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Leveraging Mobile Technology for Public Health Promotion: A Multidisciplinary Perspective

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Abstract

Health behaviors are inextricably linked to health and well-being, yet issues such as physical inactivity and insufficient sleep remain significant global public health problems. Mobile technology—and the unprecedented scope and quantity of data it generates—has a promising but largely untapped potential to promote health behaviors at the individual and population levels. This perspective article provides multidisciplinary recommendations on the design and use of mobile technology, and the concomitant wealth of data, to promote behaviors that support overall health. Using physical activity as an exemplar health behavior, we review emerging strategies for health behavior change interventions. We describe progress on personalizing interventions to an individual and their social, cultural, and built environments, as well as on evaluating relationships between mobile technology data and health to establish evidence-based guidelines. In reviewing these strategies and highlighting directions for future research, we advance the use of theory-based, personalized, and human-centered approaches in promoting health behaviors.

INTRODUCTION

Reducing behavioral risk factors such as physical inactivity, poor nutrition, smoking, and excessive alcohol consumption would decrease the global burden of disease and lengthen life spans (10, 87). Mobile technology is a low-cost and scalable means of measuring behaviors and intervening to reduce health behavior risk factors. Approximately 76% of people in advanced economies own a smartphone, as do a growing proportion (a median of 45%) of individuals in emerging economies (106). Wearable fitness trackers have also grown in use, with an ownership rate of 37% in the United States (57). Engagement with smartphones is high; the average smartphone user interacts with their device 60 times, for a total of 117 minutes, per day (40, 41). Mobile interventions seek to harness this engagement by using smartphone apps and wearable devices to deliver behavior change interventions in a timely and accessible fashion. Furthermore, with high-resolution, real-world data from a growing number of available sensors (e.g., to monitor skin conductivity, electrical activity in the heart, metabolism, and sleep), mobile technology also has the potential to uncover the drivers and effects of health behaviors.

There is a gap, however, between the potential of mobile technology and its current impacts on public health. Interventions to date that target health-promoting behaviors have small to moderate effects on behavior (53, 119); engagement, and the associated health benefits, typically declines over time (7, 16, 102, 103). Previous reviews have shed light on reasons for the untapped potential of mobile technology for promoting health behaviors. A common theme is that integrating knowledge across fields will help close the gap between the potential and impact of mobile technology (38, 67, 99). For example, there remains a lack of theory-based interventions, even though decades of research demonstrate efficacy of these approaches. Despite advances in machine learning and biomechanical modeling, personalization of interventions is limited, so current approaches often fail to account for factors such as the individual's psychology, physiology, biomechanics, or physical, social, and cultural environment. There is also a missing feedback loop from mobile sensor data to discoveries about relationships between physical activity and health, which could be used to refine and optimize interventions.

Our goal in writing this perspective article is to improve the efficacy of current health-focused apps and wearables and inspire a new wave of research. We provide a multidisciplinary framework (**Figure 1**) and specific recommendations for designing mobile technology interventions to improve health behaviors (see the sidebar titled Recommendations for Improving the Efficacy of Health-Focused Mobile Technology). For each of these recommendations, we review the current state of evidence, providing pointers to foundational papers when they are available. We also give examples from our work and the work of other groups that have inspired the recommendations we provide and suggest strategies for implementing each of the recommendations. While some of the examples we highlight are in the pilot phase of development, they draw on approaches that have significant potential for sustained, positive improvements in physical activity and health. The

