Karl, J.A., Malanchuk, O., Murata, A., Na, J., O, J., Rizwan, M., Roth, E., Salgado, S.A.S., Samoylenko, E., Savchenko, T., Sevincer, A.T., Stanciu, A., Suh, E.M., Talhelm, T., Uskul, A.K., Uz, I., Zambrano, D., & Kenrick, D.T. (2019). Family matters: Rethinking the psychology of human social motivation. *Perspectives on Psychological Science*, 15(1), 173–201. <https://doi.org/10.1177/1745691619872986>.
- Kramer, A.D.I., Guillory, J.E., & Hancock, J.T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, 111(24), 8788–8790. <https://doi.org/10.1073/pnas.1320040111>.
- Li, J., Ma, Q., Chan, A.H., & Man, S.S. (2019). Health monitoring through wearable technologies for older adults: Smart wearables acceptance model. *Applied Ergonomics*, 75, 162–169. <https://doi.org/10.1016/j.apergo.2018.10.006>.
- Lustria, M., Noar, S.M., Cortese, J., Van Stee, S.K., Glueckauf, R., & Lee, J. (2013). A meta-analysis of web-delivered tailored health behavior change interventions. *Journal of Health Communication*, 18(9), 1039–1069. <https://doi.org/10.1080/10810730.2013.768727>.
- Lv, X., Guo, X., Xu, Y., Yuan, J., & Yu, X. (2012). Explaining the mobile health services acceptance from different age groups: a protection motivation theory perspective. *International Journal of Advancements in Computing Technology*, 4(3), 1–9.
- Lyons E.J., Swartz, M.C., Lewis, Z.H., Martinez, E., & Jennings, K. (2017). Feasibility and acceptability of a wearable technology physical activity intervention with telephone counseling for mid-aged and older adults: A randomized controlled pilot trial. *Journal of MIR Mhealth Uhealth*, 5(3), e28. <https://doi.org/10.2196/mhealth.6967>
- Madden, M. (2014). *Public perceptions of privacy and security in the post-Snowden era*. Pew Research Center. Available: [https://www.pewresearch.org/wp-content/uploads/sites/9/2014/11/PI\\_PublicPerceptionsofPrivacy\\_111214.pdf](https://www.pewresearch.org/wp-content/uploads/sites/9/2014/11/PI_PublicPerceptionsofPrivacy_111214.pdf).
- Mistry, N., Keepanasseril, A., Wilczynski, N.L., Nieuwlaat, R., Ravall, M., Haynes, R.B., & Patient Adherence Review Team. (2015). Technology-mediated interventions for enhancing medication adherence. *Journal of the American Medical Informatics Association*, 22(e1), e177–e193.

- Morey, S.A., Stuck, R.E., Chong, A.W., Barg-Walkow, L.H., Mitzner, T.L., & Rogers, W.A. (2019). Mobile health apps: Improving usability for older adult users. *Ergonomics in Design: The Quarterly of Human Factors Applications*, 27(4), 4–13. <https://doi.org/10.64804619840731>.
- Morrow-Howell, N. (2010). Volunteering in later life: Research frontiers. *Journal of Gerontology: Social Sciences*, 65B(4), 461–469. <https://doi.org/10.1093/geronb/gbq024>.
- Nahum-Shani, I., Smith, S.N., Spring, B.J., Collins, L.M., Witkiewitz, K., Tewari, A., & Murphy, S.A. (2017). Just-in-time adaptive interventions (JITAI) in mobile health: Key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine*, 52(6), 446–462.
- Newell, A., & Simon, H.A. (1972). *Human problem solving*. Englewood Cliffs, NJ: Prentice-Hall.
- Ng, C., She, J., & Ran, R. (2019). A Compressive Sensing Approach to Detect the Proximity Between Smartphones and BLE Beacons. *IEEE Internet of Things Journal*, 6(4), 7162–7174.
- Nieuwlaat, R., Wilczynski, N., Navarro, T., Hobson, N., Jeffery, R., Keepanasseril, A., Agoritsas, T., Mistry, N., Iorio, A., Jack, S., Sivaramalingam, B., Iserman, E., Mustafa, R.A., Jedraszewski, D., Cotoi, C., & Haynes, R.B. (2014). Interventions for enhancing medication adherence. *Cochrane Database of Systematic Reviews*, (11), article number CD000011. doi: 10.1002/14651858.CD000011.pub4.
- The OECD Privacy Framework (2013). The Organisation for Economic Co-operation and Development (OECD). Available: [http://www.oecd.org/sti/ieconomy/oecd\\_privacy\\_framework.pdf](http://www.oecd.org/sti/ieconomy/oecd_privacy_framework.pdf), accessed 12/13/2019.
- Park, D.C., Hertzog, C., Leventhal, H., Morrell, R.W., Leventhal, E., Birchmore, D., Martin, M., & Bennett, J. (1999). Medication adherence in rheumatoid arthritis patients: Older is wiser. *Journal of the American Geriatrics Society*, 47(2), 172–183.
- Perrin, A. (2018). *Americans are changing their relationship with Facebook*. Pew Research Center. Available: <https://www.pewresearch.org/fact-tank/2018/09/05/americans-are-changing-their-relationship-with-facebook/>.
- Pew Research Center. (2019). *Mobile Fact Sheet, June 2019*. Available: <https://www.pewresearch.org/internet/fact-sheet/mobile/>.
- Rantz, M. J., Skubic, M., Abbott, C., Galambos, C., Popescu, M., Keller, J., Stone, E., Back, J., Miller, S.J., & Petroski, G.F. (2015). Automated in-home fall risk assessment and detection sensor system for elders. *Gerontologist*, 55(S1), S78–S87. doi:10.1093/geront/gnv044.
- Reeder, B., & David, A. (2016). Health at hand: A systematic review of smart watch uses for health and wellness. *Journal of Biomedical Informatics*, 63, 269–276. <http://dx.doi.org/10.1016/j.jbi.2016.09.001>.
- Roque, N.A., & Boot, W.R. (2016). A new tool for assessing mobile device proficiency in older adults: The Mobile Device Proficiency Questionnaire. *Journal of Applied Gerontology*, 37(2), 131–156. <https://doi.org/10.1177/0733464816642582>.
- Sanchez, W., Martinez, A., Campos, W., Estrada, H., & Pelechano, V. (2015). Inferring loneliness levels in older adults from smartphones. *Journal of Ambient Intelligence and Smart Environments* 7(1), 85–98. <https://doi.org/10.3233/AIS-140297>.
- Sandstrom, G., Lathia, N., Mascolo, C., & Rentfrow, P. (2017). Putting mood in context: Using smartphones to examine how people feel in different locations. *Journal of Research in Personality*, 69, 96–101.



- Scherbina, A., Hershman, S.G., Lazzeroni, L., King, A.C., O'Sullivan, J.W., Hekler, E., Moayed, Y., Pavlovic, A., Waggott, D., Sharma, A., Yeung, A., Christle, J.W., Wheeler, M.T., McConnell, M.V., Harrington, R.A., & Ashley, E.A. (2019). The effect of digital physical activity interventions on daily step count: A randomised controlled crossover substudy of the MyHeart Counts Cardiovascular Health Study. *The Lancet Digital Health*, 1(7), e344–e352. [https://doi.org/10.1016/S2589-7500\(19\)30129-3](https://doi.org/10.1016/S2589-7500(19)30129-3)
- Schmidt, L.I., & Wahl, H.W. (2018). Predictors of performance in everyday technology tasks in older adults with and without mild cognitive impairment. *The Gerontologist*, 59(1), 90–100.
- Schulz, R. (Ed.) (2012). *Quality of life technology handbook*. New York: Taylor & Francis/CRC Press.
- Seifert, A., Christen, M., & Martin, M. (2018). Willingness of older adults to share mobile health data with researchers. *GeroPsych: The Journal of Gerontopsychology and Geriatric Psychiatry*, 31(1), 41–49. <https://doi.org/10.1024/1662-9647/a000181>.
- Simons, D.J., Boot, W.R., Charness, N., Gathercole, S.E., Chabris, C.F., Hambrick, D.Z., & Stine-Morrow, E.A.L. (2016). Do “Brain Training” programs work? *Psychological Science in the Public Interest*, 17, 108–191. <https://doi.org/10.1177/1529100616661983>.
- Skubic M., Jimison, H., & Keller J., Pepescu, M., Rantz, M., Kaye, J., & Pavel, M. (2014). A framework for harmonizing sensor data to support embedded health assessment. *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, IL, 2014, pp. 1747–1751, <https://doi.org/10.1109/EMBC.2014.6943946>.
- Steventon, A., Bardsley, M., Billings, J., Dixon, J., Doll, H., Hirani, S, Cartwright, M., Rixon, L., Knapp, M., Henderson, C., Rogers, A., Fitzpatrick, R., Hendy, J., & Newman, S. (2012). Effect of telehealth on use of secondary care and mortality: Findings from the Whole System Demonstrator cluster randomised trial. *British Medical Journal*, 344, e3874. <https://doi.org/10.1136/bmj.e3874>.
- Suhara, Y., Xu, Y., & Pentland, A. (2017). DeepMood: Forecasting Depressed Mood Based on Self-Reported Histories via Recurrent Neural Networks. *Proceedings of the 26th International Conference on World Wide Web*.
- Tsai, H.S., Jiang, M., Alhabash, S., LaRose, R., Rifon, N.J., & Cotten, S.R. (2016). Understanding online safety behaviors: A protection motivation theory perspective. *Computers & Security*, 59, 138–150. <https://doi.org/10.1016/j.cose.2016.02.009>.
- Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36, 157–178.
- Wang, L., & Miller, L.C. (2019). Just-in-the-Moment Adaptive Interventions (JITAI): A meta-analytical review. *Health Communication*, 1–14. <https://doi.org/10.1080/10410236.2019.1652388>.
- Wildenbos, G.A., Jaspers, M.W., Schijven, M.P., & Dusseljee-Peute, L.W. (2019). Mobile health for older adult patients: Using an aging barriers framework to classify usability problems. *International Journal of Medical Informatics*, 124, 68–77.
- Xie, B. (2011). Effects of an eHealth literacy intervention for older adults. *Journal of Medical Internet Research*, 13(4), e90.
- Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, 43, 342–350.

## 3

# Mobile and Sensor Technology as a Tool for Health Measurement, Management, and Research with Aging Populations

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## INTRODUCTION

Advances in medicine, science, and technology over the last century have produced demographic changes—and in particular, a growing population of older adults. Life expectancy is up, premature death is down, and people are living longer than ever before (NCHS, 2019). Further, the overall age distribution is shifting, with more people in the U.S. now over age 60 than under age 15 (Carstensen et al., 2015); and over the next 20 to 30 years, the number of adults over 65 is estimated to double, to account for 1/5 of the global population (WHO, 2013). While a huge achievement, aging societies also present novel challenges to health care. In particular, as incidence of infectious illnesses common in the early 20th century fell and people started living longer, rates have considerably grown for non-communicable chronic diseases, mental health problems, and age-related declines (WHO, 2015). Such conditions are now the leading cause of sickness, disability, and death around the world and account for over 70% of the global burden of disease (Forouzanfar et al., 2016; WHO, 2014). Apart from mortality, most chronic diseases also negatively impact functioning and overall quality of life (Megari, 2013). These statistics also foreshadow an unsustainable financial burden (Banerjee, 2017), with global health care expenditures anticipated to reach \$47 trillion by 2030 (Bloom et al., 2018), as prevalence continues to increase worldwide (Saranummi et al., 2013).

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For older adults, the occurrence of such conditions is even higher and estimated to continue growing. Over 80% of people 65 years and older have at least one chronic illness (Anderson et al., 2002), and over 75% have two or more (NCOA, 2015), including mental health issues such as anxiety, dementia, depression, substance abuse, and elevated suicide rates (NCOA, 2015). Critically, however, 2/3 of seniors are unable to receive the treatment they need (NIMH, 2014).

Important to note is that these conditions are linked with how people live their lives. Today's top risk factors for premature death all relate to lifestyle choices (diet, physical activity, smoking, and excessive alcohol consumption) (Mensah, 2006), with such behaviors contributing more to mortality rates than infectious or toxic agents (Mokdad et al., 2004). Worth acknowledging is the major influence environmental exposures, quality of care, and socioeconomic factors do have on health, including inequities (Saranummi et al., 2013); and it is not necessarily fair to consider, for example, poor diet or physical inactivity strictly as "choices" if a person lives in a food desert or an area with poor walkability. Still, research increasingly links behavioral factors with physiological and psychological wellness, including during the later life span (Cowie et al., 2016; Macera et al., 2017), contributing to a growing consensus that "the single greatest opportunity to improve health and reduce premature deaths lies in personal behavior" (Schroeder, 2007, p. 1,222) and that for older people specifically, behavior-based approaches can promote positive aging (Cowie et al., 2016). Indeed, the health domain is witnessing a major shift (Christensen et al., 2009) from an illness-centric, visit-test-treat model toward more proactive, self-driven strategies, with a focus on prevention and overall well-being (Swan, 2012). On the research front, public agencies, including the National Institutes of Health, are launching programs to prioritize behavior change (Nielsen et al., 2018), and clinical approaches are increasingly incorporating behavioral treatments, which not only get people more directly involved in their own care but also help reduce pharmacological risks (Petrovic et al., 2012).

Technology presents a powerful mechanism for monitoring and managing behavior in such ways, while reducing costs and buffering physician shortages. Digital health solutions that combine mobile applications, sensors, and wearables can provide personalized diagnosis and detection of health indicators as well as care and coaching that is continuously available and directly delivered to end-users. Further, such strategies can reach those facing financial and physical barriers to accessing care (Mohr et al., 2010; 2013) and also act as a window through which researchers can examine and understand the practices, needs, and outcomes of traditionally understudied and underserved groups.

This chapter overviews the use of mobile and sensor technologies as a tool for both health research as well as health management, to support

adaptive aging efforts. We present examples from our own and others' research in this emerging area to illustrate the promising opportunities mHealth offers, while also highlighting important future steps and critical considerations.

## MOBILE HEALTH (MHEALTH)

### What Is mHealth?

Mobile health, or mHealth, broadly refers to the use of mobile phones or other wireless devices to support health care (Kay et al., 2011). mHealth grew out of telehealth, with both enabled by the introduction of modern telecommunication and information technology as a way to deliver health care from a distance. mHealth and telehealth can be considered subsets of eHealth (Oh et al., 2005), an umbrella term that describes the local or remote use of digital data or technology to support health care (Della Mea, 2001). Beyond telehealth services, eHealth includes electronic health records, clinical decision support systems, and physician instruction tools. The clinical use of such technologies is often referred to as health or medical informatics and is concerned with the collection, storage, retrieval, management, and use of health information by a patient's care providers. In this chapter, however, we focus less on the clinical context and more on the at-home, self-driven, vernacular use of mHealth tools (which may be in combination with or entirely outside of physician-guided care), focusing on "*people*" rather than exclusively "*patients*."

To date, the bulk of mHealth attention has been on mobile phones, which continue to gain sophistication in terms of data capture features and interactive affordances. A variety of wearable devices (e.g., eyewear, rings, shoes, watches, wristbands) are now entering the retail market with similar capabilities. Such functionality permits broad-scale, naturalistic collection of health-relevant data in an extremely granular and unobtrusive manner. The ability to observe behavior continuously and in context also makes it possible to tailor interventions to optimize effectiveness for an individual user, plus these technologies provide an interface through which such feedback can be delivered.

### Adoption and Acceptability of mHealth Tools by Older Adults

Recent years have seen a swell in personal technology penetration, especially mobile phones. In the U.S., over 95% of people own mobile phones, with over 80% owning smartphones specifically (Pew, 2017); globally, 85% of adults own a mobile phone, with a median of 45–76% owning smartphones in emerging and advanced economies (Pew, 2018). Smartphone

ownership does decline with age, but that trend is changing over time; and studies indicate that stereotypes of older adults being unable and unwilling to try new technologies is a misconception (Erber and Szuchman, 2014; Kurniawan, 2008). Over 3/4 of individuals aged 65+ own a cellphone and 1/5 a smartphone, nearly 1/2 of those 75+ own a cellphone (Anderson, 2017; Anderson and Perrin, 2017; Levine et al., 2016), and research observes frequent use by older adults of text messaging especially, given the low usage barriers (Schülke et al., 2010). Further, studies show more older individuals register for mobile phones every day, with market research indicating that smartphone use among some older adult segments is actually growing at a faster rate compared to other age groups (Deloitte, 2017).

In terms of attitudes, studies find older adults exhibit open-minded receptivity and willingness toward mHealth (de Veer et al., 2015; Parker et al., 2013; Zhou et al., 2014), especially tools to monitor and manage symptoms, encourage physical activity, and remind of appointments (Klimova, 2016). However, older adults also express perceptions that modern technology is not necessarily designed to suit their abilities (Goddard and Nicolle, 2012). mHealth adoption may therefore not be constrained by seniors' disinterest but rather devices' failure to meet their needs—needs designers could better consider to accommodate cognitive, motor, visual, or other age-related changes.

### Common Applications of mHealth in the Healthy Aging Context

mHealth technologies often focus on diagnosis, monitoring, and/or intervention; and their functionality can be broadly organized across an information flow involving data input, translation, and output (Murnane, 2017). First, rich datasets about behavior can be collected in context, through both manual self-report and automated sensing. From this information, health metrics can be computed, symptoms detected, and future status forecasted. Given this model of an individual's health and contributing factors, tailored feedback can then be delivered to end-users, care teams, and other stakeholders to support awareness, action, and long-term management (Kang et al., 2010).

With specific respect to older adults' use of mHealth, early work commonly focused on collecting data about symptom levels (e.g., of depression, fatigue, pain), tracking medication intake and side effects, delivering health education and literacy materials, and serving reminders through text messages or notifications to adhere to medication schedules or attend health care appointments (Free et al., 2013; Tomlinson et al., 2013). As the field continues to advance, we are seeing more sophisticated monitoring—for example, fall detection systems (Chaudhuri et al., 2014; Stone and Skubic, 2015) and lower-burden interfaces tailored to older adults—for example,

designed with motor, visual, or other age-related changes in mind (Adams et al., 2018; Wildenbos et al., 2018). Further details and examples of such mHealth applications are presented in the next section.

## MHEALTH FOR MONITORING AND INTERVENTION

### Collecting Data Relevant to Behavior, Health, and Contributing Factors

A central feature of mHealth systems is an ability to capture data. This input provides details about the user's behaviors, environment, or other personal attributes relevant to the health outcome(s) the tool is targeting. These data can be collected manually by a user, automatically by sensors, or through some hybrid approach. Here we overview ways mHealth technology captures data, providing examples and pointing out advantages, drawbacks, and tradeoffs among these various approaches.

### Manual Reporting

People have self-tracked health information long before digital tools existed to support the activity. In the 1940s, clinical research began using written diaries, in which people could self-report symptoms and health actions as they occurred (Allport, 1942; Verbrugge, 1980). While such pen-and-paper approaches are familiar and easy to use for many people, they do face well-known limitations, including the risk of forgetfulness, retrospection errors, and inadherence (Bolger et al., 2003), especially for older populations (Adams et al., 2017). Over the past few decades, research has looked at how technology can help address these limitations. At first, studies used digital devices, such as pagers, pre-programmed wristwatches, or text messages to deliver reminders to record information, though the recording itself was still made on paper. This sort of prompted self-report is associated with ecological momentary assessment (EMA; Stone and Shiffman, 1994) and experience sampling method (ESM; Csikszentmihalyi and Larson, 2014), which are methods used to collect information about various aspects of daily life in the moments they are being experienced.

Today, mHealth research on applying this style of in situ reporting to aging contexts has largely focused on the smartphone, given both its ubiquity as well as its support for rich interactions. Typically targeted indicators include physical activity (Maher et al., 2018), mental health (Moore et al., 2016), symptoms of chronic conditions such as diabetes (Whitlock and McLaughlin, 2012) or pain (Adams et al., 2017; García Palacios et al., 2014), and more general well-being indicators e.g., mood, sleep, and social interactions (Doyle et al., 2014). Research shows that older adults would additionally like to track restful and stress-relief activities as well

as healthy eating (Davidson and Jensen, 2013) and abnormal changes in health (Caldeira et al., 2016).

The manual capture of data is associated with several benefits. Self-tracking can empower users with a sense of agency (Murnane et al., 2016) and foster self-awareness (Bentley et al., 2013; Choe et al., 2014). The “obtrusiveness” is the main advantage, as it enhances mindfulness about behavioral choices and adherence to goals (Kopp, 1988; Korotitsch and Nelson-Gray, 1999). Further, manual tracking allows more personal control over what information is disclosed, which is important to older adults from a privacy perspective (Consolvo, et al., 2004a; 2004b).

However, manual self-tracking is associated with disadvantages as well. Foremost, self-report can be burdensome (Connelly et al., 2006) due to the time and effort it requires. This is a particular challenge if a technology is intended for long-term use (e.g., to manage a chronic health condition). Data inaccuracy can also occur in cases where a person’s capacity for reliable self-assessment is compromised, for instance due to cognitive or memory declines. Further, while increased self-awareness can induce desirable behavioral changes, psychological reactance can also result by drawing one’s attention to uncomfortable symptoms or thoughts (Kohl et al., 2013). Finally, it can be infeasible for a person to capture the array and granularity of data necessary for a system to produce a sufficiently comprehensive profile about that individual, comprising the multiple personal variables, behavioral determinants, and other indicators needed to accurately model a health outcome of interest (Bentley et al., 2013). This motivates more system-driven approaches to data collection that are either fully automated or that complement self-report with passively captured information.

## Passive Sensing

With automated or “passive” data collection, physiological or behavioral data are captured using sensors embedded in phones, wearables, or surrounding environments. As mentioned, the mobile phone has rapidly evolved into a powerful computing platform, with a variety of sensors for capturing motion (e.g., accelerometers, gravity sensors, gyroscopes), location (e.g., GPS, orientation sensors, magnetometers), and environmental data (e.g., barometers, photometers, thermometers, cameras, microphones). Reviews provide a summary of prominent health-oriented smartphone sensing systems (Chen et al., 2014; Cornet and Holden, 2018; Klasnja and Pratt, 2012). Much existing work on mobile sensing for older populations has focused on passively tracking mobility—for example, using accelerometer and GPS data to assess physical activity and frailty (Castro et al., 2015) or automate standing and balance tests based on inertial sensors (Madhushri et al., 2016). Another recent thrust aims to determine

“digital biomarkers” of older adult functioning, especially for cognitive declines (Piau et al., 2019) or to derive computational proxies for subjectively experienced symptoms, such as pain intensity (Aung et al., 2016). Speech-based biomarkers are also becoming more robust, including to assess neurodegeneration in older adults (Cormack et al., 2019), such as in Parkinson’s disease (Moro-Velazquez et al., 2019). Rather than utilizing hardware sensors, “soft sensing” captures data from software usage logs to passively infer health indicators (De Choudhury, 2014), for example, to predict cognitive declines in older adults based on smartphone use, based on features including app switching, bursts of app use, and the daily timing of use (Gordon et al., 2019).

