
DETAILS
146 pages | 6 x 9 | PAPERBACK

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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.

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