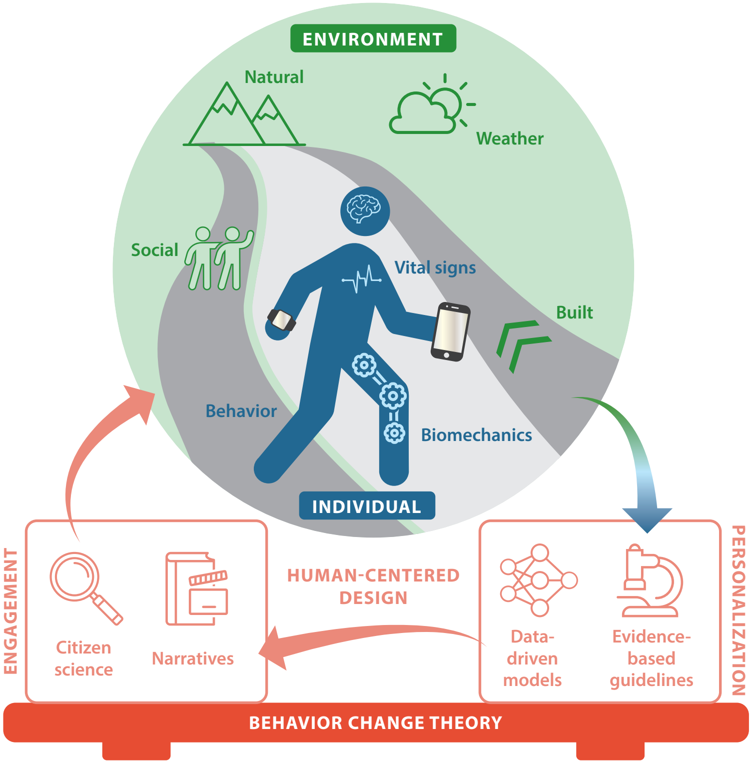

Figure 1

A multidisciplinary and adaptive approach to motivating physical activity and health. The foundation of the approach is based in behavior change theory and developed and refined in an iterative fashion using human-centered design. This foundation guides the data that are collected and how interventions are designed. Sensors and mobile apps, such as those in smartwatches and smartphones, collect data about individuals and their environments. Data might include common measures such as steps, heart rate, and weather or more novel quantities such as metabolite concentrations from sweat or fatigue as assessed by smartphone typing accuracy. These data are used in data-driven models and combined with scientific evidence to personalize precise feedback and engagement strategies provided to an individual. A variety of approaches can be employed to engage the user, such as incorporating narratives as part of apps, customizing suggestions based on an individual's schedule, and integrating citizen science–derived suggestions influenced by individuals' local contexts, such as relationships with family and friends.

closing section highlights knowledge gaps and promising research directions. We use physical activity as a primary example, but many of the recommendations can be applied to other health behaviors. Integrating state-of-the-art mobile technology with multidisciplinary scientific theory and research will help realize the potential of mobile technology to transform public health.

RECOMMENDATIONS

Recommendation 1: Employ Health Behavior Change Theory and Human-Centered Design

Decades of research have established effective behavior change theories and human-centered design, but both remain underutilized primarily due to a lack of knowledge about these approaches and how to implement them in mobile technology interventions.

RECOMMENDATIONS FOR IMPROVING THE EFFICACY OF HEALTH-FOCUSED MOBILE TECHNOLOGY

1. Employ health behavior change theory and human-centered design.
2. Test emerging health behavior promotion approaches, such as citizen science and narrative interventions that utilize the strengths of mobile technology and the power of stories.
3. Cultivate adaptive mindsets that inspire behavior change and improve health and well-being beyond the effects of behavior change.
4. Personalize interventions to intrinsic and extrinsic factors, such as biomechanical and physiological capacity, and social, cultural, and built environments.
5. Collect data on individual and environmental factors to evaluate relationships between intrinsic and extrinsic factors, health behaviors, and health to establish evidence-based health recommendations.

Behavior change theory. Theory-based interventions are driven by a specific theory or set of theories that specify presumed mediators and mechanisms for the outcome or behavior change of interest. For example, social cognitive theory posits that behavior is influenced by how one learns from dynamic personal, social, and environmental factors (9). To apply this theory to the design of an intervention, researchers implement strategies that support observational learning (e.g., observing other participants), enhance social support and self-efficacy for the specific behavior change of interest (e.g., problem-solving around barriers to change), and, ideally, are culturally adapted (104). The social-ecological model may be a particularly advantageous theory because it emphasizes how behavior is impacted by factors that span multiple levels, including person-level, interpersonal, organization, environmental, and policy (14). The behavior change wheel is a helpful framework that guides implementation of theory-based behavior change interventions, helping designers choose appropriate behavior change techniques that will impact an individual's capability, opportunity, and motivation to perform the health behavior of interest (66). Additional taxonomies of behavior change techniques (65) can guide development and ensure consistent reporting between studies.