On-body sensing approaches have used a variety of wearable sensors over the years, such as pedometers (Consolvo et al., 2006; Lin et al., 2006) and biometric sensors like electrocardiography (ECG) (de Oliveira and Oliver, 2008) to capture sound, temperature, light, and humidity among other inputs (Choudhury et al., 2008). Many of the recent commercial wearable devices for healthy monitoring (e.g., Apple watch, Fitbit) are essentially accelerometer-based wristbands that passively monitor activity and sleep (Rawassizadeh et al., 2015); some newer models incorporate additional sensors, for instance, to measure heart rate or galvanic skin response, and new form factors (e.g., the Oura ring) are also emerging. For older adults, most applications again focus on measuring mobility (De Bruin et al., 2008) as well as cardiac vital signs (Baig et al., 2013). Wearable device development continues advancing, including to incorporate sensors into clothes and jewelry. For instance, e-textile pants have been developed to collect data about acceleration, angular velocity, and pressure in order to assess motion impairments in older users (Liu et al., 2008), while the recent Phyjama system can monitor older adults’ heart and respiration rates as well as detect posture during naps (Kiaghadi et al., 2019). As another example, the Smart Jewelry Bracelet embeds an accelerometer, gyroscope, and flex and temperature sensors to collect data on which machine learning is run to automatically distinguish regular movement from potential physical attacks or falls (Patel and Hasan, 2018).

The main disadvantages associated with on-body sensing are potential discomfort of wearing the device, its limited battery life, and the fact that smaller (e.g., wrist- or finger-worn) form factors constrain the sensors that can be contained, although battery advances and miniaturization are helping address some of these issues (Jayatilaka et al., 2019; Rawassizadeh et al., 2015). As with manual data collection, forgetfulness can be an issue for passive strategies, given a user may forget to wear or charge the sensing device, especially potentially an older user with declining memory. Additionally, older adults’ drier skin is also known to impede the responsiveness of capacitive interfaces (Merilampi and Sirkka, 2016).

As environment-based, contactless sensors are not as affected by these constraints, researchers have also been exploring how instrumented homes and other spaces can automatically capture health data. One early system captured weight using a scale built into the toilet, heart rate data using an ECG monitor in the tub, and body temperature from a bed sensor (Ogawa et al., 1998; Tamura et al., 1998). More recently, others have placed sensors to automatically collect health metrics into furniture like chairs (Griffiths et al., 2014) or mattresses (Ko et al., 2015). Internet of Things (IoT)-connected smart homes and hospitals could further extend such capability to numerous other objects in living spaces or dedicated care environments (Marques, 2019). Regarding older adults, systems have used radio signals to detect falls (Tian et al., 2018), measure gait velocity and stride length (Hsu et al., 2017a), and monitor insomnia and sleep (Hsu et al., 2017b). Computer vision researchers have also developed contactless approaches using depth and thermal sensors to automatically watch for acute incidents (e.g., fever, immobility, substance abuse) as well as clinically relevant long-term activities (e.g., eating, restroom use, sleeping) for seniors living independently (Luo et al., 2017; 2018).

Overall, automated sensing helps relieve user burdens by reducing both the time and the mental overhead associated with self-tracking, plus sensed data can be more accurate and granular than manually tracked data. Passive sensing can also capture informative quantitative signals that are imperceptible to the person generating them (Whitson, 2013). However, sensors can be privacy invasive (Reeder et al., 2016) or uncomfortable to wear for older adults (Steele et al., 2009), and they can reduce personal awareness about collected data (Li, 2009). Automated tracking can also generate massive volumes of data that impose storage and security challenges. In addition, while automatic data collection can work well to acquire some objective information like heart rate or location, accuracy is still elusive for some types of behavioral tracking (e.g., food intake) especially outside the lab, and sensing does not lend itself to measurement of subjective experiences.

### **Hybrid and Semi-automated Approaches to Health Measurement**

Hybrid strategies that support both manual and passive modes, including adaptively shifting between the two based on user status, may help to relieve burdens while preserving agency, autonomy, and opportunities for experiential sharing and self-reflection. One early hybrid example is the UbiFit system, which automatically inferred walking, running, and cycling but also allowed the user to add activities it could not automatically track like yoga or swimming (Consolvo et al., 2008). To infer activities, UbiFit made use of the similarly seminal Mobile Sensing Platform (Choudhury et al., 2008), which was extended in follow-up work to passively assess



older adults' physical and mental well-being based on a combination of accelerometer, barometer, and audio data, using an ensemble of classifiers and privacy-sensitive speech-processing techniques (Rabbi et al., 2011).

Recently, researchers have worked to formally characterize the spectrum from fully manual, to semi-automated, to fully automated tracking, including to identify strengths and weaknesses of these various approaches and their respective applicability for various contexts, populations, and health targets (Choe et al., 2017). The OmniTrack system develops an architecture that instantiates such principles and enables users to flexibly define custom tracking setups (Kim et al., 2017).

### **Digitally Delivered Informatics and Interventions**

In addition to collecting data and analyzing them to derive health metrics, the other important feature of mHealth systems is the representation of this information through legible feedback that provides opportunities for self-awareness, wellness management, and, potentially, behavior change. However, compared to the aforementioned work to develop mHealth-based data collection and health assessment techniques, the research on the informatics and interventions side of the equation is more limited for aging groups. As mentioned, most interfaces focus on delivering text-based reminders and nudges (e.g., to take medication, complete condition-specific tasks, or perform general physical activity); see Klimova (2016) and Changizi (2017) for reviews. Or, given that the field is still emerging, work often offers roadmaps to chart out future directions for mHealth interventions (Faiola et al., 2019) but has not yet reached the implementation stage. Such ideas that are gaining increasing interest include virtual health advisors, robotic assistants, or commodity devices that supply neuro-feedback for stroke rehabilitation and cognitive functioning in elders.

### **Feedback Design Dimensions**

In designing mHealth interventions, important dimensions to consider are the feedback's format, delivery medium, attentional demand, prescriptiveness, and level of personalization. Existing mHealth systems largely display information in a visual format (e.g., text, charts, or other graphics). In the aging context, natural language and haptic feedback are increasingly being explored—for example, to support stroke rehabilitation (Micallef et al., 2016) or improve walking stability (Costa et al., 2015), as such formats are seen as intuitive alternatives to graphical user interfaces for low-vision older users. However, age-related declines in hearing or motor skills can present usage barriers for audio- or tangible-based interaction, and such usability trade-offs must be weighed as appropriate for a specific applica-



tion. Regarding the delivery medium, smartphone screens do predominate, though other mechanisms include wearable displays, smart speakers, or virtual reality, including low-cost cardboard viewers that wrap around a smartphone to make the experience more immersive, and built environments can deliver information via walls or other objects in one's living or work spaces (Liu et al., 2016). Important considerations when selecting a feedback medium are affordability and usability as well as ensuring information receipt, especially if time- or context-sensitive. This makes phones attractive due to their portability and the tendency for users to keep them nearby, plus it relieves the need to carry a separate, dedicated health management device.

In terms of attentional demand, feedback can be provided via subtle cues or more conspicuously. Ambient displays often focus on aesthetics and aim to integrate well into the environment without being distracting, while overt feedback more directly demands that a person notices and engages with it (Matthews et al., 2007). Just-in-time interventions, which deliver personalized, contextually aware, and well-timed feedback, tend to fall at the overt end of this spectrum; see Nahum-Shani et al. (2014) for a review. On the more ambient side, research focusing on older adults has explored physical artifacts and portrait-based displays, such as a touch-screen tablet placed inside a wood frame (Consolvo et al., 2004) or a photograph border that uses butterflies, trees, and swans to represent daily activity, health, and relationship information (Mynatt et al., 2001). Recent work has built on these foundations to explore the use of ambient displays and visualizations to promote older adults' exercise (Rodríguez et al., 2013), medication adherence (Zárate-Bravo et al., 2016), and intergenerational connectedness (Cornejo et al., 2013).

Prescriptiveness refers to whether a tool's feedback is more directive versus descriptive. On the prescriptive side, feedback might leave little room for user interpretation; for example, the MyBehavior system (Rabbi et al., 2015) conveys dietary feedback with explicit directives (e.g., "Avoid large meal"). On the other hand, many existing personal informatics research apps and consumer tools provide more open-ended, descriptive reports (e.g., a chart of step counts across the week) that leave the interpretation to the user. Each style comes with tradeoffs to consider, such as the user's (in)ability to do this sensemaking and whether personal value might be derived from the deliberate effort of determining how to act on presented information.

Finally, the level of personalization is important to consider. In the aging context, pursuing more personalized and adaptive solutions is likely worthwhile, given the variety in older adults' expressed preferences regarding health topics to track (Davidson and Jensen 2013), together with the fact that "older adults" can actually span multiple decades in age and may have therefore experienced highly variable historical contexts, life circumstances, and health trajectories.

Overall, this is not meant to be an exhaustive set of all the possible attributes feedback can possess. Other characteristics to consider include audience (e.g., private vs. public viewability), scope of input (e.g., personal-, family-, or community-level data), and data permanence (e.g., temporary vs. archival), among a variety of other possible dimensions. Still, we see format, delivery medium, attentional demand, prescriptiveness, and personalization as key design levers to be configured when deciding how information will be conveyed by mHealth technology for adaptive aging.

### **mHealth as a Research Tool**

Beyond supporting diagnosis, treatment, and long-term care, mHealth approaches can help drive basic research to advance fundamental scientific understanding about health and related behaviors in naturalistic settings, over longitudinal periods, and with large and diverse groups.

### **Open Platforms**

To date, there have been a number of academic projects that contribute reusable and extensible mHealth research platforms for capturing passive and self-reported data as well as testing interventions at scale. AWARE (Ferreira et al., 2015) and Purple Robot (CBITS, 2015) provide access to the Android sensor framework, and since its initial introduction, AWARE's development team has continued to expand its functionality, for example, to add support for the iOS operating system. MyExperience (Froehlich et al., 2007) similarly supported passive sensing, together with context- and physiologically triggered prompts for subjective self-reports. In addition to data collection, the open-source Ohmage toolkit (Ramanathan et al., 2012) offers functionality specifically aimed at visualizing and analyzing captured data. The Open mHealth Platform (Estrin and Sim, 2010) aims to organize a community around developing a standard for mobile health data. Important to note, however, is that these open platforms have been developed for general purpose use, which motivates research to investigate and take steps to extend their accuracy, coverage, and overall appropriateness when used by older populations and applied to adaptive aging contexts.

Through the deployment of such platforms, it is possible to conduct research that circumvents limitations of standard scientific approaches. Specifically, while lab studies enable rigorous control over conditions, experiments depend on substantial experimenter labor, are costly to conduct, face known issues with sample representativeness, and do not support examining phenomena “in the wild” during everyday life and over time. Randomized controlled trials (RCTs) get out of the lab to test interventions with larger samples and for longer periods; however, RCTs are also

resource intensive, which precludes many important trials from ever being conducted. For example, it has been estimated that it would require 127 RCTs involving 63,500 patients over 286 years to produce the evidence necessary to inform clinical decisions about Alzheimer's disease (Saver and Kalafut, 2001).

### From Self-Knowledge to Scientific Knowledge

Recently, mHealth researchers have begun designing technology to support a notion of self-experimentation, which has a long history in medicine and psychology whereby doctors traditionally volunteered for ethical reasons as the first subject in an experiment with unknown risks (Altman, 1998). Today in the mHealth context, this practice is being explored as a way, for instance, to assist an individual with irritable bowel syndrome identify foods that trigger symptoms or to help a person determine whether exercising in the morning results in more energy later in the day (Karkar et al., 2016). This work is motivated by the idea that people want to use mHealth technologies to answer specific questions like these about their health, but current tools fail to effectively support such diagnostic self-tracking (Karkar et al., 2015). For example, many tools output graphs of raw data that users find difficult to interpret or act on (Epstein et al., 2014), and tools generally do not support personal experiments that have sufficient methodological rigor (Choe et al., 2014).

Self-experimentation technologies help a user self-administer a controlled study; the tool creates a schedule, encourages adherence to conditions, and automatically runs statistical tests from which a user can draw causal conclusions. The experiment follows a single-subject design (also known as an *n-of-1* study), which is sensitive to individual differences and where a person serves as his or her own control (Lillie et al., 2011). These *n-of-1*-style mHealth efforts coincide with interest from the medical community to adopt models of precision medicine that focus on individual, rather than average, responses to particular treatments. Such an approach can be advantageous compared to methodologies involving larger samples (e.g., RCTs), which can lead to therapeutic solutions that are beneficial to some patients but minimally effective or even detrimental for others (Gabler et al., 2011). For example, some routinely used medications benefit as few as 1 in 50 individuals; other drugs have been found to be harmful for entire ethnic groups—an outcome not often identified in clinical trials, since they are typically biased toward white Western participants (Schork, 2015). Similarly, clinical trials that skew toward younger populations do not necessarily reveal adverse drug reactions in older adults (Petrovic et al., 2012).

Altogether, there is a massive opportunity to push forward the development of mHealth infrastructures to generate population-level knowledge

from personal-level data. Doing so will require addressing a variety of open questions, such as how to create tools that adequately scaffold older individuals in designing and running their own n-of-1 studies to rigorously test hypotheses about themselves, how to determine appropriate statistical approaches for causal inferences in these cases, and ultimately how to synthesize individual findings into generalizable knowledge.

## CONCLUSION

### Realizing the Potential of mHealth for Adaptive Aging

mHealth technologies have the potential to play a positive, perhaps transformative, role in supporting the health and well-being of our aging population. To fully realize this potential, however, some barriers must be overcome and facilitating steps taken, including to both address general challenges as well as develop age-specific design solutions.

### Barriers and Facilitators to mHealth Use

In general, the need for reliable network coverage can be a challenge, particularly in rural or developing areas (Salemink et al., 2017), which has implications for data fidelity and care delivery. Developing solutions that do not require continuous real-time cloud connections or sending large amounts of data and that can continue to function offline would help in low-internet conditions. For example, progressive web apps could be a desirable strategy.

Other previously identified barriers to entry for older adults include the cost of and lack of familiarity with mHealth tools (Bujnowska-Fedak and Pirogowicz, 2014; Lee and Coughlin, 2015; Mercer et al., 2016; Parker et al., 2013; Peek et al., 2014). Android pricing is more affordable compared to iOS devices, so choosing to build an Android app or host functionality on a website that can be accessed on any platform could help. For older patients with low digital literacy, it is necessary to devise effective strategies for training, which studies show boosts self-efficacy and lowers anxiety regarding the use of health technology (Wild et al., 2012). Such onboarding might take place in inpatient settings, outpatient clinics, or as part of community-based programs; or understandable tutorials could also be built into the mHealth application so that the user would have the option to complete it at home either alone or with family. Built-in support could then continue over time, gradually introducing more advanced features or to assist with device maintenance.

Such training could help build skills, but developing more usable, age-tailored interactive functionality could also substantially boost adoption

(Parker et al., 2013), especially for cases where lower engagement with digital health technologies can be attributed at least in part to functional limitations (e.g., age-related declines in psychomotor skills, vision, or hearing). Interface and interaction design processes can accommodate such constraints, both to improve existing and to inform novel devices. The next subsection offers specific strategies.

### Design Constraints and Goals for Adaptive Aging Tools

Unfortunately, research indicates most self-tracking technology is not designed to support older adults' needs, including limitations in cognition, motivation, perception, and physical ability (Doyle et al., 2014; Wildenbos et al., 2018). To improve accessibility, interfaces could include large touch-target regions, readable fonts and font sizes, high-contrast screens, simple interactions, low manipulability, and enhanced volume control. For example, aiming to support pain reporting for older adults, the Meter mobile app (Adams et al., 2017) implements similar strategies (e.g., oversized fonts and graphics as well as large touch regions that accommodate low accuracy), while the Keppi device (Adams et al., 2018) moves away from the screen entirely by providing a tangible user interface that the user can hold, press, and squeeze to report pain levels in a more natural and intuitive manner. To further relieve dependence on visual and motor-based interactions, the design of voice-based interfaces could be explored for seniors, who now account for over one-third of all voice assistant users (Olmstead, 2017). While recent studies do indicate voice assistants are useful for older adults (Pradhan et al., 2019), trade-offs related to hearing loss would be important to weigh.

Beyond usability issues that relate to physical functioning, it is also imperative to consider challenges of information overload and devise designs for delivering content in a way that is also cognitively legible. One promising strategy is moving from heavily quantitative or text-based reporting—which prior research establishes is often overwhelming, demotivating, and hard to interpret (Cohen and Sherman, 2014) including for older adults (King et al., 2016)—and toward more qualitative representations of personal data and health feedback. For example, work on designing for populations with compromised concentration or other perception difficulties has developed novel informatics approaches that encode personal data (e.g., activity levels, hours slept, social interactions) as visual features (e.g., wave height, water color, or amount of sediment in an ocean encoding scheme) in ways that resonate with the lived experiences the information represents (Snyder et al., 2019). There is substantial opportunity to similarly explore other media formats (light, audio, haptic) for delivering intuitive feedback.

### **Ethical, Privacy, and Safety Considerations**

A variety of ethical concerns are necessary to take into account. Foremost, responsible management of collected data is critical given the highly personal nature of behavioral, emotional, and other health-relevant information, which also may be sensitive, stigmatic, and exploitable, especially for a potentially vulnerable group, such as older adults. Older adults have indeed raised general privacy concerns in previous research on mHealth interventions (Chung et al., 2014; Consolvo et al., 2004; Gao 2015; Reeder et al., 2016; Steele et al., 2009; Young et al., 2014). Going forward, there is a need to directly investigate questions related to older adults' understanding and comfort levels with the collection of various types of data.

Specific strategies could include designing mechanisms for users to better communicate privacy preferences to mHealth tools, turn on and off data collection (Caine et al., 2010), and receive information about the implications of sharing one's data. Usable controls to access, view, and delete captured data could enhance security, as could making two-factor authentication more inclusive for older adults (Das et al., 2019). Privacy-preserving sensing methods can also be developed, such as processing locally and extracting features insufficient to reconstruct raw data (Rabbi et al., 2011).

When mHealth tools are treated as a platform for research, this will require policies for restricting which analyses and queries different researchers can perform on the data through access controls, anonymization, and differential privacy. Crafting such a set of data protections will require human-centric security design and also open up additional research opportunities to explore how cognitive models of security and data risk affect how careful scientists are with data.

Regulations and lawmaking are also necessary to consider, such as implementing protections to guard against insurance companies setting rates based on a person's historical mHealth data or predicted future health. Procedures for formal vetting of mHealth technologies (e.g., FDA approval) are also imperative, given these sorts of potential risks to personal welfare.

### **Future Directions for mHealth Solutions**

In addition to pursuing novel design strategies and data policies that are more inclusive and protective of the needs and safety of older adults, other mHealth opportunities also abound. For example, prior mHealth studies have typically involved small and potentially nonrepresentative samples over relatively short periods of time. More rigorous examinations are necessary to establish the efficacy of mHealth approaches in adaptive aging contexts. Further, existing mHealth systems are often one-off applications rather than extensible platforms, and implementation is needed of

more common-format interoperable systems, including to enable these sorts of robust at-scale evaluations. More generally, mHealth's rapid emergence and innovation pace motivate ongoing reexaminations and reflections on the field, to continue refining such recommendations.

In addition, despite the collaborative nature of managing the aging process, mHealth systems have largely had an exclusive focus on the individual, which motivates the development of tools that are aware of and can support the social ecologies in which personal health management practices take place (Murnane et al., 2018). Relatedly, while personal lifestyle choices are key to improving health outcomes, interventions that rest predominantly on individual-level responsibility will be insufficient for achieving large-scale, long-term solutions to many public health issues we face today. In addition to user-driven, bottom-up approaches, more population-wide, top-down changes are necessary too (e.g., to improve access to healthy food choices and well-being-promoting urban infrastructure). mHealth pipelines can be instrumental in gathering the sort of evidence necessary to inform such institutional-level changes. Similarly, mHealth strategies for large-scale measurement can help surface systematic health inequities, for example, by using accelerometry data from smartphones to reveal physical activity disparities in different cities around the world (Althoff et al., 2017).

Further, research indicates that older individuals who are from minority ethnic groups have lower health and digital literacy, or are marginalized from accessing traditional forms of health care may similarly face barriers to using personal health care technologies and have different needs and expectations for such tools (White et al., 2015). Novel strategies are necessary to bridge this gap, such as more accessible education and training, inclusive transitional care initiatives, such as ConnectHome (Leeman and Toles, 2019), and empowering community organizations with preventive mHealth tools. Another emerging inequity relates to algorithmic biases—for example, research has demonstrated that user models often encode significant age bias (Diaz et al., 2018), which will likely require new tactics to identify and address.

Finally, framing technology as an intervention to treat age-related changes can portray aging in a negative light and neglect the positive aspects of growing older (Durick et al., 2013; Ferri et al., 2017; Nassir et al., 2015; Vines et al., 2015). Going forward, we hope to see the design of mHealth technology challenge these stereotypes and support a framing of flourishing in later life.

## REFERENCES

- Adams, A.T., E.L. Murnane, P. Adams, M. Elfenbein, P.F. Chang, S. Sannon, G. Gay, and T. Choudhury. (2018). Keppi: A Tangible User Interface for Self-Reporting Pain. In *Proceedings of CHI '18*, 502:1–502:13. ACM.



- Adams, P., E.L. Murnane, M. Elfenbein, E. Wethington, and G. Gay. (2017). Supporting the Self-Management of Chronic Pain Conditions with Tailored Momentary Self-Assessments. In *Proceedings of CHI '17*: 1065–1077. ACM.
- Allport, G.W. (1942). The Use of Personal Documents in Psychological Science. *Social Science Research Council Bulletin*.
- Altman, L.K. (1998). *Who Goes First?: The Story of Self-Experimentation in Medicine*. University of California Press.
- Anderson, G.O. (2017). Technology Use and Attitudes among Mid-Life and Older Americans. AARP Research.
- Anderson, G., & Horvath, J. (2002). *Chronic Conditions: Making the Case for Ongoing Care*. Johns Hopkins University, Partnership for Solutions, & Robert Wood Johnson Foundation. <http://www.partnershipforsolutions.org/DMS/files/chronicbook2002.pdf>.
- Anderson, M., and A. Perrin. (2017). Technology Use among Seniors. Pew Research Center for Internet & Technology.
- Aung, M.S.H., F. Alquaddoomi, C.-K. Hsieh, M. Rabbi, et al. (2016). Leveraging Multi-Modal Sensing for Mobile Health: A Case Review in Chronic Pain. *IEEE Journal of Selected Topics in Signal Processing* 10, no. 5 (August): 962–974.
- Baig, M.M., H. Gholamhosseini, and M.J. Connolly. (2013). A Comprehensive Survey of Wearable and Wireless ECG Monitoring Systems for Older Adults. *Medical & Biological Engineering & Computing* 51, no. 5 (May): 485–495.
- Banerjee, B. (2017). WHO Global Action Plan and Monitoring Framework for Prevention and Control of Non-Communicable Diseases.
- Bentley, F., K. Tollmar, P. Stephenson, L. Levy, B. Jones, S. Robertson, E. Price, R. Catrambone, and J. Wilson. (2013). Health Mashups: Presenting Statistical Patterns Between Wellbeing Data and Context in Natural Language to Promote Behavior Change. *ACM Transactions on Computer-Human Interaction* 20, no. 5: 30:1–30:27.
- Bloom, D.E., S. Chen, and M.E. McGovern. (2018). The Economic Burden of Noncommunicable Diseases and Mental Health Conditions. *Journal of Public Health* 42 (February 28): e18.
- Bolger, N., A. Davis, and E. Rafaeli. (2003). Diary Methods: Capturing Life as It Is Lived. *Annual Review of Psychology* 54: 579–616.
- Bujnowska-Fedak, M.M., and I. Pirogowicz. (2014). Support for E-Health Services among Elderly Primary Care Patients. *Telemedicine Journal and E-Health* 20, no. 8 (August): 696–704.
- Caine, K. E., Zimmerman, C. Y., Camp, L. J., & Shankar, K. (2010). DigiSwitch: Design and Evaluation of a Device for Older Adults to Preserve Privacy While Monitoring Health at Home. *ACM International Health Informatics Symposium*.
- Caldeira, C., M. Bietz, and Y. Chen. (2016). Looking for the Unusual: How Older Adults Utilize Self-Tracking Techniques for Health Management. *Proceedings of the 10th EAI*.
- Carstensen, L.L., M.E. Rosenberger, K. Smith, and S. Modrek. (2015). Optimizing Health in Aging Societies. *Public Policy & Aging Report*, 1–5. <https://doi.org/10.1093/ppar/prv004>.
- Castro, L.A., J. Favela, E. Quintana, and M. Perez. (2015). Behavioral Data Gathering for Assessing Functional Status and Health in Older Adults Using Mobile Phones. *Personal and Ubiquitous Computing* 19, no. 2 (February): 379–391.
- Center for Behavioral Intervention Technologies. (2015). Mobile Apps for Depression: A Brief Overview. <http://cbits.northwestern.edu/mobile-apps-for-depression-a-brief-overview/>.
- Changizi, M., & Kaveh, M.H. (2017). Effectiveness of the mHealth Technology in Improvement of Healthy Behaviors in an Elderly Population: A Systematic Review. *mHealth*, 3, 51. <https://doi.org/10.21037/mhealth.2017.08.06>.



- Chaudhuri, S., H. Thompson, and G. Demiris. (2014). Fall Detection Devices and Their Use with Older Adults: A Systematic Review. *Journal of Geriatric Physical Therapy*, 37, no. 4 (October): 178–196.
- Chen, C.-Y., Y.-H. Chen, C.-F. Lin, C.-J. Weng, and H.-C. Chien. (2014). A Review of Ubiquitous Mobile Sensing Based on Smartphones. *International Journal of Automation and Smart Technology* 4, no. 1 (March 1): 13–19.
- Choe, E.K., N. Lee, B. Lee, W. Pratt, J. Kientz. (2014). Understanding Quantified-Selfers' Practices in Collecting and Exploring Personal Data. *SIGCHI Conference on Human Factors in Computing Systems*, 1143–1152.
- Choe, E.K., S. Abdullah, M. Rabbi, E. Thomaz, D.A. Epstein, F. Cordeiro, M. Kay, et al. (2017). Semi-Automated Tracking: A Balanced Approach for Self-Monitoring Applications. *IEEE Pervasive Computing* 16, no. 1: 74–84.
- Choudhury, T., G. Borriello, S. Consolvo, D. Haehnel, B. Harrison, B. Hemingway, J. Hightower, et al., (2008). The Mobile Sensing Platform: An Embedded Activity Recognition System. *IEEE Pervasive Computing* 7, no. 2: 32–41.
- Christensen, C., J. Grossman, and J. Hwang. (2009). *The Innovator's Prescription: A Disruptive Solution for Health Care*. McGraw-Hill.
- Chung, J., B. Reeder, A. Lazar, J. Joe, G. Demiris, and H.J. Thompson. (2014). Exploring an Informed Decision-Making Framework Using in-Home Sensors: Older Adults' Perceptions. *Informatics in Primary Care*, 21(2), 73–77. <https://doi.org/10.14236/jhi.v21i2.53>.
- Cohen, G.L., and D.K. Sherman. (2014). The Psychology of Change: Self-Affirmation and Social Psychological Intervention. *Annual Review of Psychology* 65: 333–371.
- Connelly, K.H., A.M. Faber, Y. Rogers, K.A. Siek, and T. Toscos. (2006). Mobile Applications That Empower People to Monitor Their Personal Health. *E & I Elektrotechnik Und Informationstechnik* 123, no. 4: 124–128.
- Consolvo, S., P. Roessler, and B.E. Shelton. (2004a). The CareNet Display: Lessons Learned from an In Home Evaluation of an Ambient Display. In *UbiComp 2004: Ubiquitous Computing*, 1–17. Springer Berlin Heidelberg.
- Consolvo, S., P. Roessler, B.E. Shelton, A. LaMarca, B. Schilit, and S. Bly. (2004b). Technology for Care Networks of Elders. *IEEE Pervasive Computing* 3, no. 2 (April): 22–29.
- Consolvo, S., K. Everitt, I. Smith, and J.A. Landay. (2006). Design Requirements for Technologies That Encourage Physical Activity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 457–466.
- Consolvo, S., D.W. McDonald, T. Toscos, M.Y. Chen, J. Froehlich, B. Harrison, et al. (2008). Activity Sensing in the Wild: A Field Trial of Ubifit Garden. *SIGCHI Conference on Human Factors in Computing Systems*, 1797–1806.
- Cormack, F.K., N. Taptiklis, J.H. Barnett, and M. Su. (2019). Large-Scale Remote Assessment of Verbal Cognitive Function Using Automatic Speech Recognition. *Alzheimer's & Dementia* 15, no. 7 (July 1): P162–P163.
- Cornejo, R., M. Tentori, and J. Favela. (2013). Ambient Awareness to Strengthen the Family Social Network of Older Adults. *Computer Supported Cooperative Work: CSCW: An International Journal* 22, no. 2-3 (April 1): 309–344.
- Cornet, V.P., and R.J. Holden. (2018). Systematic Review of Smartphone-Based Passive Sensing for Health and Wellbeing. *Journal of Biomedical Informatics* 77 (January): 120–132.
- Costa, A.A. da S., P.A.R. Mancio, E. Mauerberg-deCastro, and R. Moraes. (2015). Haptic Information Provided by the “Anchor System” Reduces Trunk Sway Acceleration in the Frontal Plane during Tandem Walking in Older Adults. *Neuroscience Letters* 609 (November 16): 1–6.
- Cowie, M.R., J. Bax, N. Bruining, J.G.F. Cleland, F. Koehler, M. Malik, F. Pinto, E. van der Velde, and P. Vardas. (2016). E-Health: A Position Statement of the European Society of Cardiology. *European Heart Journal* 37, no. 1: 63–66.

- Csikszentmihalyi, M., and R. Larson. (2014). Validity and Reliability of the Experience-Sampling Method. In *Flow and the Foundations of Positive Psychology: The Collected Works of Mihaly Csikszentmihalyi*, 35–54. Springer.
- Das, S., A. Kim, B. Jelen, J. Streiff, L.J. Camp, and L. Huber. (2019). Towards Implementing Inclusive Authentication Technologies for Older Adults. *Who Are You*.
- Davidson, J.L., and C. Jensen. (2013). What Health Topics Older Adults Want to Track: A Participatory Design Study. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility*, 26:1–26:8.
- De Bruin, E.D., A. Hartmann, D. Uebelhart, K. Murer, and W. Zijlstra. (2008). Wearable Systems for Monitoring Mobility-Related Activities in Older People: A Systematic Review. *Clinical Rehabilitation* 22, no. 10-11: 878–895.
- De Choudhury, M. (2014). Opportunities of Social Media in Health and Well-Being. *XRDS: Crossroads* 21, no. 2: 23–27.
- Della Mea, V. (2001). What Is E-Health: The Death of Telemedicine? *Journal of Medical Internet Research* 3, no. 2: e22.
- Deloitte. (2017). 2017 Global Mobile Consumer Survey: US Edition: The Dawn of the next Era in Mobile. Deloitte. <https://www2.deloitte.com/content/dam/Deloitte/us/Documents/technology-media-telecommunications/us-tmt-2017-global-mobile-consumer-survey-executive-summary.pdf>.
- de Oliveira, R., and N. Oliver. (2008). TripleBeat: Enhancing Exercise Performance with Persuasion. In *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services*, 255–264. ACM.
- de Veer, A.J.E., J.M. Peeters, A.E.M. Brabers, F.G. Schellevis, J. Rademakers, and A.L. Francke. (2015). Determinants of the Intention to Use E-Health by Community Dwelling Older People. *BMC Health Services Research* 15: 103.
- Diaz, M., I. Johnson, A. Lazar, A.M. Piper, and D. Gergle. (2018). Addressing Age-Related Bias in Sentiment Analysis. 2018 CHI Conference on Human Factors in Computing Systems, Montreal, QC, Canada. <https://doi.org/10.1145/3173574.3173986>.
- Doyle, J., L. Walsh, A. Sassu, and T. McDonagh. (2014). Designing a Wellness Self-Management Tool for Older Adults—Results from a Field Trial of Your Wellness. 8th International Conference on Pervasive Computing Technologies for Healthcare, Oldenburg, Germany. <https://doi.org/10.4108/icst.pervasivehealth.2014.254950>.
- Durick, J., T. Robertson, M. Brereton, and F. Vetere. (2013). Dispelling Ageing Myths in Technology Design. <https://doi.org/10.1145/2541016.2541040>.
- Epstein, D., F. Cordeiro, E. Bales, J. Fogarty, and S. Munson. (2014). Taming Data Complexity in Lifelogs: Exploring Visual Cuts of Personal Informatics Data. In *Proceedings of Designing Interactive Systems*, 667–676.
- Erber, J.T., and L.T. Szuchman. (2014). *Great Myths of Aging*. John Wiley & Sons.
- Estrin, D., I. Sim. 2010. Open mHealth Architecture: An Engine for Health Care Innovation. *Science* 330, 6005: 759–760.
- Faiola, A., E.L. Papautsky, and M. Isola. (2019). Empowering the Aging with Mobile Health: A mHealth Framework for Supporting Sustainable Healthy Lifestyle Behavior. *Current Problems in Cardiology* 44, no. 8 (August): 232–266.
- Ferreira, D.V. Kostakos, and A.K. Dey. (2015). AWARE: Mobile Context Instrumentation Framework. *Frontiers in ICT* 2.
- Ferri, G., J. Bardzell, S. Bardzell. (2017). Rethinking Age in HCI Through Anti-Ageist Playful Interactions. *Interacting with Computers*, 29(6): 779–793.
- Forouzanfar et al. (2016). Global, Regional, and National Comparative Risk Assessment of 79 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks, 1990-2015: A Systematic Analysis for the Global Burden of Disease Study 2015. *The Lancet* 388, no. 10053 (October 8): 1659–1724.

- Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., Patel, V., and Haines, A. (2013). The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review. *PLoS Medical*, 10(1), e1001362. <https://doi.org/10.1371/journal.pmed.1001362>.
- Frøehlich, J., M.Y. Chen, S. Consolvo, B. Harrison, and J.A. Landay. (2007). MyExperience: A System for in Situ Tracing and Capturing of User Feedback on Mobile Phones. In *MobiSys '07*: 57–70.
- Gabler, N.B., N. Duan, S. Vohra, R.L. Kravitz. (2011). N-of-1 Trials in the Medical Literature. *Medical Care*: 761–768.
- Gao, Y. (2015). An Empirical Study of Wearable Technology Acceptance in Healthcare. *IMDS* 115, no. 9: 1704–1723.
- García-Palacios, A., R. Herrero, M.A. Belmonte, et al. (2014). Ecological Momentary Assessment for Chronic Pain in Fibromyalgia Using a Smartphone: A Randomized Crossover Study. *European Journal of Pain* 18, no. 6: 862–872.
- Goddard, N., and C. Nicolle. (2012). What Is Good Design in the Eyes of Older Users? Designing Inclusive Systems, 175–183. Springer. [https://doi.org/10.1007/978-1-4471-2867-0\\_18](https://doi.org/10.1007/978-1-4471-2867-0_18).
- Gordon, M.L., L. Gatys, C. Guestrin, J.P. Bigham, A. Trister, and K. Patel. (2019). App Usage Predicts Cognitive Ability in Older Adults. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 168:1–168:12.
- Griffiths, E., T.S. Saponas, and A.J.B. Brush. (2014). Health Chair: Implicitly Sensing Heart and Respiratory Rate. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 661–671.
- Hsu, C.-Y., A. Ahuja, S. Yue, R. Hristov, Z. Kabelac, and D. Katabi. (2017a). Zero-Effort In-Home Sleep and Insomnia Monitoring Using Radio Signals. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, no. 3: 59:1–59:18.
- Hsu, C.-Y., Y. Liu, Z. Kabelac, R. Hristov, D. Katabi, and C. Liu. (2017b). Extracting Gait Velocity and Stride Length from Surrounding Radio Signals. In *CHI Conference on Human Factors in Computing Systems*, 2116–2126.
- Jayatilaka, A., Q.H. Dang, S.J. Chen, R. Visvanathan, C. Fumeaux, and D.C. Ranasinghe. (2019). Designing Batteryless Wearables for Hospitalized Older People. *23rd International Symposium on Wearable Computers*, 91–95.
- Kang, H.G., D.F. Mahoney, H. Hoenig, V.A. Hirth, P. Bonato, I. Hajjar, and L.A. Lipsitz. (2010). In Situ Monitoring of Health in Older Adults: Technologies and Issues. *Journal of the American Geriatrics Society* 58, no. 8: 1579–1586.
- Karkar, R., J. Fogarty, J.A. Kientz, and S.A. Munson. (2015). Opportunities and Challenges for Self-Experimentation in Self-Tracking. *Adjunct Proceedings of UbiComp/ISWC*.
- Karkar, R., J. Zia, R. Vilardaga, S. Mishra, J. Fogarty, S. Munson, J. Kientz. (2016). A Framework for Self-Experimentation in Personalized Health. *Journal of the American Medical Informatics Association: JAMIA* 23, no. 3: 440–448.
- Kay, M., J. Santos, and M. Takane. (2011). mHealth: New Horizons for Health through Mobile Technologies. *World Health Organization* 64, no. 7: 66–71.
- Kiaghadi, A., S.Z. Homayounfar, J. Gummeson, T. Andrew, and D. Ganesan. (2019). Phyjama: Physiological Sensing via Fiber-Enhanced Pyjamas. *Proceedings of the ACM on IMWUT*. 3, no. 3 (September): 89:1–89:29.
- Kim, Y.H., J.H. Jeon, B. Lee, E.K. Choe, and J. Seo. (2017). OmniTrack: A Flexible Self-Tracking Approach Leveraging Semi-Automated Tracking. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*.
- King, A.C., E.B. Hekler, L.A. Grieco, et al. (2016). Effects of Three Motivationally Targeted Mobile Device Applications on Initial Physical Activity and Sedentary Behavior Change in Midlife and Older Adults. *PLOS ONE*.

- Klasnja, P., and W. Pratt. (2012). Healthcare in the Pocket: Mapping the Space of Mobile-Phone Health Interventions. *Journal of Biomedical Informatics* 45, no. 1 (February): 184–198.
- Klimova, B. 2016. Mobile Health Devices for Aging Population Groups: A Review Study. In *MobiWIS*, 295–301.
- Ko, P.-R.T., J.A. Kientz, E.K. Choe, M. Kay, C.A. Landis, and N.F. Watson. (2015). Consumer Sleep Technologies: A Review of the Landscape. *Journal of Clinical Sleep Medicine*: 11, no. 12: 1455–1461.
- Kohl, A., W. Rief, and J.A. Glombiewski. (2013). Acceptance, Cognitive Restructuring, and Distraction as Coping Strategies for Acute Pain. *The Journal of Pain: Official Journal of the American Pain Society* 14, no. 3: 305–315.
- Kopp, J. (1988). Self-Monitoring: A Literature Review of Research and Practice. *Social Work Research* 24(4): 8–20.
- Korotitsch, W.J., and R.O. Nelson-Gray. (1999). An Overview of Self-Monitoring Research in Assessment and Treatment. *Psychological Assessment* 11, no. 4 (December): 415–425.
- Kurniawan, S. (2008). Older People and Mobile Phones: A Multi-Method Investigation. *International Journal of Human-Computer Studies* 66, no. 12 (1): 889–901.
- Lane, N.D., E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A.T. Campbell. (2010). A Survey of Mobile Phone Sensing. *IEEE Communications Magazine* 48, no. 9: 140–150.
- Lee, C., and J.F. Coughlin. (2015). Older Adults' Adoption of Technology: An Integrated Approach to Identifying Determinants and Barriers. *Journal of Product Innovation Management* 32, no. 5 (September 3): 747–759.
- Leeman, J., and M. Toles. (2019). What Does It Take to Scale Up a Complex Intervention? Lessons Learned from the Connect-Home Transitional Care Intervention. *Journal of Advanced Nursing* 4 (November 20): 50.
- Levine, D.M., S.R. Lipsitz, and J.A. Linder. (2016). Trends in Seniors' Use of Digital Health Technology in the United States, 2011–2014. *Journal of the American Medical Association*, 316(5), 538–540. <https://doi.org/10.1001/jama.2016.9124>.
- Li, I. (2009). Designing Personal Informatics Applications and Tools That Facilitate Monitoring of Behaviors. UIST, Victoria, BC, Canada.
- Lillie, E.O., B. Patay, J. Diamant, B. Issell, E.J. Topol, and N.J. Schork. (2011). The N-of-1 Clinical Trial: The Ultimate Strategy for Individualizing Medicine? *Personalized Medicine* 8, no. 2: 161–173.
- Lin, J.J., L. Mamykina, S. Lindtner, G. Delajoux, and H.B. Strub. (2006). Fish'n'Steps: Encouraging Physical Activity with an Interactive Computer Game. In *International Conference on Ubiquitous Computing*, 261–278. Springer.
- Liu, J., T.E. Lockhart, M. Jones, and T. Martin. (2008). Local Dynamic Stability Assessment of Motion Impaired Elderly Using Electronic Textile Pants. *IEEE Transactions on Automation Science and Engineering* 5, no. 4: 696–702.
- Liu, L., E. Stroulia, I. Nikolaidis, A. Miguel-Cruz, and A. Rios Rincon. (2016). Smart Homes and Home Health Monitoring Technologies for Older Adults: A Systematic Review. *International Journal of Medical Informatics* 91 (July): 44–59.
- Luo, Z., et al. (2017). Computer Vision-Based Approach to Maintain Independent Living for Seniors. *AMIA 2017 Annual Symposium*, Washington, DC.
- Luo, Z., Hsieh, J.T., Balachandar, N., Yeung, S., Pusiol, G., Luxenberg, J., Li, G., Li, L.J., Downing, N.L., & Milstein, A. (2018). Computer Vision-Based Descriptive Analytics of Seniors' Daily Activities for Long-Term Health Monitoring. *Proceedings of the 2018 Machine Learning for Healthcare*, 85, 102–118.
- Macera, C.A., A. Cavanaugh, and J. Bellettiere. (2017). State of the Art Review: Physical Activity and Older Adults. *American Journal of Lifestyle Medicine* 11, no. 1 (January): 42–57. <https://doi.org/10.1177/1559827615571897>.

- Madhushri, P., A. Dzhangaryan, E. Jovanov, A. Milenkovic. (2016). An mHealth Tool Suite for Mobility Assessment. *Information (Switzerland)*, 7(3), Article 47. <https://doi.org/10.3390/info7030047>.
- Maier, J.P., A.L. Rebar, and G.F. Dunton. (2018). Ecological Momentary Assessment Is a Feasible and Valid Methodological Tool to Measure Older Adults' Physical Activity and Sedentary Behavior. *Frontiers in Psychology*. 9(AUG), Article 1485. <https://doi.org/10.3389/fpsyg.2018.01485>.
- Marques, G. (2019). Ambient Assisted Living and Internet of Things. In *Harnessing the Internet of Everything (IoE) for Accelerated Innovation Opportunities*, 100–115. IGI Global. <https://doi.org/10.4018/978-1-5225-7332-6.ch005>.
- Matthews, T., T. Rattenbury, and S. Carter. (2007). Defining, Designing, and Evaluating Peripheral Displays: An Analysis Using Activity Theory. *Human-Computer Interaction* 22, no. 1–2 (May 17): 221–261.
- Megari, K. (2013). Quality of Life in Chronic Disease Patients. *Health Psychology Research*, 1(3), e27. <https://doi.org/10.4081/hpr.2013.e27>.
- Mensah, G. (2006). Global and Domestic Health Priorities: Spotlight on Chronic Disease. National Business Group on Health Webinar. <http://www.businessgrouphealth.org/opportunities/webinar052306chronicdiseases.pdf>.
- Mercer, K., L. Giangregorio, E. Schneider, P. Chilana, M. Li, K. Grindrod. 2016. Acceptance of Commercially Available Wearable Activity Trackers Among Adults Aged Over 50 and With Chronic Illness. *JMIR mHealth/uHealth* 4, no. 1: e7.
- Merilampi, S., and A. Sirkka. (2016). *Introduction to Smart eHealth and eCare Technologies*. CRC Press.
- Micallef, N., L. Baillie, and S. Uzun. (2016). Time to Exercise!: An Aide-Memoire Stroke App for Post-Stroke Arm Rehabilitation. In *MobileHCI*, 112–123. ACM.
- Mohr, D.C., J. Ho, J. Duffecy, K.G. Baron, K.A. Lehman, L. Jin, and D. Reifler. (2010). Perceived Barriers to Psychological Treatments and Their Relationship to Depression. *Journal of Clinical Psychology* 66, no. 4: 394–409.
- Mohr, D.C., M.N. Burns, S. Schueller, G. Clarke, M. Klinkman. (2013). Behavioral Intervention Technologies: Evidence Review and Recommendations for Future Research in Mental Health. *General Hospital Psychiatry* 35, 4: 332–338.
- Mokdad, A.H., J.S. Marks, D.F. Stroup, and J.L. Gerberding. (2004). Actual Causes of Death in the United States, 2000. *JAMA*, 291(10), 1238–1245.
- Moore, R.C., C.A. Depp, J.L. Wetherell, and E.J. Lenze. 2016. Ecological Momentary Assessment vs Standard Assessment Instruments for Measuring Mindfulness, Depressed Mood, and Anxiety among Older Adults. *Journal of Psychiatric Research*, 75, 116–123. <https://doi.org/10.1016/j.jpsychires.2016.01.011>.
- Moro-Velazquez, L., J. Cho, S. Watanabe, M.A. Hasegawa-Johnson, O. Scharenborg, H. Kim, and N. Dehak. (2019). Study of the Performance of Automatic Speech Recognition Systems in Speakers with Parkinson's Disease. *Interspeech*.
- Murnane, E.L. (2017). *A Framework for Domain-Driven Development of Personal Health Informatics Technologies*. [Doctoral Dissertation, Cornell University]. eCommons. <https://doi.org/10.7298/X4CR5RBR>.
- Murnane, E.L., D. Cosley, P. Chang, S. Guha, E. Frank, G. Gay, and M. Matthews. (2016). Self-Monitoring Practices, Attitudes, and Needs of Individuals with Bipolar Disorder: Implications for the Design of Technologies to Manage Mental Health. *Journal of the American Medical Informatics Association: JAMIA* 23, no. 3 (May): 477–484.
- Murnane, E.L., T.G. Walker, B. Tench, S. Volda, and J. Snyder. (2018). Personal Informatics in Interpersonal Contexts. *Proceedings of the ACM on Human-Computer Interaction*.

- Mynatt, E.D., J. Rowan, S. Craighill, and A. Jacobs. (2001). Digital Family Portraits: Supporting Peace of Mind for Extended Family Members. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 333–340.
- Nahum-Shani, I., S.N. Smith, A. Tewari, K. Witkiewitz, L.M. Collins, B. Spring, and S. Murphy. (2014). Just in Time Adaptive Interventions (JITAIS): An Organizing Framework for Ongoing Health Behavior Support. Methodology Center Technical Report 2014: 14–126.
- Nassir, S., T.W. Leong, and T. Robertson. (2015). Positive Ageing: Elements and Factors for Design. In Proceedings of the Annual Meeting of the Australian Special Interest Group for Computer Human Interaction, 264–268. OzCHI '15.
- National Center for Health Statistics. (2019). Health, United States, 2017: With Special Feature on Mortality. <https://www.cdc.gov/nchs/data/health/2017.pdf>.
- National Council on Aging. (2015). Facts About Healthy Aging. National Council on Aging. <https://www.ncoa.org/news/resources-for-reporters/get-the-facts/healthy-aging-facts/>.
- National Institute of Mental Health. (2014). Older Adults: Depression and Suicide Fact Sheet.
- Nielsen, L., M. Riddle, J.W. King, et al., 2018. The NIH Science of Behavior Change Program: Transforming the Science through a Focus on Mechanisms of Change. Behaviour Research and Therapy 101 (February): 3–11.
- Ogawa, M., T. Tamura, and T. Togawa. (1998). Automated Acquisition System for Routine, Noninvasive Monitoring of Physiological Data. Telemedicine Journal 4, no. 2: 177–185.
- Oh, H., C. Rizo, M. Enkin, and A. Jadad. (2005). What Is eHealth: A Systematic Review of Published Definitions. Journal of Medical Internet Research, 7, 1.
- Parker, S.J., S. Jessel, J.E. Richardson, and M.C. Reid. (2013). Older Adults Are Mobile Too! Identifying the Barriers and Facilitators to Older Adults' Use of mHealth for Pain Management. BMC Geriatrics 13, no. 1: 43.
- Patel, J., and R. Hasan. (2018). Smart Bracelets: Towards Automating Personal Safety Using Wearable Smart Jewelry. In 2018 15th IEEE Annual Consumer Communications Networking Conference (CCNC), 1–2.
- Peek, S.T.M., E.J.M. Wouters, J. van Hoof, K.G. Luijkx, H.R. Boeije, and H.J.M. Vrijhoef. (2014). Factors Influencing Acceptance of Technology for Aging in Place: A Systematic Review. Int Journal of Med Informatics 83, 4: 235–248.
- Petrovic, M., T. van der Cammen, and G. Onder. (2012). Adverse Drug Reactions in Older People. Drugs & Aging 29(6): 453.
- Pew Research Center. (2017). *Nearly Half of Americans Use Digital Voice Assistants, Mostly on Their Smartphones*. <https://www.pewresearch.org/fact-tank/2017/12/12/nearly-half-of-americans-use-digital-voice-assistants-mostly-on-their-smartphones/>.
- Pew Research Center. (2018). Global Attitudes Survey. <https://www.pewresearch.org/global/dataset/spring-2018-survey-data/>.
- Piau, A., K. Wild, N. Mattek, and J. Kaye. (2019). Current State of Digital Biomarker Technologies for Real-Life, Home-Based Monitoring of Cognitive Function for Mild Cognitive Impairment to Mild Alzheimer Disease and Implications for Clinical Care: Systematic Review. Journal of Medical Internet Research 21, no. 8: e12785.
- Pradhan, A., L. Findlater, and A. Lazar. (2019). Phantom Friend or Just a Box with Information: Personification and Ontological Categorization of Smart Speaker-Based Voice Assistants by Older Adults. Computer Supported Cooperative Work, 3: 214.
- Rabbi, M., S. Ali, T. Choudhury, and E. Berke. (2011). Passive and In-Situ Assessment of Mental and Physical Well-Being Using Mobile Sensors. Proceedings of the ACM International Conference on Ubiquitous Computing: 385–394.
- Rabbi, M., M.H. Aung, M. Zhang, and T. Choudhury. (2015). MyBehavior: Automatic Personalized Health Feedback from User Behaviors and Preferences Using Smartphones. In UbiComp: 707–718. ACM.



- Ramanathan, N., F. Alquaddoomi, H. Falaki, D. George, C.-K. Hsieh, J. Jenkins, C. Ketcham, et al., (2012). Ohmage: An Open Mobile System for Activity and Experience Sampling. *Pervasive Computing Technologies for Healthcare*.
- Rawassizadeh, R., B.A. Price, and M. Petre. (2015). Wearables: Has the Age of Smartwatches Finally Arrived? *Communications of the ACM* 58, no. 1: 45–47.
- Reeder, B., J. Chung, J. Joe, A. Lazar, H.J. Thompson, and G. Demiris. (2016). Understanding Older Adults' Perceptions of In-Home Sensors Using an Obtrusiveness Framework. *Lecture Notes in Computer Science*.
- Rodríguez, M.D., J.R. Roa, A.L. Morán, and S. Nava-Muñoz. (2013). CAMMInA: A Mobile Ambient Information System to Motivate Elders to Exercise. *Personal and Ubiquitous Computing* 17, no. 6 (August): 1127–1134.
- Salemink, K., D. Strijker, and G. Bosworth. (2017). Rural Development in the Digital Age: A Systematic Literature Review on Unequal ICT Availability, Adoption, and Use in Rural Areas. *Journal of Rural Studies* 54: 360–371.
- Saranummi, N., D. Spruijt-Metz, S.S. Intille, I. Korhonen, W.J. Nilsen, and M. Pavel. (2013). Moving the Science of Behavioral Change into the 21st Century: Part 2. *IEEE Pulse* 4, no. 6 (November): 32–33.
- Saver, J.L., and M. Kalafut. (2001). Combination Therapies and the Theoretical Limits of Evidence-Based Medicine. *Neuroepidemiology* 20, no. 2 (May): 57–64.
- Schork, N.J. (2015). Personalized Medicine: Time for One-Person Trials. *Nature* 520, no. 7549 (April 30): 609–611.
- Schroeder, S.A. (2007). We Can Do Better: Improving the Health of the American People. *The New England Journal of Medicine* 357, no. 12: 1221–1228.
- Schülke, A.M., H. Plischke, and N.B. Kohls. (2010). Ambient Assistive Technologies (AAT): Socio-Technology as a Powerful Tool for Facing the Inevitable Sociodemographic Challenges? *Philosophy, Ethics, and Humanities in Medicine* 5: 8.
- Smith, A., and D. Page. (2015). US Smartphone Use in 2015. <https://www.pewresearch.org/internet/2015/04/01/us-smartphone-use-in-2015/>.
- Snyder, J., E. Murnane, C. Lustig, and S. Volda. (2019). Visually Encoding the Lived Experience of Bipolar Disorder. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19*, 1–14.
- Steele, R., A. Lo, C. Secombe, and Y.K. Wong. (2009). Elderly Persons' Perception and Acceptance of Using Wireless Sensor Networks to Assist Healthcare. *International Journal of Medical Informatics* 78, no. 12: 788–801.
- Stone, A.A., and S. Shiffman. (1994). Ecological Momentary Assessment (EMA) in Behavioral Medicine. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine* 16, no. 3: 199–202.
- Stone, E.E., and M. Skubic. (2015). Fall Detection in Homes of Older Adults Using the Microsoft Kinect. *IEEE Journal of Biomedical and Health Informatics* 19, no. 1 (January): 290–301.
- Swan, M. (2012). Health 2050: The Realization of Personalized Medicine through Crowdsourcing, the Quantified Self, and the Participatory Biocitizen. *Journal of Personalized Medicine* 2, no. 3 (September 12): 93–118.
- Tamura, T., T. Togawa, M. Ogawa, and M. Yoda. (1998). Fully Automated Health Monitoring System in the Home. *Medical Engineering & Physics* 20, no. 8 (November): 573–579.
- Tian, Y., G.-H. Lee, H. He, C.-Y. Hsu, and D. Katabi. (2018). RF-Based Fall Monitoring Using Convolutional Neural Networks. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, no. 3 (September): 137:1–137:24.
- Tomlinson, M., Rotheram-Borus, M.J., Swartz, L., & Tsai, A.C. (2013). Scaling Up mHealth: Where Is the Evidence? *PLoS Medical*, 10(2), e1001382. <https://doi.org/10.1371/journal.pmed.1001382>.

- Verbrugge, L.M. (1980). Health Diaries. *Medical Care* 18, no. 1 (January): 73–95.
- Vines, J., G. Pritchard, P. Wright, et al. 2015. An Age-Old Problem: Examining the Discourses of Ageing in HCI and Strategies for Future Research. *ACM Transactions on Computer-Human Interaction*. 22, no. 1: 2:1–2:27.
- White, G., T. Singh, K. Caine, and K. Connelly. (2015). Limited but Satisfied: Low SES Older Adults Experiences of Aging in Place. In 9th International Conference on Pervasive Computing Technologies for Healthcare, 121–128.
- Whitlock, L.A., and A.C. McLaughlin. (2012). Identifying Usability Problems of Blood Glucose Tracking Apps for Older Adult Users. *Proceedings of the Human Factors and Ergonomics Society* 56, no. 1 (September 1): 115–119.
- Whitson, J.R. (2013). Gaming the Quantified Self. *Surveillance & Society* 11, no. 1/2 (May 27): 163–176.
- Wildenbos, G.A., L. Peute, and M. Jaspers. (2018). Aging Barriers Influencing Mobile Health Usability for Older Adults: A Literature Based Framework (MOLD-US). *International Journal of Medical Informatics* 114 (June): 66–75.
- Wild, K.V., N.C. Mattek, S.A. Maxwell, H.H. Dodge, H.B. Jimison, and J.A. Kaye. (2012). Computer-Related Self-Efficacy and Anxiety in Older Adults with and without Mild Cognitive Impairment. *Alzheimer's & Dementia* 8, 6: 544–552.
- World Health Organization. (2013). Ageing and the Life Course. <https://www.who.int/ageing/en/>.
- World Health Organization. (2014). Global Status Report on Noncommunicable Diseases 2014.
- World Health Organization. (2015). 2015 World Health Statistics. [https://www.who.int/gho/publications/world\\_health\\_statistics/2015/en/](https://www.who.int/gho/publications/world_health_statistics/2015/en/).
- Young, R., E. Willis, G. Cameron, and M. Geana. (2014). “Willing but Unwilling”: Attitudinal Barriers to Adoption of Home-Based Health Information Technology among Older Adults. *Health Informatics Journal*.
- Zárate-Bravo, E., J.-P. García-Vázquez, and M.D. Rodríguez. (2016). An Ambient Medication Display to Heighten the Peace of Mind of Family Caregivers of Older Adults. In *Pervasive Computing Paradigms for Mental Health*, 274–283.
- Zhou, J., P.-L.P. Rau, and G. Salvendy. (2014). Age-Related Difference in the Use of Mobile Phones. *Universal Access in the Information Society* 13, no. 4 (November 1): 401–413.





# 4

## Use of Technologies for Social Connectedness and Well-Being and as a Tool for Research Data Collection in Older Adults

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### INTRODUCTION AND OVERVIEW

Frequent social connectivity with a variety of social partners is associated with better psychological well-being and physical health, as well as increased longevity (Umberson and Montez, 2010). We can think of social connectivity along a spectrum from fully socially engaged to socially isolated. Empirical evidence suggests a dose–response association between degree of social connection and positive health outcomes (Tanskanen and Anttila, 2016); that is, the more social connection, the greater the impact on health and well-being.

Globally, there is increasing concern about trends in social connectivity, loneliness, and social isolation (Holt-Lunstad et al., 2017; Klinenberg, 2016). Indeed, Great Britain established a national commission on loneliness to address this concern (Klinenberg, 2016). Prevalence of social isolation in the US is difficult to estimate, but demographic trends portend

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increasing social disconnectedness in the future due to rising rates of childlessness, increasing numbers of never married and previously married individuals, smaller households, and falling community involvement in formal groups (Holt-Lunstad et al., 2017). Given population aging, lack of social connectivity is likely to become an increasing population concern.

Social networks tend to diminish in size as people age—in part, due to retirement and deaths of friends and family, as well as increased physical frailty and reduced mobility (Klinenberg, 2016). The Pew Research Center (2009) reports that social networks have declined by about a third in size over the past few decades. Moreover, among older people in the United States, men may be more at risk of social isolation than women (Klinenberg, 2016), and Black Americans may be more at risk than their non-Black counterparts (Umberson et al., 2017).

A number of public health and research initiatives address the issue of social dis/connection in older populations. This chapter addresses how different technologies may promote social connection and decrease social isolation in late life. We consider two related issues. First, we marshal available evidence to consider whether and how technologies can be used to promote social connection and well-being in older populations. Second, we consider how mobile technologies can be used to study social connectivity and health linkages in older adults. Social connections are fundamental to overall health and well-being throughout life, and mobile technologies may provide critical tools for generating and supporting those connections for older populations.

## INFORMATION AND COMMUNICATION TECHNOLOGIES IN LATE LIFE

The term “information and communication technologies” (ICTs) has been used to encompass the broad range of these technologies, which include smartphones, specialized apps, web-based sites with information about health and other topics, social media, videoconferences, voice activated virtual assistants, and a variety of other applications (see Table 4-1 for a full listing; Mitzner et al., 2019). Recent national surveys conducted by the Pew Research Center reported that nearly three quarters of adults over aged 65 used the internet (73%; Anderson et al., 2019), and the majority of adults over age 65 have cell phones (91%).

Older adults lag behind younger age groups in use of many technologies. For example, most young adults use smartphones (90%) and social media (86%). Yet only 40 percent of older adults use smartphones, with use declining with age (e.g., 59% of 65 to 69-year-olds compared to 17% of adults over age 80), and only a third of older adults use social media (34%; Anderson and Perrin, 2017; Anderson et al., 2019). Further, Cotten

**TABLE 4-1** Types of ICTs and Definitions

| Type of ICT | Definition                                                                                                                                                                                                                           | Software & Devices       | Examples                                                                                                                                 |
|-------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Health      | Often wearable technology that has the ability to inform doctors and other health care providers of a patient's well-being. Information that can be communicated includes heart rate, pulse, blood pressure, sleep, step count, etc. | Smart watches            | Apple Watch, Whoop Fitness Tracker, Samsung Watch, FitBit<br><br>Measures: heart rate, accelerometer, sleep analysis, calories burned,   |
|             |                                                                                                                                                                                                                                      | Smart clothing           | Levi's Commuter x Jacquard, Sensoria Fitness Socks, Nadi X<br><br>Measures: heart rate, distance traveled, altitude, posture adjustments |
|             |                                                                                                                                                                                                                                      | Mobile phone health apps | Apple Health app, MyFitnessPal, Strava<br><br>Measures: step count, distance, heart rate, calories burned                                |
| Business    | A category of ICT that is concerned with the presentation, preservation, and manipulation of data in a workplace or classroom.                                                                                                       | Word processors          | Word, Google Docs, Pages                                                                                                                 |
|             |                                                                                                                                                                                                                                      | Spreadsheets             | Excel, Google Sheets                                                                                                                     |
|             |                                                                                                                                                                                                                                      | Presentation software    | Powerpoint, Prezi, Keynote                                                                                                               |
|             |                                                                                                                                                                                                                                      | Communication meetings   | Webex, Zoom, GoToMeeting                                                                                                                 |
| Social      | A type of ICT that facilitates information exchange and communication between two or more individuals                                                                                                                                | Social media             | Instagram, Facebook, Twitter, Snapchat, Pinterest                                                                                        |
|             |                                                                                                                                                                                                                                      | Video messaging          | Skype, FaceTime                                                                                                                          |
|             |                                                                                                                                                                                                                                      | Text messaging           | Mobile phone apps: Messenger, GroupMe, WhatsApp, iMessages                                                                               |
|             |                                                                                                                                                                                                                                      | Dating                   | Bumble, Tinder, Match.com                                                                                                                |
|             |                                                                                                                                                                                                                                      | Video sharing            | YouTube, Tik Tok                                                                                                                         |
|             |                                                                                                                                                                                                                                      | Digital assistants       | Alexa, Siri, Google Home                                                                                                                 |
|             |                                                                                                                                                                                                                                      | Transactions             | Venmo, PayPal, Cash App, mobile banking apps                                                                                             |

(2017) points out that Pew Research Center data likely overestimate technology use in old age due to exclusion of older adults who are unlikely to use technologies (e.g., those in skilled nursing care or suffering dementias) and who are unable to respond to smartphone or web-based surveys.

Among adults over the age of 65 who use ICTs, facilitation of social connection and communication with friends and family are among the most prevalent reasons (Cotten et al., 2012; Sims et al., 2017). Several types of ICTs may be especially useful in fostering social connection, but older adults may use these technologies selectively. For example, older adults may be more comfortable placing calls on mobile phones, due to familiarity with phones in general. They may be less likely to use smartphones that allow texting or apps such as YouTube and Twitter where individuals share information.

Research also suggests that older adults are willing to embrace voice-activated intelligent assistants (e.g., Alexa; Google assistant; Siri), but it is not clear that these assistants improve feelings of social connection (Koon et al., 2019). One small study involved semi-structured interviews with 12 older adults to evaluate their experience with Amazon Echo. Older adults were positive overall about the voice-activated assistant for music, weather, and information but reported frustrations with social aspects, such as the device's inability to understand their accent or giving the response "I don't know what you mean." Even adults who mastered tasks that facilitated communication with friends or family questioned whether it was more useful than the phone (Koons et al., 2019). Thus, the devices may assist with practical tasks, but it is not clear whether these technologies assist in social connection or that they can substitute for human interactions in some situations.

### **Facilitating Factors and Barriers to Use of ICTs for Social Connection**

Many older adults use technologies for social communication, but a large proportion do not (Anderson and Perin, 2017; Anderson et al., 2019; Hargattai, 2018). These disparities reflect access to resources. Nearly all young adults of all socioeconomic backgrounds have access to an array of technologies and regularly use ICTs to connect with other people, but for older adults, a lack of economic, educational, and social resources may place constraints on access to, and effective use of technologies for social connection.

Demographic factors associated with technology use in old age include advantaged statuses, such as younger age, higher education and income, better health, being non-Hispanic White and speaking English (Berkowsky, Sharit, and Czaja, 2018), and residing in more urban areas, as opposed to rural areas (Findlay and Nies, 2017). For example, a study of 1,700 older adults in the Chicago area revealed that income determined ownership

and use of a wide array of ICTs (e.g., smartphone, e-reader, tablet; Ihm and Hsieh, 2016). Similarly, a convenience sample of 350 older adults in rural Idaho (where ICT use is low), revealed that older adults who use social networking sites have socioeconomic advantages that contribute to internet use (Findlay and Nies, 2017).

Data regarding factors that determine ICT use in later life are available from two large national longitudinal studies of older populations. The National Health and Aging Trends Study (NHATS) started in 2011 and involved nearly 6,500 adults aged 65 and older representative of the US older population. Participants answered questions about information and communication technology, including having a cell phone or a computer and whether the individual has texted, emailed, used the internet, and gone online for health information, shopping, etc. in the prior month (Elliot et al., 2013). The Health and Retirement Study (HRS) is a large longitudinal national survey of approximately 20,000 adults over the age of 50 with follow-ups every two years starting in 1992. The HRS survey included a single item about use of the internet (presumably via a computer) starting in 2002. In 2012, the HRS administered a module asking about use of ten types of ICTs, such as video chatting, social networks, devices to monitor health, and e-readers or tablets to a subset of approximately 1,800 participants (Chopik et al., 2017).

These studies documented cross-sectional associations between cognitive functioning and use of ICTs in late life. Not surprisingly, better cognitive functioning is linked to adoption of a great number of ICTs (in the HRS; Chopik et al., 2017) and to use of ICTs for texting or email (in the NHATS; Elliot et al., 2013). Furthermore, the design of ICTs may present challenges in the face of psychomotor and cognitive changes in late life; such designs may limit use of technologies among some older populations. For example, smartphone apps or other technologies that have the potential to facilitate communication in late life may be too complicated for many older adults or may require fine motor skills that are too demanding (Charness and Boot, 2016). Technical updates and new operating systems can also alter the format of technologies after older adults have mastered them, and may present barriers to continued utilization.

Technology use and purpose of use also vary by gender. Data from the NHATS revealed that men are more likely to use technologies in general and are more likely to use technologies for informational purposes in particular, whereas older women who use technologies do so to foster social engagement (Kim et al., 2017). Consistent with this gender difference, data from the HRS documents that women are more likely than men to use social networking sites (SNSs) like Facebook (Yu et al., 2016).

In sum, there is a digital divide in older adults' adoption of technologies based on structural factors (Fang et al., 2019). Older adults who have more resources and better education and cognitive function are more likely

to use technologies that may enhance their social connectedness. Gender differences complicate these patterns, however, with men more likely to use ICTs in general, but women more likely to use technologies specific to communication (e.g., text messaging, SNSs). Other individual factors (e.g., race/ethnicity) condition ICT use as well. As such, it is not clear which factors influence use of these technologies specifically for communication and social engagement, although extant data hint that individuals who are advantaged with a larger social network are also the ones who are most likely to use ICT to connect to social partners.

### Use of Technologies for Communication and Social Connection

A fundamental question in the study of technologies in late life is the extent to which older adults who do use these new technologies (e.g., smartphone, video conference, social media) do so for communications and social connection (for a discussion, see Hult and McDonald, 2020). Researchers suggest that older adults who use technologies for social connection do so for two motivations: (a) the complementary use of technologies for communication to supplement and reinforce existing social ties, and (b) the compensatory use of technologies for communication to make up for lack of social ties and disadvantages (Sims et al., 2017).

Evidence suggests complementary use of these media. Older adults are more likely to use these technologies when their social partners assist them and encourage them to do so (Francis et al., 2018). Similarly, older adults who wish to use technologies such as SNSs are often motivated by a desire to communicate with family members and friends who also use these network sites (Charney and Boot, 2016). Social partners may play a key role in motivating older adults to use technologies, helping them set up and learn to use these technologies, and problem-solving difficulties (i.e., “glitches”) that arise. Children, grandchildren, and other younger people may assist in using and updating technologies in ways that strengthen older adults’ sense of connection to these helpers.

A study relying on focus groups in the Midwest found that older adults’ requests for assistance with ICT generated stronger bonds to family members and generated interactions with experts in technology (e.g., customer service) outside the older adults’ family (Francis et al., 2018). A clinical trial introduced older adults to the internet, social media, and emails in a continuous care retirement community (i.e., a single facility with older adults residing in independent living units, assisted living units, and skilled nursing facilities; Cotten et al., 2017). The study introduced peer teaching in promoting ICT use; these peer connections were successful for technology adoption because older learners enjoyed learning from an age mate, and individuals of similar ages shared experiences.

Data also support the compensation model. Yu and colleagues (2016) suggested that individuals who are widowed or are homemakers may be compensating for lack of social networks in their greater use of SNSs. A study conducted with a subset of the HRS sample found that older adults who live alone benefited more from use of the internet than did older adults who resided with others (Cotten et al., 2014). Likewise, a growing number of older adults use dating websites to find new romantic partners (Davis and Fingerman, 2016; Griffin and Fingerman, 2018).

Many studies have focused on use of SNSs such as Facebook in old age. In addition to constraints on use of technologies in general, barriers to use of SNSs include older adults' concerns about privacy, fear of identity theft, and perceived lack of security that may be specific to social media (Bixter et al., 2019; Hutto et al., 2015). Nevertheless, many older adults do use SNSs. According to a Pew Research Center survey, 46 percent of older adults reported use of Facebook in 2019 (Perrin and Anderson, 2019). It is not clear that older adults use Facebook in the same manner as younger adults, however. A cross-sectional nationally representative study of 1,000 adults aged 18 to 93 revealed age differences in Facebook networks. Compared with younger adults, older adults reported smaller Facebook friend networks, but a greater proportion of actual friends (i.e., also friends outside of Facebook; Chang et al., 2015). That is, older adults who use Facebook do so to engage with people they already know. In sum, ICTs, including social media, have the potential to help retain and reinforce existing supportive ties and also have the potential to generate new social connections.

## SOCIAL USE OF TECHNOLOGIES AND WELL-BEING IN LATE LIFE

Researchers are particularly interested in whether ICTs can be used for social connection to improve social engagement, social isolation, loneliness, depressive symptoms and depression, life satisfaction, and physical well-being. To date, many studies have documented benefits of different forms of ICT use on these outcomes (Cotten et al., 2012, 2014; Heo et al., 2015). In documenting these associations, however, the majority of research has relied on cross-sectional data, with only a few studies using longitudinal data. Moreover, one study of 92 adults over the age of 50 found that introducing tablets increased (rather than decreased) loneliness (Pauly et al., 2019), perhaps due to social comparisons that arise via SNSs.

On the whole, however, adults seem to benefit from use of ICTs. Reciprocally, older adults with better well-being may be more motivated to use technologies. Data from the HRS (i.e., 2006, 2008 or 2012 waves of data) revealed that internet use was associated with fewer symptoms of depression cross-sectionally and longitudinally (Cotten et al., 2012, 2014). Chopik (2016) examined cross-sectional data from the HRS and linked use



of social technologies (e.g., email, SNS, online video/phone calls, online chatting/instant messaging, smartphone usage) to a variety of positive outcomes (e.g., reduced loneliness, better life satisfaction, fewer chronic conditions, better health). These associations are also evident among adults in very late life. Sims et al. (2017) recruited a nationally representative sample of 445 adults over age 80. Older adults reported their use of 16 technologies (e.g., online banking, video games, digital books, fitness trackers, email, video calls). Using more devices or apps was positively associated with feeling connected to loved ones and life satisfaction and negatively associated with loneliness and functional limitations. Furthermore, use of ICTs for social connection was associated with less loneliness and better psychological well-being, above and beyond the number of devices.

Longitudinal studies have also confirmed the direction of these associations over time. Cotten and colleagues examined ratings of internet use from 2002 to 2008 in the HRS. Controlling for prior depression and prior internet use, they found that internet use reduced the probability of a future depressive state by about 33%. Likewise, Szabo and colleagues (2019) studied over 1,000 New Zealand adults aged 60 to 77 and assessed three purposes for online engagement: social (e.g., engaging with friends/family), instrumental (e.g., banking), and informational (e.g., health information). Over four years, from 2013 to 2016, use of technologies for social purposes was associated with decreased loneliness and increased social engagement, which in turn were associated with better psychological well-being.

The literature has also focused more specifically on benefits of using SNSs. The Georgia Tech Home Lab study provided detailed information regarding Facebook use. This cross-sectional convenience study included 142 volunteer participants over the age of 50 who completed a brief survey of social media use (e.g., Skype and Facebook) and traditional communication media (e.g., phone, face-to-face, letter). Bell et al. (2013) analyzed these data and found that older adults who used Facebook were more satisfied with their social lives than older adults who did not use Facebook, but they were not less lonely.

Individuals use SNSs in several ways, but three types of behaviors stand out: (a) social communication directed at specific individuals, (b) broadcast communications to the broader network, and (c) passive consumption of social partners' posts. Hutto and colleagues (2015) also drew on the convenience sample in the Georgia Tech Home Lab to show that older adults who engaged in directed communications via SNSs (as opposed to broadcast and passive communications) were less lonely and more satisfied with their lives.

National data may tell a different story about Facebook use and well-being in adulthood. Shakya and Christakis (2017) conducted a longitudinal study of US households using three waves of Gallup's web-based polling data (2013 to 2015). The survey asked about the people that participants could

confide in or spend time with (referred to as “real world” social networks). Participants also provided the researchers access to their Facebook accounts. Notably, the study by definition excluded adults who did not use Facebook (i.e., over half of older adults). The researchers examined the number of Facebook friends, the number of times participants “liked” someone else’s content, clicked on links posted by friends, and updated their own status on Facebook. Cross-sectional and prospective analyses revealed that real-world social connections were associated with better self-rated psychological health, life satisfaction, and physical health. Facebook behaviors (e.g., liking another’s content and clicking links posted by friends) were associated with poorer well-being. Furthermore, the negative effects of Facebook were comparable or greater than the positive effects of having real-world social connections. This study did not provide analyses by age, and future research is necessary to disentangle these patterns in older populations.

In sum, ICTs may not substitute for face-to-face social contact and connection but may provide older people with opportunities to connect to the social world virtually. Additional research is necessary to understand how phone use, texting, video conferencing, and other one-to-one social connections via ICT might be beneficial in the absence of other face-to-face connection.

### INTERVENTIONS TO IMPROVE SOCIAL CONNECTION VIA ICT USE

Given the number of devices available to facilitate communication easily and inexpensively, interventions to mitigate social isolation and improve social connectedness in late life are tenable. For example, the World Health Organization recently launched a digital application (or app) to provide healthcare and social workers resources necessary to reduce social isolation in late life (Chaib, 2019).

Randomized controlled studies of interventions have begun to examine ICT use to alleviate social distress or promote social connection. A synthesis of this literature is limited because studies use different definitions of social involvement, vary in ICTs examined, and may not include long-term follow-up. Likewise, some intervention studies intended to enhance social connection via ICTs have relied on small samples, qualitative data, or demonstration projects. Furthermore, because these interventions typically target older adults who are not familiar with the technologies, the intervention must include training elements. Training may introduce social contacts that are difficult to account for in assessments of the intervention (Shillair et al., 2015).

Intervention studies with control groups present convincing findings regarding the benefits of ICT use. Shillair and colleagues (2015) conducted

a randomized controlled trial (RCT) introducing laptop computers and internet access to improve loneliness and social isolation. The study drew on a convenience sample residing in assisted living and independent living communities. The intervention occurred over 8 weeks and involved training on laptop computers. The study also included a placebo group (received the same number of sessions with the trainers, but no ICT use) and a true control (no ICT/no placebo training). The effects of the ICTs on life satisfaction over time (3 months, 6 months, 12 months) depended on attitudes toward ICT use (Tsai et al., 2019). Older adults who grew more confident about using ICTs to communicate also felt more socially supported, and their overall life satisfaction grew higher over time (Shillair et al., 2015). As such, introduction of ICTs is not a panacea, but rather depends on training and time for the person to become comfortable with these technologies.

Another intervention, the Personal Reminder Information Social Management System (PRISM) study recruited 300 volunteers over the age of 65 residing independently in the community. The intervention provided participants with a mini desktop PC with free internet access, a printer, and free access to the internet, including a calendar, photo feature, emails, and online help. The email feature included a “buddy tab” intended to foster social connections between study participants. A control group received similar information in a binder with opportunities to form connections to other participants by sharing their phone number and interests with other participants in their group. At 6 months postrandomization, participants in the PRISM condition showed greater improvements in ratings of loneliness and social support than the binder group, but these differences disappeared at 12 months postrandomization when both groups showed improvements (Czaja et al., 2018). Although these intervention studies point in the direction of benefits from technology for social involvement, some smaller studies have shown opposite effects of using social functions on portable ICTs, perhaps due to feelings of exclusion that increase loneliness (Pauly et al., 2019).

Finally, older adults’ social lives typically involve enclaves of social partners who have long histories of interactions, who are educationally similar, and who share cultural backgrounds (McPherson et al., 2001). As such, older adults who do not use technologies are likely to have older friends and relatives who do not use technologies for communication. Interventions that target one older adult may be ineffective in the absence of including the broader social circle.

### USING MOBILE TECHNOLOGIES IN RESEARCH ON SOCIAL CONNECTIVITY

Although the literature regarding older adults’ use of mobile technology has focused broadly on ICTs, researchers have specifically used mobile tech-

nologies to examine older adults’ social lives. Using mobile technologies, scholars have generated self-reports of activities and mood throughout the day, observations of conversations, location, and activity level, and links between daily social connections and well-being outcomes.

Self-Reported Social Connectivity via Mobile Devices

Studies of older adults’ social lives have used daily diary methods to assess self-reported social interactions throughout the day (see Table 4-2 for types of measurement and definitions). Many of those studies (e.g., Birditt, 2013) have relied on telephone interviews at the end of the day, without placing demands on older adults to utilize technologies.

Other studies have used ecological momentary assessments (EMAs; surveys that participants complete at intervals throughout the day as they go about their daily life) relying on smartphones preprogrammed specifically for that study, and sometimes including less-educated older adults by providing training and instruction, and technical support follow-ups (Birditt et al., 2018; Fingerman et al., 2020). These methods, by which individuals report on their social connections multiple times a day, shed light on social interactions and how such interactions contribute to health and well-being. These methods can provide insights into the temporal sequencing of events and help identify potential mechanisms linking social connectivity and health or well-being. For example, Birditt et al. (2018) assessed older adults aged 65 and older every three hours for 5 to 6 days, and found that older adults rarely reported social isolation (defined as no contact via face-to-face, telephone, or electronically for three consecutive hours).

TABLE 4-2 Mobile Assessments and Definitions

| Type                                     | Definition                                                          |
|------------------------------------------|---------------------------------------------------------------------|
| Self-reported                            |                                                                     |
| Daily diary                              | Surveys completed once a day                                        |
| Ecological momentary assessment          | Surveys completed multiple times a day                              |
| Interval-based assessments               | Surveys arrive at set times                                         |
| Event based                              | Surveys completed when particular events occur                      |
| Random                                   | Surveys arrive at random times                                      |
| Observational                            |                                                                     |
| Mobile phone logs                        | Logs of text messages and phone calls                               |
| GPS                                      | Location information                                                |
| Electronically Activated Recorder (EAR ) | App that records snippets of sound at random intervals              |
| Blue tooth                               | Used to assess size of social groups and connection                 |
| Measures of health                       |                                                                     |
| Ambulatory blood pressure and heart rate | Assesses blood pressure and heart rate randomly or at set intervals |
| Accelerometers                           | Measures acceleration. When sleeping is referred to as actigraphy.  |

Researchers have also used a variety of ambulatory devices to measure associations between social interactions and health indicators, including physical activity, sleep, heart rate, and blood pressure, throughout the day. These studies provide insights into the mechanisms linking social connections and health. Our recent research identified associations between social integration, daily activities, and physical activity in late life using Ecological Momentary Assessments on handheld Android devices—supplemented by objective indicators of physical activity measured with Actical accelerometers (Fingerman et al., 2019). We found that connecting with a wider variety of social partners was associated with greater physical activity and better mood. Social connections and relationship quality are also associated with sleep duration and quality as measured with actigraphs. Cross-sectional research using the National Social Life Health and Aging (NSHAP) data (individuals aged 57 to 85) have focused on sleep and marital quality using actigraph/accelerometer (Chen et al., 2014). Likewise, researchers have examined daily social interactions and ambulatory blood pressure in younger adults but have often not examined older adults (Cornelius et al., 2019). Overall, these studies show that mobile technology can be used to assess many facets of social connection and health and allow examination of temporal links between social ties and health outcomes as they unfold.

### Observational Studies of Social Connectivity

Observational studies use smartphone technology to obtain information regarding types of communication, geographic location, and recordings of the natural environment. Mobile devices can be used to assess proximity to social partners using Bluetooth data to determine the strength of the connection between individuals (Boonstra et al., 2015) or the size of social groups (Chen et al., 2014). Researchers can also use the GPS data from mobile devices to assess the geographical location of respondents, including distance from home. A study of older adults found that time spent out of the house (measured with GPS) was associated with exercise and social activities (York and Cagney, 2017).

Another mobile device, the Electronically Activated Recorder (EAR) records participants' utterances as they occur in the natural environment (Mehl, 2017). Studies have shown that the EAR provides unique predictive information beyond self-report. The EAR device can also be used to track human behaviors that are less conscious, including sighing, swearing, and laughing, as well as emotional tone, all of which can provide important information about mental and physical health. The EAR device may also provide information about the effects of early-stage cognitive impairments and the effects of hearing loss on conversation and social engagement, but has not been used specifically in these contexts.

## CONCLUSION

Social networks become smaller as people age, and older people are more likely than their younger counterparts to report feeling lonely and socially isolated (Kemperman et al., 2019). ICT use in older populations offers great promise for fostering social connection. The use of mobile technologies to gather data on the social connectivity of older people in relation to their health and well-being can lay groundwork for effective policies and practice strategies to enhance social connection. However, the limitations of such strategies must also be considered by recognizing that mobile technologies may not always be effective substitutes for in-person social contact. Below, we briefly review several major themes in the current research evidence on mobile technology use and social connectivity with older populations and identify strategic directions for future research.

The first major theme concerns the need for additional research on information and communication technologies and social connection among older adults. Today's older people grew up in an era devoid of such technologies, and thus opportunities, constraints, and rewards of information and communication technologies are highly likely to differ for younger and older age cohorts. Use of technology has largely saturated younger cohorts, whereas there are sizable discrepancies in use of technologies in late life. Older adults who are well off typically use new technologies, whereas those who are less well off typically do not (Hargittai, 2018). These discrepancies reflect education and resources; older adults who have greater access and knowledge are more likely to adopt these technologies. Moreover, Black and Hispanic Americans are less likely to have broadband connections at home, which reduces the usefulness of ICTs (and the potential human capital they are associated with) and may lead to disparities.

Other disparities reflect social resources. Individuals who are more socially engaged and socially connected through family and friends are also more likely to have social partners who provide them with technologies, provide instruction in usage, and serve as targets for connection through SNSs (e.g., Facebook). Further, women are more likely than men to use technology for social networking (Kim et al., 2017).

Second, current research evidence on the use of and benefits from ICT is limited because many studies rely on small samples and cross-sectional designs. These approaches reflect the challenges of defining sampling in older adults. It is highly likely that the use of mobile technologies for social connection are affected by the mental, physical, and cognitive status of people as they age, and disentangling these factors in research is complex. Studies that have used national samples with longitudinal data suggest that ICT use in late life is beneficial (e.g., Cotten, et al., 2014). Nevertheless, much of this research is limited to two national datasets (NHATS, HRS),

both of which have limited items addressing ICT use. Substantial investment is required to execute studies that draw on multiple items and multiple methods to assess social connection and use of technologies over time.

Third, given the growing burden of dementia in aging societies, there is a pressing need for research examining interventions to increase the use of ICTs to foster social connectivity. Interventions and programs using such technologies may be particularly important to assist people with cognitive impairment and their caregivers. Nevertheless, early intervention studies on how technologies can alleviate caregiver burden have had limited success, and the costs of the technologies outweighed the benefits. Relatively low cost technologies, such as GPS, may assist caregivers to locate persons with dementia who tend to wander, though the ethics of using such devices has also been questioned (Mahoney and Mahoney, 2010). Future intervention research might focus on the feasibility, ethics, and dissemination of these existing low-cost technologies.

In this chapter, we discussed several ways in which ICTs intersect with the well-being of older populations: (a) older people's use of ICTs with regard to social connection, (b) factors that facilitate or set up barriers for the use of such technologies, (c) the impact of using these technologies for social connection to improve well-being in late life, (d) interventions to increase social connectivity via adoptions of ICTs, and (e) research applications using mobile technologies. ICTs offer many opportunities to enhance feelings of social connection among older populations, and to promote their well-being. ICTs may also confer benefits outside of promoting social connection, such as health monitoring, banking, and other daily tasks. Future research should consider the potential costs and benefits across ICTs used by older people, with close attention to the purpose and consequences of different types of ICTs. As future cohorts grow older, the use of ICTs for social connection in late life may continue to grow.

## REFERENCES

- Anderson, M., & Perrin, A. (2017, May 17). *Technology use climbs among older adults*. Pew Research Center. Available: <http://www.pewinternet.org/2017/05/17/technologyuse-among-seniors/>.
- Anderson, M., Perrin, A., Jiang, J., & Kumar, M. (2019, April 22). *10% of Americans don't use the internet. Who are they?* Pew Research Center. Available: <https://www.pewresearch.org/fact-tank/2019/04/22/some-americans-dont-use-the-internet-who-are-they/>.
- Bell, C., Fausset, C., Farmer, S., Nguyen, J., Harley, L., & Fain, W.B. (2013). Examining social media use among older adults. In *Proceedings of the 24th ACM Conference on Hypertext and Social Media* (pp. 158–163). New York, NY: Association for Computing Machinery. <https://doi.org/10.1145/2481492.2481509>.
- Berkowsky, R.W., Sharit, J., & Czaja, S.J. (2018). Factors predicting decisions about technology adoption among older adults. *Innovation in Aging*, 1, igy002. <https://doi.org/10.1093/geroni/igy002>.



- Birditt, K.S. (2013). Age differences in emotional reactions to daily negative social encounters. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 69, 557–566. <https://doi.org/10.1093/geronb/gbt045>.
- Birditt, K.S., Manalel, J.A., Sommers, H., Luong, G., & Fingerman, K.L. (2018). Better off alone: Daily solitude is associated with lower negative affect in more conflictual social networks. *The Gerontologist*, 1–10. <https://doi.org/10.1093/geront/gny060>.
- Bixter, M.T., Blocker, K.A., Mitzner, T.L., Prakash, A., & Rogers, W.A. (2019). Understanding the use and non-use of social communication technologies by older adults: A qualitative test and extension of the UTAUT model. *Gerontechnology*, 18, 70–88. <https://doi.org/10.4017/gt.2019.18.2.002.00>.
- Boonstra, T.W., Larsen, M.E., & Christensen, H. (2015). Mapping dynamic social networks in real life using participants' own smartphones. *Heliyon*, 1, e00037. <https://doi.org/10.1016/j.heliyon.2015.e00037>.
- Chaib, F. (2019). *WHO launches digital app to improve care for older people*. World Health Organization. Available: <https://www.who.int/news-room/detail/30-09-2019-who-launches-digital-app-to-improve-care-for-older-people>.
- Chang, P.F., Choi, Y.H., Bazarova, N.N., & Löckenhoff, C.E. (2015). Age differences in online social networking: Extending Socioemotional Selectivity Theory to social network sites. *Journal of Broadcasting and Electronic Media*, 59, 221–239. <https://doi.org/10.1080/08838151.2015.1029126>.
- Charness, N., & Boot, W.R. (2016). Technology, gaming, and social networking. In Schaie, K.W. & S. Willis (Eds.), *Handbook of the Psychology of Aging* (pp. 389–407). Amsterdam: Academic Press. <https://doi.org/10.1016/B978-0-12-411469-2.00020-0>.
- Chen, Z., Chen, Y., Hu, L., Wang, S., Jiang, X., Ma, X., Lane, N.D., & Campbell, A.T. (2014). ContextSense: Unobtrusive discovery of incremental social context using dynamic Bluetooth data. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication* (pp. 23–26). New York: ACM.
- Chopik, W.J. (2016). The benefits of social technology use among older adults are mediated by reduced loneliness. *Cyberpsychology, Behavior, and Social Networking*, 19, 551–556. <https://doi.org/10.1089/cyber.2016.0151>.
- Chopik, W.J., Rikard, R.V., & Cotten, S.R. (2017). Individual difference predictors of ICT use in older adulthood: A study of 17 candidate characteristics. *Computers in Human Behavior*, 76, 526–533. <https://doi.org/10.1016/j.chb.2017.08.014>.
- Cornelius, T., Birk, J.L., Edmondson, D., & Schwartz, J.E. (2019). Romantic relationship satisfaction and ambulatory blood pressure during social interactions: Specificity or spillover effects? *Annals of Behavioral Medicine*, 53, 223–231. <https://doi.org/10.1093/abm/kay030>.
- Cotten, S.R. (2017). Examining the roles of technology in aging and quality of life. *Journals of Gerontology, Series B: Psychological and Social Sciences*, 72, 823–826. <https://doi.org/10.1093/geronb/gbx109>.
- Cotten, S.R., McCullough, B.M., & Adams, R.G. (2012). Technological influences on social ties across the lifespan. In K.L. Fingerman, C.A. Berg, J. Smith, & T.C. Antonucci (Eds.), *Handbook of lifespan development* (pp. 647–672). New York, NY: Springer Publishers.
- Cotten, S.R., Ford, G., Ford, S., & Hale, T.M. (2014). Internet use and depression among retired older adults in the United States: A longitudinal analysis. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 69, 763–771. <https://doi.org/10.1093/geronb/gbu018>.
- Cotten, S.R., Yost, E., Berkowsky, R., Winstead, V., & Anderson, W. (2017). *Designing technology training for older adults in continuing care retirement communities*. Boca Raton, FL: Human Factors and Aging Series: CRC Press (a division of Taylor and Francis).



- Czaja, S.J., Boot, W.R., Charness, N., Rogers, W.A., & Sharit, J. (2018). Improving social support for older adults through technology: Findings from the PRISM randomized controlled trial. *The Gerontologist*, 58, 467–477. <https://doi.org/10.1093/geront/gnw249>.
- Davis, E.M., & Fingerman, K.L. (2016). Digital dating: Online profile content of older and younger adults. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 71, 959–967. <https://doi.org/10.1093/geronb/gbv042>.
- Elliot, A.J., Mooney, C.J., Douthit, K.Z., & Lynch, M.F. (2013). Predictors of older adults' technology use and its relationship to depressive symptoms and well-being. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 69, 667–677. <https://doi.org/10.1093/geronb/gbt109>.
- Fang, M.L., Canham, S.L., Battersby, L., Sixsmith, J., Wada, M., & Sixsmith, A. (2019). Exploring privilege in the digital divide: Implications for theory, policy, and practice. *The Gerontologist*, 59, e1–e15. <https://doi.org/10.1093/geront/gny037>.
- Findlay, A.H., & Nies, M.A. (2017). Understanding social networking use for social connectedness among rural older adults. *Healthy Aging Research*, 6, e12. <https://doi.org/10.1097/HXR.0000000000000012>.
- Fingerman, K.L., Huo, M., Charles, S.T., & Umberson, D.J. (2020). Variety is the spice of late life: Social integration and daily activity. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 75(2), 377–388. <https://doi.org/10.1093/geronb/gbz007>.
- Francis, J., Kadylak T., Makki, T., Rikard, R.V., & Cotten, S.R. (2018). Catalyst to connection: When technical difficulties lead to social support for older adults. *American Behavioral Scientist*, 62, 1167–1185. <https://doi.org/10.1177/0002764218773829>.
- Griffin, E.M., & Fingerman, K.L. (2018). Online dating profile contact of older adults seeking same and cross-sex relationships. *Journal of GLBT Family Studies*, 14(5), 446–466.
- Hargittai, E. (2018). The digital reproduction of inequality. In D. Grusky (Ed.), *The Inequality Reader* (second ed., pp. 660–670). New York: Routledge.
- Harlow H.F., Dodsworth R.O., & Harlow M.K. (1965). Total social isolation in monkeys. *Proceedings of the National Academy of Sciences of the United States of America*, 54(1), 90–97. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC285801/pdf/pnas00159-0105.pdf>.
- Holt-Lunstad, J., Robles, T.F., & Sbarra, D.A. (2017). Advancing social connection as a public health priority in the United States. *The American Psychologist*, 72, 517–530. <https://doi.org/10.1037/amp0000103>.
- Hulur, G., & McDonald, B. (2020). Rethinking social relationships in old age: Digitalization and the social lives of older adults. *American Psychologist*, 75(4), 554–566. <https://doi.org/10.1037/amp0000604>.
- Hutto, C.J., Bell, C., Farmer, S., Fausset, C., Harley, L., Nguyen, J., & Fain, B. (2015). Social media gerontology: Understanding social media usage among older adults. *Web Intelligence*, 13, 69–87. <https://doi.org/10.3233/WEB-150310>.
- Ihm, J., & Hsieh, Y.P. (2016). The implications of information and communication technology use for the social well-being of older adults. *Information, Communication, and Society*, 18, 1123–1138. <https://doi.org/10.1080/1369118X.2015.1019912>.
- Kim, J., Lee, H.Y., Christensen, M.C., & Merighi, J.R. (2017). Technology access and use, and their associations with social engagement among older adults: Do women and men differ? *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 72, 836–845. <https://doi.org/10.1093/geronb/gbw123>.
- Kemperman, A., van den Berg, P., Weijs-Perrée, M., & Uijtendewillegen, K. (2019). Loneliness of older adults: Social network and the living environment. *International Journal of Environmental Research and Public Health*, 16, 1–16. <https://doi.org/10.3390/ijerph16030406>.

- Klinenberg, E. (2016). Social isolation, loneliness, and living alone: Identifying the risks for public health. *American Journal of Public Health*, 106, 786–787. <https://doi.org/10.2105/AJPH.2016.303166>.
- Koon, L.M., McGlynn, S.A., Blocker, K.A., & Rogers W.A. (2019). Perceptions of digital assistants from early adopters aged 55+. *Ergonomics in Design*, 28(1), 16–23. <https://doi.org/10.1177/1064804619842501>.
- Mahoney, E.L., & Mahoney, D.F. (2010). Acceptance of wearable technology by people with Alzheimer's disease: Issues and accommodations. *American Journal of Alzheimer's Disease and Other Dementias*, 25, 527–531. <https://doi.org/10.1177/1533317510376944>.
- McPherson, M., Smith-Lovin, L., & Cook, J.M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27, 415–444. <https://doi.org/10.1146/annurev.soc.27.1.415>.
- Mehl, M.R. (2017). The electronically activated recorder (EAR): A method for the naturalistic observation of daily social behavior. *Current Directions in Psychological Science*, 26, 184–190. <https://doi.org/10.1177/0963721416680611>.
- Mitzner, T.L., Savla, J., Boot, W.R., Sharit, J., Charness, N., Czaja, S.J., & Rogers, W.A. (2019). Technology adoption by older adults: Findings from the PRISM trial. *The Gerontologist*, 59, 34–44. <https://doi.org/10.1093/geront/gny113>.
- Pauly, T., Lay, J.C., Kozik, P., Graf, P., Mahmood, A., & Hoppmann, C.A. (2019). Technology, physical activity, loneliness, and cognitive functioning in old age. *GeroPsych: The Journal of Gerontopsychology and Geriatric Psychiatry*, 32, 111–123. <https://doi.org/10.1024/1662-9647/a000208>.
- Perrin, A., & Anderson, M. (2019, April 10). Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018. *Pew Research Center*. Available: <https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/>.
- Shakya, H.B., & Christakis, N.A. (2017). Association of Facebook use with compromised well-being: A longitudinal study. *American Journal of Epidemiology*, 185, 203–211. <https://doi.org/10.1093/aje/kww189>.
- Shillair, R.J., Rikard, R.V., Cotten, S.R., & Tsai, H.Y. (2015). Not so lonely surfers: Loneliness, social support, internet use and life satisfaction in older adults. Paper presented at the Proceedings at the University of California, Irvine, Newport Beach, CA. <http://hdl.handle.net/2142/73666>.
- Sims, T., Reed, A.E., & Carr, D.C. (2017). Information and communication technology use is related to higher well-being among the oldest-old. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 72, 761–770. <https://doi.org/10.1093/geronb/gbw130>.
- Szabo, A., Allen, J., Stephens, C., & Alpass, F. (2019). Longitudinal analysis of the relationship between purposes of internet use and well-being among older adults. *The Gerontologist*, 59, 58–68. <https://doi.org/10.1093/geront/gny036>.
- Tanskanen, J., & Anttila, T. (2016). A prospective study of social isolation, loneliness, and mortality in Finland. *American Journal of Public Health*, 106, 2042–2048. <https://doi.org/10.2105/AJPH.2016.303431>.
- Tsai, H.Y., Rikard, R.V., Cotton, S.R., & Shillair, R. (2019) Senior technology exploration, learning, and acceptance (STELA) model: From exploration to use—a longitudinal randomized controlled trial. *Educational Gerontology*, 45, 728–743. <https://doi.org/10.1080/03601277.2019.1690802>.
- Umberson, D. & Montez, J.K. (2010) Social relationships and health: A flashpoint for health policy. *Journal of Health and Social Behavior*, 51, S54–S66. <https://doi.org/10.1177/0022146510383501>.

- Umberson, D., Olson, J.S., Crosnoe, R., Liu, H., Pudrovska, T., & Donnelly, R. (2017). Death of family members as an overlooked source of racial disadvantage in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, 114, 915–920. <https://doi.org/10.1073/pnas.1605599114>.
- York, C.E., & Cagney, K.A. (2017). Aging in activity space: Results from smartphone-based GPS-tracking of urban seniors. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 72, 864–875. <https://doi.org/10.1093/geronb/gbx063>.
- Yu, R.P., Mccammon, R.J., Ellison, N.B., & Langa, K.M. (2016). The relationships that matter: Social network site use and social wellbeing among older adults in the United States of America. *Ageing and Society*, 36, 1826–1852. <https://doi.org/10.1017/S0144686X15000677>.

## 5

# Using Machine Learning to Forecast and Improve Clinical Outcomes and Healthy Aging Using Sensor Data

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## INTRODUCTION

Our understanding of health and aging comes from snapshots of measurements collected in healthcare settings, such as yearly blood testing for glucose, or responses to antidepressants measured episodically every few months by a clinician. Yet the vast majority of people's daily experiences unfold outside the eyes of the healthcare system, leaving habits, dietary choices, sleep, environmental, and social exposures unmeasured, along with important outcomes that are hard to collect with a questionnaire in a physician's office, such as daily perception of how they feel, functional independence, and emotional state.

By analyzing real time locations and speeds of cars, apps can automatically detect traffic and re-route you to your destination to arrive sooner. It seems natural that if a system could collect lifestyle habits of millions of people through ubiquitous sensors, such as those in cell phones, and follow what happened to them—whether they developed diseases or disability—then it could direct people how to live better to reduce the risk of diabetes or to inform how we can promote an aging parent to live safely at home, effectively re-routing their life to a longer, independent life. At a high level, we are all on the same journey of aging, and while young we generally rebound back to our expected levels of functioning after illness, accidents, or life-events, but as we age, we lose our ability to return to our

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prior function after increasingly small stressors and physiological insults (Clegg et al., 2013). Finding the path that maintains health and robustness of individuals and populations is therefore a universal need.

However, the optimism that large data sets and complex data analysis can help us learn personalized insights to optimize our way of living to promote personal betterment or graceful aging must be tempered with the humility that this endeavor is exceedingly difficult.

The amount of data collected from individual participants in trials already exceeds the ability of a human expert clinician to review, evaluate, and interpret, and machine intelligence plays a pivotal role for analysis. The question is how can researchers thoughtfully apply best practices in machine learning (ML) *and* clinical research as they use data to forecast progression of aging and clinical trajectories and identify ways to improve patient outcomes.

This chapter will begin by reviewing the core aspects that constitute an ML system: input data, desired outputs, and generation of training and test data. Following this review, the chapter will discuss ways in which ML can be applied to sensor data gathered in clinical trial settings as a means of identifying potential outcomes, forecasting health trajectories, and developing interventions to improve health for older adults.

## MACHINE LEARNING CONSIDERATIONS

### Overview of Machine Learning

The details of ML were recently summarized (Rajkomar, Dean, and Kohane, 2019). This chapter will focus on the most commonly used type of ML, referred to as supervised ML. While supervised ML is featured here, other types of ML have been used for proof-of-concepts (Fisher et al., 2019) and show promising results.

Supervised ML differs from traditional computer programs, which are written by software engineers who specify the step-by-step computations of transforming input data (called features) to output data (called labels). For example, to use the weight and height of a patient (features, or input data) to calculate the body mass index (BMI; a label, or output), a computer program can be written to perform the known calculation of  $BMI = \text{weight} / \text{height}$  (Clegg et al., 2013). In supervised ML, rather than providing the formula, the programmer simply gives these algorithms examples of patients with known weights, heights, and BMIs, and specific algorithms designed to learn from examples are used to build an ML model that predicts the BMIs for combinations of height and weight that were never seen in the initial set of examples provided. While ML would be a poor choice to determine BMI calculations from the weight and height since the relationship is known

ahead of time, it can be useful when the association is hard or impossible to specify by hand, such as using a digital picture of a person (features) to classify his or her BMI (label).

In medicine, ML models have been used to automate analysis of medical images, such as using eye fundus images (features) to diagnose diabetic retinopathy (labels; Gulshan et al., 2016) or using the sequence of data in a medical record (features) to predict patient outcomes, such as whether they are readmitted to the hospital (label; Rajkomar et al., 2018). Consented collection of digital data from patients during their daily life from wearable or ambient sensors can be used as input (features; Perez et al., 2019) for a variety of prediction tasks, such as onset of cognitive decline or worsened mobility (labels), which will be discussed in further detail below.

## Input Data

### Types of Sensors

The ubiquity of low-cost, miniature, and novel sensors allows for the collection of data that were previously too expensive or inconvenient to collect at scale. There is inconsistent terminology to categorize these sensors; some authors use the term “wearable” to emphasize the form factor and ease of collection, others use mobile health to highlight connection to a sensor carried in a mobile phone. However, data can be collected with sensors embedded in the environment (e.g., cameras or pressure sensors under a mattress to detect movement) that are similar to data collected with sensors worn on the body. This chapter considers the type of sensors that would detect data from daily living under proper consent regardless of whether they are wearable or ambient and refers to them as sensors despite the imprecision of this name.

Table 5-1 lists common sensors that are currently available commercially or in research devices that measure a host of signals, such as electrical signals (i.e., for electrocardiograms), acceleration/orientation (e.g., for movement), temperature, or audio (Heikenfeld et al., 2018; Mohr, Zhang, and Schueller, 2017; Ray et al., 2019). There are also a wide class of biosensors that use biological elements in the sensor itself (e.g., enzymes, cell receptors) that can be measured from the eye, mouth, skin, and more, although these are generally not commercially available and will not be discussed at length in this manuscript (Kim et al., 2019).

For ML, a key point is that the sensor data produce a raw signal that often undergoes further processing before outputting a human-understandable reading. For example, a photoplethysmographic sensor often outputs many readings of the heart rate that are averaged together in a process that produces a “final” reading periodically. The final reading is then fed into

**TABLE 5-1** Selected Types of Sensors that Collect Data Outside Healthcare Settings

|                                     | Category of Measurement          | Examples of Specific Sensors           | Examples of Measurements                                                       | Derived Measurements                                  |
|-------------------------------------|----------------------------------|----------------------------------------|--------------------------------------------------------------------------------|-------------------------------------------------------|
| Data measured from wearable sensors |                                  |                                        |                                                                                |                                                       |
|                                     | Inertia                          | Accelerometer, gyroscope, magnetometer | Linear and angular motion                                                      | Types of activity (e.g., walking), step length, falls |
|                                     | Light transmittance through skin | Photoplethysmographic (PPG)            | Oxygen saturation, heart rate, heart rate variability                          | Measurements of cardiovascular health                 |
|                                     | Electrical activity              | Electrodes                             | Electrocardiograms (EKG), electroencephalograms (EEG), Galvanic skin responses | Heart rhythms, sleep states, emotional state          |
|                                     | Mechanical movements             | Piezoelectric sensors                  | Pulsations on skin from heart beats                                            |                                                       |

|                                   |                           |                                         |                                                |                                                                                   |
|-----------------------------------|---------------------------|-----------------------------------------|------------------------------------------------|-----------------------------------------------------------------------------------|
|                                   | Chemical analytes on skin | Potentiometric and amperometric sensors | Glucose, lactate, sodium measurements in sweat |                                                                                   |
|                                   | Temperature               | Thermistor                              | Body temperature                               | Elevated risk of infection (Abbasi, 2017)                                         |
|                                   | Location                  | Global position satellite measurements  | Movement                                       | Location entropy to indicate depression                                           |
|                                   |                           |                                         |                                                |                                                                                   |
| Measurements from ambient sources |                           |                                         |                                                |                                                                                   |
|                                   | Video                     | Cameras                                 | Pixels                                         | Activity classification in the home, vital signs (Prakash and Tucker, 2018), gait |
|                                   | Audio                     | Microphones                             | Waveforms                                      | Respiratory status from breath                                                    |



|  |                                        |                                    |                                               |                                                                                                                                                                              |
|--|----------------------------------------|------------------------------------|-----------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|  |                                        |                                    |                                               | sounds, emotion<br>from voice                                                                                                                                                |
|  | Interactions with<br>computing devices | Smartphones,<br>Tablets, Keyboards | Patterns of typing<br>and scrolling           | Fine motor control<br>that tracks<br>development of<br>Alzheimer disease<br>(Kourtis et al.,<br>2019), digital<br>phenotypes for<br>psychiatric<br>diseases (Insel,<br>2017) |
|  | Smart devices                          | Smart pill caps                    | How often<br>medication bottles<br>are opened | Medication<br>adherence                                                                                                                                                      |

NOTE: These sensors can be used passively or actively, depending on the clinical application.

an ML model. The details of this preprocessing done prior to the output of a visible sensor “reading” are idiosyncratic to a manufacturer, and these idiosyncracies are on top of the known issue that sensor data from the same type of device but different manufacturers are not equally accurate. Variations in sensor quality and sensor-data processing make validation and comparability of readings across all devices used in a study critical (Wang et al., 2017).

Active versus Passive Data Collection

Sensors commonly collect data passively, meaning a person is not actively engaging with the sensor as they go about their day (Sim, 2019).

For example, simply carrying a smartphone is sufficient for accelerometers, barometers, and GPS sensors to track activity and movement. Passive sensing generates a sequence of measurements of variable duration and therefore length, and ML models specific to dealing with sequences exist to model this type of data.

Use of passive sensor data is likely more suitable for aging populations who may not wish to actively engage with devices, have difficulty using them, or are less comfortable performing active assessments themselves.

Sensors can also be intentionally engaged for active or functional assessment, such as performing a 6-minute walk test by carrying a phone; in this case, data collection would require the user to actively indicate the beginning and end of the test (even though the phone is also passively tracking movement as well). The active engagement might be triggered by a sensor reading, as when a user's wristwatch sensor detects an arrhythmia and so prompts the user to report whether they are experiencing any symptoms of atrial fibrillation. Because active data collection like time exertion and electronic patient-reported outcomes is done under more controlled settings or with specific prompts than passive data collection throughout the day, the generated sensor data have less variation, and models can potentially be built with fewer data.

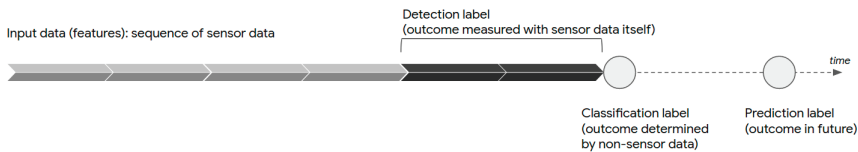
### Outputs of a Model

A supervised ML model is trained to associate a sequence of sensor measurements with a specific output (i.e., label), and the output is intimately tied to the clinical purpose of the model. This section describes attributes of outputs from a machine learning and clinical research perspective.

### Detection, Classification, and Prediction Machine Learning Outcomes

In traditional research, the output is called the primary outcome, and it is typically assessed at the end of a prespecified follow-up period. As shown in Figure 5-1, with sensor data, “output” can refer to several things. It can designate a measurement of the sensor data (detection); a secondary measurement made while sensor data are actively being collected (classification); or an outcome that will occur in the future (prediction).

Consider a wearable sensor that produces an electrocardiogram. A model could be used to *detect* if the recorded electrical pattern is consistent with atrial fibrillation. If the user is prompted to indicate their emotional state of anxiety at the time of an elevated heart rate, a model could use the same sensor to *classify* emotional state. A model could also *predict* if a patient, currently in sinus rhythm, will develop atrial fibrillation in the future (Attia et al., 2019).



**FIGURE 5-1** Common label types for sensor data. Typically, a sequence of data points are measured over time and machine learning models can associate this input with a variety of labels. If the sensor itself measures the outcome, such as heart rate monitor detecting abnormal rhythms to detect possible atrial fibrillation, then the label is referred to as a detection label. Other studies may use a secondary source of data collection, such as a validated questionnaire on depression severity, which creates labels that are referred to as classification labels. Labels collected from subsequent activity from either the sensor or a secondary source are referred to as prediction labels. The literature does not use these terms consistently, but they are helpful to create a framework for the types of outputs of ML models.

While it is important that input data, whether passively or actively collected, be collected over representative populations, it is critical that labels, whether they are detections, classifications, or predictions, be of high quality compared to a reference standard. Reference standards themselves often require subjective clinical judgment, which may require multiple expert raters to reduce the intra- and inter-rater variability (Liu et al., 2019). Sensor data have the additional challenge of being extremely long, and annotating every segment of data may be infeasible; additional techniques may be necessary to coarsely tag parts of the sequence that require precise labeling (Yeung et al., 2019).

Detection and classification have numerous uses for aging populations, such as detecting abnormal vital signs or classifying activity (e.g., getting out of a chair) as indicative of frailty. Trends of classification, such as decreased activity or movement, can be used for direct clinical management (e.g., identification of worsening heart failure) or used as an interpretable feature and input of another ML model to predict admission to the hospital.

Prediction is critical to enable healthy aging because one of the most problematic expressions of aging is frailty, which has not been shown to be reversible (Clegg et al., 2013). Identifying patients who will become frail *before* they actually do is the critical first step to delaying or averting its onset. However, since frailty is a progressive clinical condition across a variety of age- and disease-related changes, even detection of the initial stages of frailty is a form of prediction, highlighting the related nature of detection, classification, and prediction. However, as noted below, predicting the future does not mean it is possible to change it.

## Clinically Applicable Outcomes

A commonly described label is “onset of a disease state,” so that patients and their clinicians can be alerted early of an impending condition and take preventive action. For example, a continuous glucose monitor might be used to predict onset of diabetes within 3 years. Related extensions include detecting or predicting worsening of disease (e.g., automatic monitoring of daily tremor activity in patients with parkinsonism or prediction of manic episodes) and identifying patients who have specific subtypes of a disease and so may have a different expected trajectory or respond to different management.

For all outcomes, it is critical to distinguish hard versus surrogate endpoints. Hard, or clinical, endpoints, like survival or clinically noticeable change of how patients feel or function, are of true interest to patients and investigators, although these labels may be difficult or time consuming to collect for large groups of patients. Surrogate outcomes are laboratory or sensor measurements that are thought to be correlated with hard endpoints, such as detection of atrial fibrillation, which is strongly associated with stroke. However, it is well known in clinical research that successful prediction of surrogate endpoints is not guaranteed to lead to better hard outcomes, and in many cases, it can lead to worse or unintended consequences (Mandl and Manrai, 2019; Prasad et al., 2015; Weintraub, Lüscher, and Pocock, 2015).

## Cohort Selection as It Relates to Outcomes

ML research traditionally focuses on defining input features and output labels, but for clinical applications, the population of patients for whom data and outcomes are collected—referred to here as the cohort—is equally significant but doesn’t always register in the input features.

ML models are more accurate when trained on data with high proportions of positive labels; in clinical research this corresponds to the percentage of enrolled patients who meet the definition of the primary outcome. While that can be modulated by selection of the output of interest (e.g., detecting a commonly seen surrogate outcome versus predicting a rare hard endpoint), it is also affected by the patient population studied, or the cohort.

This effect is so pronounced that in clinical research, the cohort of enrolled patients determines the classification of the study itself. Consider building a model to predict the increase of a patient’s hemoglobin A1c (label), a marker of diabetes, using consented activity and heart rate monitoring. If healthy patients are enrolled, the model becomes a risk biomarker (risk of disease), but if the patients already have diabetes, it becomes a monitoring biomarker (monitoring of known disease), and if the patient is

on treatment, it becomes a pharmacodynamic response biomarker (predicting treatment response).

From an ML perspective, these differences do not affect how a model is constructed, trained, or evaluated. But there are significant clinical implications as to whether the model is appropriate to use for various clinical populations. In addition to the cohort's effect on the rate of positive labels and clinical generalizability, the type of data collection itself may induce selection bias into the cohort. Patients who are willing to wear, charge, update, and maintain sensor equipment over long periods of time may not reflect the age or socioeconomic status of a population of interest (Hicks et al., 2019). In particular, aging populations may worry that they do not have the competence to operate technology, that abnormal readings may induce health anxiety, or that the technology may be used to displace in-person monitoring and care (Sanders et al., 2012). Therefore, understanding the cohort and possible sources of bias is a critical step before building any ML model, especially related to aging populations.

## CLINICAL STUDY CONSIDERATIONS

There are often high-level objectives for using sensor data, such as promoting healthy lifestyles and healthy aging to avert the onset of preventable diseases and enable seniors to continue living independently at home. Yet achieving these goals with sensor data and ML requires considerations of the clinical study nuances in addition to enrolling large cohorts of patients, recording high-quality input data, and obtaining adjudicated outcomes (Mohr, Zhang, and Schueller, 2017).

### What Is the Right Label?

Applying ML to clinical data gathered by sensors requires consented, discrete, measurable, and reproducible labels that may not always be possible or easy to obtain in widespread populations. Hard endpoints like cognitive decline or death may take decades to occur, and clinical outcomes, like diagnosis, require regular clinical assessments that are not uniformly rigorous or applied across a population. There is a tendency to use surrogate endpoints related to specific sensor measurements that are known to be correlated to health outcomes, such as blood pressure or glucose levels. It is assumed that accurate detection or prediction of these metrics will lead to better health, especially if the metrics are related to modifiable factors (e.g., exercise or better diet). However, there are multiple examples in healthcare where successful interventions to achieve surrogate outcomes of reduced arrhythmia burden, hypertension, and hyperglycemia, led to worse patient outcomes, as shown below in Table 5-2.

TABLE 5-2 Case Studies Where Surrogate Outcomes Were Misleading

| Outcome        | Example                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Arrhythmia     | <p>Myocardial infarctions, or heart attacks, can leave a patient’s heart vulnerable to unexpected, abnormal rhythms that manifest as sudden cardiac death. At the end of the 20th century, pharmacologists developed antiarrhythmic therapies that successfully suppressed these rhythms and physicians routinely prescribed them to patients after myocardial infarctions (Pfeffer and McMurray, 2016). In the 1980s, the Cardiac Antiarrhythmic Suppression Trial was started to assess the safety of this practice, but enrollment was slow because cardiologists refused to let their own patients participate since there was clear evidence that the medications effectively suppressed abnormal rhythms, and the link to sudden death was therefore patently obvious (Moyé and Tita, 2002). The results of the completed trials shocked the medical community: treating the abnormal rhythms was associated with <i>increased</i> mortality, forcing a rapid change in the standard of care and highlighting the dangers of using surrogate measures rather than clinical outcomes to assess the utility and safety of interventions (Pfeffer and McMurray, 2016).</p> |
| Blood Pressure | <p>High blood pressure, or hypertension, is a common and leading factor of death and cardiovascular disease, and lifestyle and pharmacologic treatments are recommended nearly universally to hypertensive patients (Taler, 2018). It seems obvious that drugs that reduce blood pressure should similarly lead</p>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |

|                  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                |
|------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                  | <p>to beneficial effects on mortality and heart attacks. However, in the early 2000s, a pivotal trial pitted atenolol—one of the most widely used antihypertensives at the time—against a new medication, losartan (Dahlöf et al., 2002). Both led to similar reductions in blood pressure, but losartan was better at preventing death and cardiovascular outcomes. In fact, a later study revealed a deeper truth: although atenolol clearly lowered blood pressure, it “did not result in a beneficial effect on mortality or myocardial infarction” (Carlberg, Samuelsson, and Lindholm, 2004). This experience highlights that an intervention of an effective surrogate outcome does not guarantee clinical benefit.</p>                                                                                                                                                 |
| Blood<br>Glucose | <p>High blood sugar, one of the hallmarks of diabetes, is associated with a host of deleterious health effects, such as risk of infection, impaired wound healing, mitochondrial injury, oxidant injury, and more (Kavanaugh and McCowen, 2010). In the early 2000s, these physiological effects together with observational and clinical trial data which suggested that patients with higher blood sugar had worse outcomes led to widespread adoption of tight blood sugar control in intensive care units. However, subsequent studies failed to show the benefit of tight glucose control and indeed showed higher risk of death and significant risks to patients (Clain, Ramar, and Surani, 2015). This experience highlights that substantial observational data do not lessen the need for rigorous evaluation of interventions to modify surrogate measurements.</p> |

## Are Relevant Data Collected Based on the Understanding of the Prediction Task?

Sensor data are modified by a host of factors that affect readings and measurements in nonobvious ways. For example, a newly physically active individual may develop a slower heart rate due to improved cardiovascular health, or the same finding may reflect that he is newly employed and now has health insurance to pay for a prescribed beta-blocker for migraine prevention. Traditional clinical studies have protocols to try to discern plausible causal factors that account for changes in outcomes. Because ML models may discern patterns not apparent to humans, if these alternative factors are not collected and analyzed, the model may produce spurious or misleading predictions. Clinical research expertise that focuses on a broad understanding of the phenomenon studied—not purely the technical details of the sensor or ML engineering—is necessary to combat this risk.

## Will Producing a Model Actually Help?

The premise of using ML to analyze personal sensor data is that knowledge of what is detected, classified, or predicted will help an individual live a better life. It is often unclear if users change behaviors in response to recorded sensor data, or that users more likely to record sensor data in the first place will change their behavior (McConnell et al., 2018; Patel, Asch, and Volpp, 2015; Sperrin et al., 2016). In cases where the data induced intended behavior change, current evidence in mobile health studies shows only temporary, limited effectiveness for domains like improved activity (McConnell et al., 2018). Indeed, one study showed that use of wearable technology to assist in weight loss compared to traditional interventions led to *less* weight loss (Jakicic et al., 2016), highlighting the risk that sensor data may actually worsen outcomes through mechanisms that, in this case, even the investigators found unclear.

This is not a small concern that can be written off as inadequate hardware or software; it is a fundamental aspect of clinical experience that accurate detection and prediction do not necessarily correspond to better outcomes. For example, thyroid cancer screening programs in South Korea led to a rapid increase in detection of this cancer, and nearly all patients diagnosed were treated (Ahn, Kim, and Welch, 2014). Yet this treatment has not led to better hard outcomes (e.g., longer survival), and treated patients have experienced substantial complications from therapy; understanding the difference between underdetection and overdiagnosis is critical.

In an extreme case, the video game Pokémon Go successfully motivated increased physical activity but was sometimes followed by severe cases of trauma due to players' inattention to their surroundings (Barbieri et al.,



2017). This is relevant to older adults because successful interventions to improve activity or other surrogate outcomes for elderly patients may concomitantly raise unanticipated risks, such as injuries that frail individuals may not recover well from.

Outcomes are also affected by constraints in the environment that are nonmodifiable, such as less activity due to living in a nonwalkable city (Sadik-Khan and Solomonow, 2017) or nonideal food choices associated with living in a food desert (Kelli et al., 2019). In these cases, policy or environmental changes may be more important interventions than personalized models.

### **How Predictive Is Sensor Data?**

Is a continuous stream of sensor data required for an ML task? Although the premise of sensors is that daily habits and physical activity can substantially alter clinical outcomes, the experience from clinical trials shows that many drugs designed to induce a physiological effect actually have only modest treatment effects (Califf and DeMets, 2002). If lifestyle habits are thought of as inducing potential physiological changes related to health outcomes, then discerning the effect of each habit, especially when multiple habits occur sequentially in various orders and combinations, is extraordinarily difficult (Gottesman et al., 2019).

Prediction using continuous, consented measurement may not be more accurate than traditional episodic data collection or may not have incremental performance worth the burden of additional collection (Insel, 2017). Moreover, if new medical therapies or environmental changes are introduced, predictions using data from past patients may become stale or inaccurate.

### **What Are the Effects of Healthcare Disparities in Data and Machine Learning?**

Collecting and using consented data from groups that have experienced discrimination or human and structural biases brings the attendant risk of worsening healthcare disparities (Rajkomar et al., 2018). It is known that healthcare outcomes are affected by social determinants of health, education, the criminal justice system, and more (Zimmerman and Anderson, 2019). The hope of using sensor data is that physiological or physical activity might be used directly to forecast health, but it is impossible to disentangle the effect of physical activity from all the other factors, especially in the face of ML. The net effect is that investigators need to carefully consider the interplay of healthcare disparities, collection of data, and creation of labels.

The complexity of ML models can create a pervasive influence of disparities that requires vigilance to detect. ML models can identify signals in the data that cannot be identified by humans (Poplin et al., 2018), and the imprints of the social determinants of health are subtly imprinted on all types of data. For example, consider a wearable sensor that measures a sequence of heart rates. To a human, the sequences from a device from one manufacturer might look the same as one from another manufacturer, but the idiosyncratic processing of the raw data can leave signatures in the data that are invisible to the human eye but distinctly present. This means that sensors that purport to measure the same physiological attribute may generate sequences that reveal as much information about the device itself as the heart rate of the patient; a model could therefore possibly distinguish data from “expensive” versus “inexpensive” sensors and use a derived socioeconomic indicator of wealth rather than the trends of the values themselves for prediction. This requires clinical and research expertise to know what to look for, and it requires data science expertise to identify and potentially address the effect of healthcare disparities on the results (Rajkomar et al., 2018).

In aging populations, there is especially the risk of privileged bias, agency bias, and informed mistrust. Privileged bias refers to the phenomenon of aging populations not having a voice in the types of technologies being developed that they can use or afford. As a result of privileged bias, systems may not be designed to solve the problems facing aging populations, such as limited internet connectivity or e-literacy that limits adoption of even interested elderly patients (Van Winkle, Carpenter, and Moscucci, 2017). Agency bias indicates a situation in which stakeholders do not have input into types of problems that they want solved. For example, aging populations may not be included in the decision-making process of building and deploying the models. Informed mistrust describes a situation where stakeholders do not trust the systems built to help them. This might happen, for example, when researchers may be financially incentivized to solve problems faced disproportionately by the well educated and wealthy, introducing possibly warranted skepticism that the models are generalizable. These problems are compounded by sources of bias in the data (e.g., nonrepresentative patients being enrolled) and the prediction of surrogate outcomes (Obermeyer et al., 2019).

There is no single solution to solve all of these problems, but there are recommendations on best practices to be upheld during all phases of developing ML models, including design, data collection, training, evaluation, launch review, and postdeployment (Rajkomar et al., 2018).

## FUTURE WORK

Investigators face significant challenges in study design, data collection, and ML-based analysis. What are some paths forward?

Large-scale studies (All of Us Research Program Investigators, 2019) studying aging populations over long time periods will likely be a critical source of new insights. Existing studies have shown the feasibility of enrolling large numbers of patients in a short time period (Perez et al., 2019), but obtaining verifiable longitudinal data on those participants remains challenging both for logistical reasons and for lack of interoperability (Rajkomar, Dean, and Kohane, 2019). Applying commercially available sensors and tracking clinically relevant hard outcomes will likely promote better forecasting of future health events and deterioration, but the full cycle of trial development, analysis, and validation of these efforts may be protracted.

However, many relevant health outcomes are largely specific to older adults, such as the onset of frailty or progression of Parkinson disease. Studies that enroll patients at higher risk for these outcomes might be less generalizable to a wide population but can still provide insight for vulnerable patients. Although using hard outcomes in large-scale studies is preferable, thoughtfully using surrogate outcomes in smaller-scale but high-risk cohorts can accelerate knowledge generation and direct limited resources to run larger, expensive trials with hard outcomes. The rapid development of new wearables means that the ability to rapidly evaluate sensors for clinical promise is increasingly important if researchers are to design studies that take advantage of new technologies (Kim et al., 2019). A key insight is that identifying the specific clinical challenges, including the relevant cohorts and outcomes, requires traditional clinical research experience; such selection requires clinical researchers working alongside engineers and ML experts.

Future work will need to consider the significant additional challenges beyond detection, classification, and prediction. The critical challenge to improve the process of aging and promoting health will be finding interventions that can ameliorate problems if they are caught in real time or in advance (Kourtis et al., 2019).

## CONCLUSIONS

Sensor data collected, with consent, from daily life promises to provide a peek at factors that lie beyond the measurement capabilities of traditional clinical studies that might affect health and aging. However, it is known that health is determined by many factors, some within individual control but many outside of it, including policy, social determinants, physical and

environmental determinants, biology, and access to health services (Determinants of Health, 2020). Moreover, while this chapter focused on key scientific challenges, there are a plethora of other key issues of regulatory, data security, privacy, workflow, interoperability, ethical, and legal considerations (Izmailova, Wagner, and Perakslis, 2018).

There should be optimism that new technology will deepen our understanding of health and aging, but clinical experience cautions that the path will be difficult and full of dead ends. It will require thoughtful application of best practices in sensor design, ML, and clinical research to yield useful and generalizable knowledge that helps older patients.

## REFERENCES

- Abbasi, J. (2017). Wearable digital thermometer improves fever detection. *JAMA*, 318(6), 510.
- Ahn, H.S., Kim, H.J., & Welch, H.G. (2014). Korea's thyroid-cancer "epidemic—screening and overdiagnosis. *New England Journal of Medicine*, 371(19), 1765–1767.
- The All of Us Research Program Investigators, Denny, J.C., Rutter, J.L., Goldstein, D.B., Philipakis, A., Smoller, J.W., Jenkins, G., & Dishman, E. (2019). The "All of Us" Research Program. *New England Journal of Medicine*, 381(7), 668–676.
- Attia, Z.I., Noseworthy, P.A., Lopez-Jimenez, F., Asirvatham, S.J., Deshmukh, A.J., Gersh, B.J., Carter, R.E., Yao, X., Rabinstein, A.A., Erikson, B.J., Kapa, S., & Friedman, P.A. (2019). An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. *Lancet*, 394(10201), 861–867. doi:10.1016/S0140-6736(19)31721-0
- Barbieri, S., Vettore, G., Pietrantonio, V., Snenghi, R., Tredese, A., Bergamini, M., Previato, S., Stefanati, A., Gaudio, R.M., & Feltracco, P. (2017). Pedestrian inattention blindness while playing Pokémon Go as an emerging health-risk behavior: A case report. *Journal of Medical Internet Research*, 19(4), e86.
- Califf, R.M., & DeMets, D.L. (2002). Principles from clinical trials relevant to clinical practice: Part I. *Circulation*, 106(8), 1015–1021.
- Carlberg, B., Samuelsson, O., & Lindholm, L.H. (2004). Atenolol in hypertension: Is it a wise choice? *Lancet*, 364(9446), 1684–1689.
- Clain, J., Ramar, K., & Surani, S.R. (2015). Glucose control in critical care. *World Journal of Diabetes*, 6(9), 1082–1091.
- Clegg, A., Young, J., Iliffe, S., Rikkert, M.O., & Rockwood, K. (2013). Frailty in elderly people. *Lancet*, 381(9868), 752–762.
- Dahlöf, B., Devereux, R.B., Kjeldsen, S.E., Julius, S., Beevers, G., de Faire, U., Fyhrquist, E., Ibsen, H., Kristiansson, K., Lederballe-Peterson, O., Lindholm, L.H., Nieminen, M.S., Omvik, P., Oparil, S., Wedel, H., & LIFE Study Group. (2002). Cardiovascular morbidity and mortality in the Losartan Intervention for Endpoint reduction in hypertension study (LIFE): A randomised trial against atenolol. *Lancet*, 359(9311), 995–1003.
- Determinants of Health. (2020). *Healthy People 2020*. Office of Disease Prevention and Health Promotion. Available: <https://www.healthypeople.gov/2020/about/foundation-health-measures/Determinants-of-Health>.

- Fisher, C.K., Smith, A.M., Walsh, J.R., Coalition Against Major Diseases, & Abbott, Alliance for Aging Research, Alzheimer's Association, Alzheimer's Foundation of America, AstraZeneca Pharmaceuticals LP, Bristol-Myers Squibb Company, Critical Path Institute, CHDI Foundation, Inc., Eli Lilly and Company, F. Hoffmann-La Roche Ltd, Forest Research Institute, Genentech, Inc., GlaxoSmithKline, Johnson & Johnson, National Health Council, Novartis Pharmaceuticals Corporation, Parkinson's Action Network, Parkinson's Disease Foundation, Pfizer, Inc., sanofi-aventis. Collaborating Organizations: Clinical Data Interchange Standards Consortium (CDISC), Ephibian, Metrum Institute. (2019). Machine learning for comprehensive forecasting of Alzheimer's Disease progression. *Scientific Reports*, 9(1), article13622.
- Gottesman, O., Johansson, F., Komorowski, M., Faisal, A., Sontag, D., Doshi-Velez, F., & Celi, L.A. (2019). Guidelines for reinforcement learning in healthcare. *Nature Medicine*, 25(1), 16–18.
- Gulshan, V., Peng, L., Coram, M., Stumpe, M.C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J., Kim, R., Raman, R., Nelson, P.C., Mega, J.L., & Webster, D.R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*, 316(22), 2402–2410.
- Heikenfeld, J., Jajack, A., Rogers, J., Gutruf, P., Tian, L., Pan, T., Li, R., Khine, M., Kim, J., Wang, J., and Kim, J. (2018). Wearable sensors: Modalities, challenges, and prospects. *Lab on a Chip*, 18(2), 217–248.
- Hicks, J.L., Althoff, T., Sosis, R., Kuhar, P., Bostjancic, B., King, A.C., Leskovec, J., & Delp, S.L. (2019). Best practices for analyzing large-scale health data from wearables and smartphone apps. *NPJ Digital Medicine*, 2, 45.
- Insel, T.R. Digital phenotyping: Technology for a new science of behavior. (2017). *JAMA*, 318(13), 1215–1216.
- Izmailova, E.S., Wagner, J.A., & Perakslis, E.D. (2018). Wearable devices in clinical trials: Hype and hypothesis. *Clinical Pharmacology & Therapeutics*, 104(1), 42–52.
- Jakicic, J.M., Davis, K.K., Rogers R.J., King, W.C., Marcus, M.D., Helsel, D., Rickman, A.D., Washed, A.S., & Belle, S.H. (2016). Effect of wearable technology combined with a lifestyle intervention on long-term weight loss: The IDEA randomized clinical trial. *JAMA*, 316(11), 1161–1171.
- Kavanagh, B.P., & McCowen, K.C. (2010). Clinical practice. Glycemic control in the ICU. *New England Journal of Medicine*, 363(26), 2540–2546.
- Kelli, H.M., Kim, J.H., Samman Tahhan, A., Liu, C., Ko, Y.A., Hammadah, M., Sullivan, S., Sandesara, P., Alkhoder, A.A., Choudhary, F.K., Gafeer, M.M., Patel, K., Qadir, S., Lewis, T.T., Vaccarino, V., Sperling, L.S., & Quyyumi, A.A. (2019). Living in food deserts and adverse cardiovascular outcomes in patients with cardiovascular disease. *Journal of the American Heart Association*, 8(4), e010694.
- Kim, J., Campbell, A.S., de Ávila B.E-F., & Wang, J. (2019). Wearable biosensors for healthcare monitoring. *Nature Biotechnology*, 37(4), 389–406.
- Kourtis, L.C., Regele, O.B., Wright, J.M., & Jones, G.B. (2019). Digital biomarkers for Alzheimer's disease: The mobile/wearable devices opportunity. *NPJ Digital Medicine*, 2, article 9. doi:10.1038/s41746-019-0084-2.
- Liu, H., Bravata, D.M., Olkin, I., Nayak, S., Roberts, B., Garber, A.m, & Hoffman, A.R. (2007). Systematic review: The safety and efficacy of growth hormone in the healthy elderly. *Annals of Internal Medicine*, 146(2), 104–115.
- Liu, Y., Chen, P-H.C., Krause, J., & Peng, L. (2019). How to read articles that use machine learning: Users' guides to the medical literature. *JAMA*, 322(18), 1806–1816.
- Mandl, K.D., & Manrai, A.K. (2019). Potential excessive testing at scale: Biomarkers, genomics, and machine learning. *JAMA*, 321(8), 739–740.

- McConnell, M.V., Turakhia, M.P., Harrington, R.A., King, A.C., & Ashley, E.A. (2018). Mobile health advances in physical activity, fitness, and atrial fibrillation: Moving hearts. *Journal of American College of Cardiology*, 71(23), 2691–2701.
- Mohr, D.C., Zhang, M., & Schueller, S.M. (2017). Personal sensing: Understanding mental health using ubiquitous sensors and machine learning. *Annual Review of Clinical Psychology*, 13, 23–47.
- Moyé, L.A., & Tita, A.T.N. (2002). Defending the rationale for the two-tailed test in clinical research. *Circulation*, 105(25), 3062–3065.
- Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447–453.
- Patel, M.S., Asch, D.A., & Volpp, K.G. (2015). Wearable devices as facilitators, not drivers, of health behavior change. *JAMA*, 313(5), 459–460.
- Perez, M.V., Mahaffey, K.W., Hedlin, H., Rumsfeld, J.S., Garcia, A., Ferris, T., Balasubramanian, V., Russo, A.M., Rajmane, A., Cheung, L., Hung, G., Lee, J., Kowey, P., Talati, N., Nag, D., Gummidipundi, S.E., Beatty, A., Hills, M.T., Desai, S., Granger, C.B., Desai, M., & Turakhia, M.P. (2019). Large-scale assessment of a smartwatch to identify atrial fibrillation. *New England Journal of Medicine*, 381(20), 1909–1917.
- Pfeffer, M.A., & McMurray, J.J.V. (2016). Lessons in uncertainty and humility—Clinical trials involving hypertension. *New England Journal of Medicine*, 375(18), 1756–1766.
- Poplin, R., Varadarajan, A.V., Blumer, K., Liu, Y., McConnell, M.V., Corrado, G.S., Peng, L., & Webster, D.R. (2018). Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nature Biomedical Engineering*, 2(3), 158–164.
- Prakash, S.K.A., & Tucker, C.S. (2018). Bounded Kalman filter method for motion-robust, non-contact heart rate estimation. *Biomedical Optics Express*, 9(2), 873–897.
- Prasad, V., Kim, C., Burotto, M., & Vandross, A. (2015). The strength of association between surrogate end points and survival in oncology: A systematic review of trial-level meta-analyses. *JAMA Internal Medicine*, 175(8), 1389–1398.
- Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380(14), 1347–1358.
- Rajkomar, A., Oren, E., Chen, K., Dai, A.M., Hajaj, N., Hardt, M., Liu, P.J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G.E., Irvine, J., Le, Q., Litsch, K., Mossin, A., Tansuwan, J., Wang, D., Wexler, J., Wilson, J., Ludwig, D., Volchenboum, S.L., Chou, K., Pearson, M., Madabushi, S., Shah, N.H., Butte, A.J., Howell, M.D., Cui, C., Corrado, G.S. & Dean, J. (2016). Scalable and accurate deep learning with electronic health records. *NPJ Digital Medicine*, 1(1), article 18.
- Rajkomar, A., Hardt, M., Howell, M.D., Corrado, G., & Chin, M.H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine*, 169(12), 866–872. doi:10.7326/M18-1990.
- Ray, T.R., Choi, J., Bandodkar, A.J., Krishnan, S., Gutruf, P., Tian, L., Ghaffari, R., & Rogers, J.A. (2019). Bio-integrated wearable systems: A comprehensive review. *Chemical Reviews*, 119(8), 5461–5533.
- Sadik-Khan, J., & Solomonow, S. (2017). Improving public health by making cities friendly to walking and biking: Safer, more active transportation starts with the street. *JAMA Internal Medicine*, 177(5), 613–614.
- Sanders, C., Rogers, A., Bowen, R., Bower, R., Hirani, S., Cartwright, M., Fitzpatrick, R., Knapp, M., Barlow, J., Hendy, J., Chrysanthaki, T., Bardsley, M., & Newman, S.P. (2012). Exploring barriers to participation and adoption of telehealth and telecare within the Whole System Demonstrator trial: A qualitative study. *BMC Health Services Research*, 12, article 220.
- Sim, I. Mobile devices and health. (2019). *New England Journal of Medicine*, 381(10), 956–968.

- Sperrin, M., Rushton, H., Dixon, W.G., Normand, A., Villard, J., Chieh, A., & Buchan, I. (2016). Who self-weighs and what do they gain from it? A retrospective comparison between smart scale users and the general population in England. *Journal of Medical Internet Research*, 18(1), e17.
- Taler, S.J. (2018). Initial treatment of hypertension. *New England Journal of Medicine*, 378(7), 636–644.
- Van Winkle, B., Carpenter, N., & Moscucci, M. (2017). Why aren't our digital solutions working for everyone? *AMA Journal of Ethics*, 19(11), 1116–1124.
- Wang, R., Blackburn, G., Desai, M., Phelan, D., Gillinov, L., Houghtaling, P., & Gillinov, M. (2017). Accuracy of wrist-worn heart rate monitors. *JAMA Cardiology*, 2(1), 104–106.
- Weintraub, W.S., Lüscher, T.F., & Pocock, S. (2015). The perils of surrogate endpoints. *European Heart Journal*, 36(33), 2212–2218.
- Yeung, S., Rinaldo, F., Jopling J., Liu, B., Mehra, R., Downing, N.L., Guo, M., Bianconi, G.M., Alahi, A., Lee, J., Campbell, B., Deru, K., Beninati, W., Fei-Fei, L., & Milstein, A. (2019). A computer vision system for deep learning-based detection of patient mobilization activities in the ICU. *NPJ Digital Medicine*, 2, article 11.
- Zimmerman, F.J., & Anderson, N.W. (2019). Trends in health equity in the United States by race/ethnicity, sex, and income, 1993–2017. *JAMA Network Open*, 2(6), e196386.

## 6

# 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 has reshaped the technology landscape. The maturing of these technologies is well timed, because an aging population needs sensor-based technologies to support its increasing health needs. In this chapter, 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.

### INTRODUCTION

We are experiencing a dramatic and unprecedented shift in national and global demographics. Soon, a quarter of our population will be aged 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 discrep-

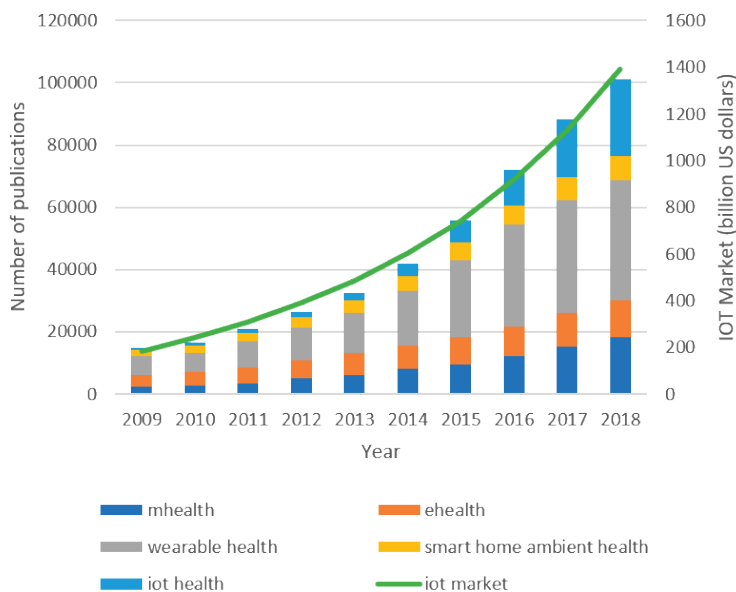
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ancy between persons needing care and those capable of providing it [1]. While the future of healthcare availability and service quality seems uncertain, the future of healthcare IT is bright, with a projected market growth to \$391 billion by 2021 [2].

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 6-1 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



**FIGURE 6-1** (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 Internet of Things (IoT) market. Numbers are reported by Statista.

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 chapter, 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.

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 6-1 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 6-1 Common Types of Sensors Employed for Health Monitoring and Assistance

| Category                | Sensors                                                                                                                                                                      |
|-------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Ambient</i>          | passive infrared (PIR) motion, magnet / contact switch, temperature, light, humidity, vibration, pressure, power usage, electric device usage, water usage, RFID             |
| <i>Wearable</i>         | accelerometer, gyroscope, magnetometer, compass, phone, text, app, battery, location                                                                                         |
| <i>Environment</i>      | frequented locations with type, outdoor walkability score, indoor and outdoor air quality, temperature, light levels, sound levels, number of residents, environment clutter |
| <i>Physiological</i>    | ECG, EEG, EMG, BCG, respiration, pulse, galvanic skin response, skin temperature, cortisol level, blood pressure, blood oxygen saturation                                    |
| <i>High-dimensional</i> | camera, depth sensor, thermal sensor, radar, microphone array                                                                                                                |
| <i>Digital traces</i>   | 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 environmental 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 a much larger data set. 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 and automated fall risk assessment, speech-based health assistance, and analysis of group activities [8], and the corresponding methods usually require a large dataset to train a classifier and are inclined to be influenced by the image quality. However, it is hard to collect fall data, and instead simulated falls are recorded to construct the training dataset, which is restricted to limited quantity. To address these problems, a three-dimensional convolutional neural network (3-D CNN) was created. 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 home [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 are 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 6-2 summarizes some of these phenotypes, or behavioral markers, that are particularly relevant for monitoring and assisting older adults.

**TABLE 6-2** Behavioral Markers that Are Extracted from Sensor Data

| Category                                   | Features                                                                                                                                                                                      |
|--------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i><b>Mobility</b></i>                     | step count, walking speed, step length, daily distance covered, number and duration of times in one spot, number walking bouts, activity level                                                |
| <i><b>Exercise</b></i>                     | number, duration, movement types, intensity, location                                                                                                                                         |
| <i><b>Sleep</b></i>                        | number and duration of daily sleep bouts, sleep times, sleep locations, sleep fitfulness, sleep interruptions, sleep apnea                                                                    |
| <i><b>Activity</b></i>                     | number, duration, and location of basic and instrumental activities of daily living                                                                                                           |
| <i><b>Environment</b></i>                  | frequented locations with type, outdoor walkability score, indoor and outdoor air quality, temperature, light levels, sound levels, number of residents, environment clutter                  |
| <i><b>Devices</b></i>                      | types of device interactions, medication frequency, use of compensatory devices                                                                                                               |
| <i><b>Socialization</b></i>                | 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 |
| <i><b>Circadian and diurnal rhythm</b></i> | 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 preventive 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 and provides predictors of health status change [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 been 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.

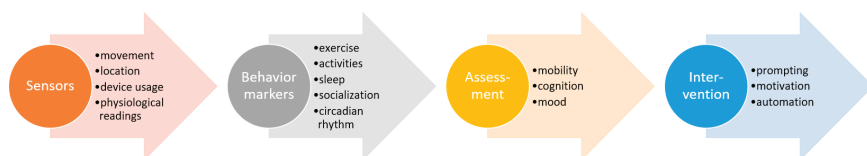
When additional sources of information are added to the mix, the number of behavior features that can be extracted is virtually unbounded. Sensors can now determine the use of water and electrical devices, monitor medication access, and detect interaction with items that offer compensatory aid [26]–[28].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

## AUTOMATED ASSESSMENT

One particular need that 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 6-2 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.



**FIGURE 6-2** 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.

**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 diagnose 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]. Such motor function can be assessed by ambient sensors in addition to wearable sensors. As an example, Newland et al. found a predictive relationship between ambient sensor-detected gait parameters and multiple sclerosis symptoms.

**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, Boukhebbha 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 through 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. Similarly, Galambos et al. found that overall activity level patterns together with detection of time out of home were predictors of clinical scores for dementia and depression [46].

**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 [47]–[49]. Deglutition and yawning help identify fine-grained physiological symptoms and chronic

psychological conditions, which are not directly observable from traditional daily activities. We propose a new wearable smart earring that is capable of differentiating Investigator's Global Assessment (IGA) in the daily environment with single integrated accelerometer sensor signal processing. Our prior framework, GetSmart, shows significant improvement in IGAs recognition based on the smart earring, which necessitates users to replace the earring batteries frequently due to its energy requirement (high sampling frequency). More recently, study participants were allowed to perform their typical uninterrupted routines at home 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 [48], but republication/redistribution requires IEEE permission. One of the many services that intelligent systems can provide is the ability to analyze the impact of different medical conditions on daily behavior. In this study, we use smart home and wearable sensors to collect data, while ( $n = 84$ ) other groups have tested these methods in actual homes over multiple months. While the sample size is often limited to 1–2 homes [50]–[52], long-term monitoring has been successfully performed in assisted living settings [53]. Traditional assessment scores have occasionally been predicted from behavioral markers observed over months or years [54], [55]. We examine the actual benefits of smart home-based analysis by monitoring daily behavior in the home and predicting clinical scores of the residents. To accomplish this goal, we propose a clinical assessment using activity behavior (CAAB). In many of these cases, walking speed and activity regularity were reliable indicators of cognitive health. However, Hellmers et al. [56] and Akl et al. [57] 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. [58] 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. [59] were able to link daily variability in room occupancy with Assessment of Motor and Process Skills and Katz Index of Independence in Activities of Daily Living 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.



## PREVENTION AND INTERVENTION

Sensor technology is better suited to observing behavior and health state than to taking preventive 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 [60]. Clearly, a prompt to take medication at a person's standard dinner time of 6:30 pm will be unsuccessful if dinner is delayed until 7:00 pm. 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. [61]. 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. [62] 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 [63], 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 [64]. 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 antici-

pated actions and needs [65], [66]. However, these capabilities have not been 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 [67], this is an opportunity that can be explored by researchers and entrepreneurs.

## 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 widespread 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.

### 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 [68].

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-reporting is gathered when clinician data are unavailable. However, these are often error prone because the retrospective details of past experiences and health states can-

not 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” [69], [70].

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 chapter. 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 [71], transfer learning [72], and domain adaptation [73] 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.

### Privacy and Security

Because data acquisition and analysis form the backbone of sensor-supported aging in place, older adults’ 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 [67]. These worries are warranted. Even after data are 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 [74]. This ability has been confirmed by several projects in which sensitive medical data were identified from seemingly obscure pieces of information [75], [76]. Thirty-three of the states that know those details do not keep the information to themselves or limit their sharing to researchers [1]. Instead, they give away or sell a version of this information, and often they're legally required to do so. The states turn to you as a computer scientist, IT specialist, policy expert, consultant, or privacy officer and ask, are the data anonymous? Can anyone be identified? Chances are you have no idea whether real-world risks exist. Here is how I matched patient names to publicly available health data sold by Washington State, and how the state responded. Doing this kind of experiment helps improve data-sharing practices, reduce privacy risks, and encourage the development of better technological solutions. Results summary: The State of Washington sells a patient-level health dataset for \$50. This publicly available dataset contained virtually all hospitalizations occurring in the state in a given year, including patient demographics, diagnoses, procedures, attending physician, hospital, a summary of charges, and how the bill was paid. It did not contain patient names or addresses (only five-digit zip codes).

The risk of reidentification is heightened when collected information is linked to ubiquitous, location-tracking mobile devices [77]. Last year, analysts found that a commercial fitness app led to the revelation of remote military outpost locations [78]. De Montjoye et al. [77] found that location data do not need to be continuous and fine-grained to perform reidentification. They theoretically determined that four spatiotemporal 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 reidentified. Wu et al. [79] found that we can train deep networks to recognize the most discriminative changes of gait patterns, which suggest the change of human identity. To the best of our knowledge, this is the first work based on deep CNNs for gait recognition in the literature. Here, we provide an extensive empirical evaluation in terms of various

scenarios, namely, cross-view and cross-walking-condition, with different preprocessing approaches and network architectures. The method is first evaluated on the challenging CASIA-B dataset in terms of cross-view gait recognition. Experimental results show that it outperforms the previous state-of-the-art methods by a significant margin. In particular, our method shows advantages when the cross-view angle is large (i.e., no less than 36 degrees). And the average recognition rate can reach 94%, much better than the previous best result (less than 65% achieved a human identification rate of 98% from gait data for 4,007 subjects). Similarly, Na et al. [80] 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 support vector machine learning algorithms to reidentify demographic and physical activity data for 14,451 subjects. Rocher et al. [81] 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 reidentified 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 [82]. 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 [73], [83], [84]. Further developing and utilizing these methods can help overcome the dangers associated with collecting sensor data for health assistance.

### Technology Adoption

Once technology is robust and secure, an important final step is for older adults to embrace it. Although privacy, discussed in the previous section, could be a concern for some, Demiris et al. found that many older adults are still often welcoming of sensors in their homes, particularly when the technology provides assurance of health and safety monitoring [85]. Again, several factors must thus 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 [86]. This income is far less than the amount that most need to meet with their day-to-day living expenses, particularly since annual healthcare costs for individuals with chronic conditions are 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

are dramatically reduced, 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 technology should be of significant interest, they prefer to invest time and resources on technology that entertains, connects, and informs. Most older adults feel that sensor-based technologies are novelties [87]. 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 [88]. Additionally, individuals with cognitive limitations will require extended teaching time, and use of technologies may be forgotten if not habituated [89], [90]. 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 [91]. Through partnership with end-users, researchers can create sensor systems that will support, not undermine, health and functional independence [92]. 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.

## 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 need to be validated on large, diverse populations to ensure their 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,” 2018.
- [2] S. Singh, “Healthcare IT Market,” *MarketsandMarkets*, 2019.
- [3] D. Arigoni, “Preparing for an aging population,” *AARP*, 2018.
- [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] J. Ortiz *et al.*, “Toward ultra-low-power remote health monitoring: An optimal and adaptive compressed sensing framework for activity recognition,” *IEEE Trans. Mob. Comput.*, 2018.
- [7] B. Ghanem *et al.*, “ActivityNet large-scale activity recognition challenge 2018,” [http://activity-net.org/challenges/2018/uploads/ActivityNet\\_Challenge\\_2018\\_Summary\\_and\\_Workshop\\_Papers.pdf](http://activity-net.org/challenges/2018/uploads/ActivityNet_Challenge_2018_Summary_and_Workshop_Papers.pdf), 2018.
- [8] N. Lu, Y. Wu, L. Feng, and J. Song, “Deep learning for fall detection: Three-dimensional CNN combined with LSTM on video dynamic 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*, pp. 1–9, 2012.
- [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.*, vol. 5, no. 8, e106, 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, doi: 10.1109/TSMCB.2012.2216873.
- [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*, pp. 139–148, 2010.
- [27] E. Larson, J. Froehlich, T. Campbell, C. Haggerty, J. Fogarty, and S.N. Patel, "Dis-aggregated 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.*, vol. 9, no. 4, 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*, pp. 97–100, 2016.
- [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, doi: 10.1016/j.parkreldis.2010.08.001.
- [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*, pp. 897–900, 2017.
- [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*, pp. 416–421, 2015.
- [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*, pp. 161–164, 2017.
- [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*, pp. 805–812, 2017.
- [43] A. Mehrotra and M. Musolesi, "Designing effective movement digital biomarkers for unobtrusive emotional state mobile monitoring," in *Workshop on Digital Biomarkers*, pp. 3–8, 2017.
- [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, pp. 280–311, 2016.
- [46] C. Galambos, M. Skubic, S. Wang, and M. Rantz, "Management of dementia and depression utilizing in-home passive sensor data," *Gerontechnology*, vol. 11, no. 3, pp. 457–468, 2013.
- [47] 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, doi: 10.1016/j.pmcj.2016.06.015.
- [48] 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, doi: 10.1109/JBHI.2015.2461659.
- [49] 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, doi: 10.1109/TSMC.2013.2252338.

- [50] A.N. Aicha, G. Englebienne, and B. Krose, "Continuous gait velocity analysis using ambient sensors in a smart home," in *Ambient Intelligence*, Springer, pp. 219–235, 2015.
- [51] 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*, pp. 6495–6498, 2011.
- [52] N. Darnall *et al.*, "Application of machine learning and numerical analysis to classify tremor in patients affected with essential tremor or Parkinson's disease (winner of NSF poster competition)," *Gerontechnology*, vol. 10, no. 4, 2012.
- [53] M. Skubic, G. Alexander, M. Popescu, M. Rantz, and J. Keller, "A smart home application to eldercare: Current status and lessons learned," *Technol. Heal. Care*, vol. 17, no. 3, pp. 183–201, 2009.
- [54] 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, doi: 10.1109/JBHI.2015.2445754.
- [55] A. Alberdi Aramendi *et al.*, "Smart home-based prediction of multi-domain symptoms related to Alzheimer's Disease," *IEEE J. Biomed. Heal. Informatics*, 2018, doi: 10.1109/JBHI.2018.2798062.
- [56] 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*, pp. 207–216, 2017.
- [57] 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.
- [58] J. Petersen, S. Thielke, D. Austin, and J. Kaye, "Phone behaviour and its relationship to loneliness in older adults," *Aging Ment. Heal.*, vol. 20, no. 10, pp. 1084–1091, 2015.
- [59] 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.
- [60] 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*, pp. 6286–6289, 2007.
- [61] 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.
- [62] 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*, pp. 279–280, 2017.
- [63] 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, pp. 191–220, 2015.
- [64] J. Dahmen and D.J. Cook, "Indirectly-supervised anomaly detection of clinically-meaningful health events from smart home data," *ACM Trans. Intell. Syst. Technol.*, 2020.
- [65] 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.
- [66] K. Gopalratnam and D.J. Cook, "Online sequential prediction via incremental parsing: The Active LeZi Algorithm," *IEEE Intell. Syst.*, vol. 22, no. 2, 2007.
- [67] B.N. Kakulla, "2019 tech and the 50+ survey," 2019.
- [68] N. Mehrabi, F. Forstatter, N. Saxena, K. Lerman, and A. Galstyan, "A survey on bias and fairness in machine learning," *arXiv*, vol. 1908.09635, 2019.

- [69] J.D. Runyan and E.G. Steinke, "Virtues, ecological momentary assessment/intervention and smartphone technology," *Front. Psychol.*, vol. 6, p. 481, May 2015, doi: 10.3389/fpsyg.2015.00481.
- [70] S. Aminikhanghahi, M. Schmitter-Edgecombe, and D. J. Cook, "Context-aware delivery of ecological momentary assessment," *IEEE Trans. Human-Machine Syst.*, 2019.
- [71] 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.
- [72] 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*, p. 16, 2018.
- [73] G. Wilson and D.J. Cook, "A survey of unsupervised deep domain adaptation," *ACM Trans. Intell. Syst. Technol.*, 2020.
- [74] E.E. Schadt, "The changing privacy landscape in the era of big data," *Mol. Syst. Biol.*, vol. 8, no. 612, pp. 1–3, 2012.
- [75] L. Sweeney, "Only you, your doctor, and many others may know," *Technol. Sci.*, vol. 2015092903, 2015.
- [76] L. Sweeney and J.S. Yoo, "De-anonymizing South Korean resident registration numbers shared in prescription data," *Technol. Sci.*, vol. 2015092901, 2015.
- [77] Y.-A. De Montjoye *et al.*, "On the privacy-conscious use of mobile phone data," *Nat. Publ. Gr.*, vol. 5, pp. 1–6, 2018.
- [78] R. Pérez-Peña and M. Rosenberg. "Strava fitness app can reveal military sites, analysts say," *The New York Times*, January 29, 2018.
- [79] 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.
- [80] 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.
- [81] 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.
- [82] C. Desmet and D J. Cook, "Recent developments and ongoing challenges for privacy-preserving mining of clinical data," *ACM Trans. Knowl. Discov. Data*, 2019.
- [83] 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.
- [84] 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.
- [85] G. Demiris, D.P. Oliver, J. Giger, M. Skubic, and M. Rantz, "Older adults' privacy considerations for vision based recognition methods of eldercare applications," *Technol. Heal. Care Off. J. Eur. Soc. Eng. Med.*, vol. 17, no. 1, pp. 41–48, 2009, doi: 10.3233/THC-2009-0530.
- [86] Pension Rights Center, "Get the facts," <http://www.pensionrights.org/get-facts>, 2018.
- [87] L. Connect, "2019 technology survey older adults age 55-100," 2019.
- [88] 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.
- [89] 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.

- [90] 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.
- [91] 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, pp. 13–34, 2016.
- [92] 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.



# Appendix A

## Workshop Agenda

December 11–12, 2019  
Keck Center of the National Academies  
500 Fifth Street, NW, Room 103  
Washington, DC 20001

### WEDNESDAY, DECEMBER 11, 2019

- |                     |                                                                                                                                                                           |
|---------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 9:45 am – 9:55 am   | <b>Welcome and Introduction to the National Academy of Sciences</b><br><i><u>Adrienne Stith Butler</u>, Board on Behavioral, Cognitive, and Sensory Sciences</i>          |
| 9:55 am – 10:00 am  | <b>Committee Welcome and Introductions</b><br><i><u>Shelia Cotten</u>, Michigan State University, Steering Committee Chair</i>                                            |
| 10:00 am – 10:15 am | <b>Sponsor Perspectives</b><br><i><u>Jonathan King</u>, National Institute on Aging<br/><u>Dana Plude</u>, National Institute on Aging</i>                                |
| 10:15 am – 11:15 am | <b>Paper on Ethics, Trust, and Privacy Issues in Mobile Technologies &amp; Committee Discussion</b><br><i><u>Jessica Vitak</u>, University of Maryland</i>                |
| 11:15 am – 11:30 am | <i>Break</i>                                                                                                                                                              |
| 11:30 am – 12:30 pm | <b>Paper on Social Connectedness and the Potential for Mobile Technologies &amp; Committee Discussion</b><br><i><u>Karen Fingerman</u>, University of Texas at Austin</i> |

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MOBILE TECHNOLOGY FOR ADAPTIVE AGING

12:30 pm - 1:30 pm

**LUNCH BREAK**

1:30 pm – 2:30 pm

**Paper on Use of Mobile and Sensor Technologies  
for Aging in Place & Committee Discussion**

Diane Cook, *Washington State University*  
(virtual)

2:30 pm – 2:45 pm

*Break*

2:45 pm – 3:45 pm

**Paper on Use and Limitations of Mobile  
Technologies for Interventions & Committee  
Discussion**

Neil Charness, *Florida State University*

3:45 pm – 4:00 pm

**Closing Comments**

Shelia Cotten, *Michigan State University*,  
*Steering Committee Chair*

4:00 pm

**Adjourn, Day One**

**THURSDAY, DECEMBER 12, 2019**

10:00 am – 10:15 am

**Recap of Workshop Day 1**

Shelia Cotten, *Michigan State University*,  
*Steering Committee Chair*

10:15 am – 11:15 am

**Paper on Gathering Data with Sensors and  
Mobile Technologies & Committee Discussion**

Elizabeth Murnane, *Dartmouth College*

11:15 am – 11:30 am

*Break*

11:30 am – 12:30 pm

**Paper on Using Mobile Technologies and AI/  
Machine Learning for Prediction & Committee  
Discussion**

Alvin Rajkomar, *University of California*,  
*San Francisco*

12:30 pm – 1:30 pm

**LUNCH BREAK**

|                   |                                                                                                                                                                                                                                                                                                                                                     |
|-------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1:30 pm – 3:30 pm | <b>Discussion: Industry Perspective on Mobile Technology for Adaptive Aging</b><br><i><u>Jim Harper</u>, Co-founder and Chief Operating Officer at Sonde Health, Inc.</i><br><i><u>Scott Moody</u>, Co-founder, CEO, and Chief Member Advocate, K4Connect</i><br><i><u>Kyle Rakow</u>, Vice President and National Director, AARP Driver Safety</i> |
| 3:30 pm – 3:45 pm | <b>Closing Comments</b><br><i><u>Shelia Cotten</u>, Michigan State University, Steering Committee Chair</i>                                                                                                                                                                                                                                         |
| 3:45 pm           | <b>Adjourn Workshop</b>                                                                                                                                                                                                                                                                                                                             |





## Appendix B

### Workshop Attendees

Audi Atienza, National Institute on Aging  
Partha Bhattacharyya, National Institute on Aging  
Neil Charness, Florida State University  
Shelia Cotten, Michigan State University  
Judy Dubno, Medical University of South Carolina  
Karen Fingerman, University of Texas at Austin  
Deepak Ganesan, University of Massachusetts Amherst  
Elena Fazio, National Institute on Aging  
James Harper, Sonde Health  
Johnathan King, National Institutes on Aging  
Megan Lowry, National Academies of Sciences, Engineering, and Medicine  
Scott Moody, K4Conect  
Elizabeth Murnane, Stanford University  
Dana Plude, National Institutes on Aging  
Alvin Rajkomar, University of California, San Francisco  
Kyle Rakow, AARP  
Carly Roszkowski, AARP  
Jessica Vitak, University of Maryland