Meta-analyses have demonstrated that digital interventions based in behavior change theory are efficacious for promoting health behaviors, including physical activity (34, 95, 119), more so than interventions that do not rely on theory (117). For example, King and colleagues (48) designed and deployed a virtual agent named "Carmen" in a community center to increase physical activity in low-income, older Latinx adults. Following social cognitive theory (9) combined with the transtheoretical model (80), Carmen employed self-regulatory skills, such as goal setting, and social environmental factors, such as social support. This culturally adapted, community-based intervention increased walking by 250 min per week in the intervention group, compared to only 25 min in the waitlist control group, and, in a larger randomized clinical trial, was as effective as trained human advisors in promoting significant physical activity increases over a 12-month period (49).

Human-centered design. Human-centered design, as described by Norman & Draper (74), is an iterative process focused on satisfying the needs of end users to ensure that interaction with technologies is efficient and satisfying. This approach actively engages the user (e.g., a patient) and other key stakeholders (e.g., a caregiver or physician) throughout stages of envisioning, implementing, and evaluating an intervention (122). Together, such approaches are commonly referred to as human-centered design, which is closely related to the design-thinking process (**Figure 2**). Design thinking emphasizes empathy with users in a cycle of rapid prototyping and testing (122).

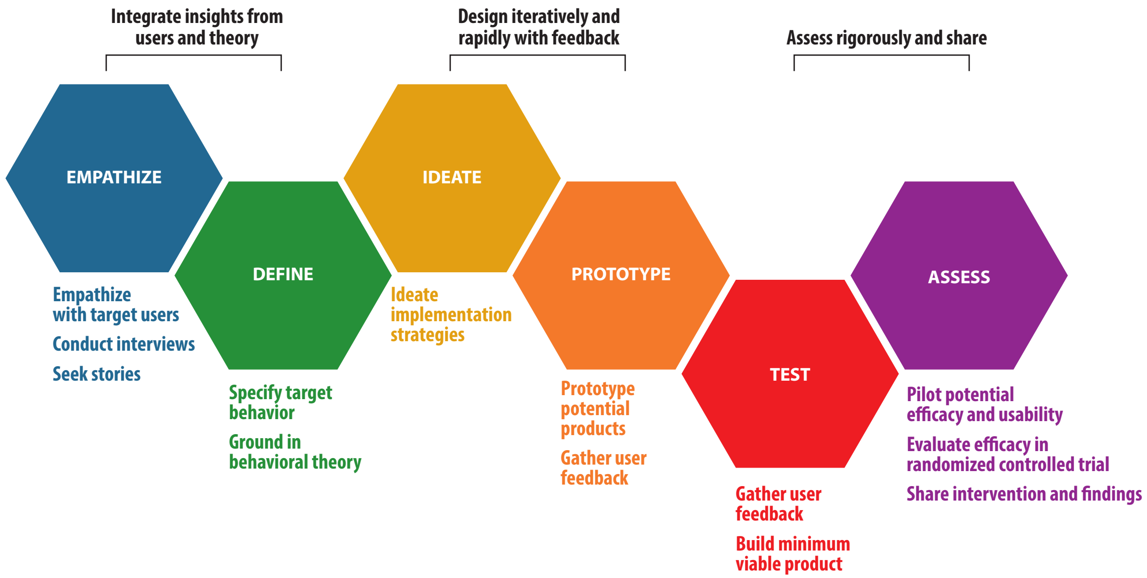

Figure 2

A human-centered, design-thinking approach to creating mobile health interventions. The design-thinking process is a valuable framework for creating interventions that are centered on user needs and grounded in behavior change theory. Stages of the process shown are adapted from Mummah and colleagues (69). Figure adapted from the Stanford d.school (CC BY-NC-SA 4.0).

As Matheson and colleagues (62) note, in the context of behavior change for health, design thinking puts the focus on "what matters most" to users rather than "what's the matter" with them.

Design thinking and human-centered design have had a significant impact on health care innovation through programs such as Stanford Biodesign, which has led to the formation of more than 40 companies that have aided more than 400,000 patients in its first 15 years (116) and accelerated to a cumulative 4.3 million patients in subsequent years (101). Such approaches have also shown promise in the context of mobile technologies for health, including "Ubifit," developed by Consolvo and colleagues (19). Through a process of user interviews and field studies, the team discovered that requiring users to actively engage with a separate app to monitor their behavior reduced engagement. Instead, Ubifit displayed progress toward physical activity goals on a glanceable flower visualization on the lock screen of the phone, leveraging the large number of times each day that users viewed their screen. The system helped participants maintain physical activity levels, including during the winter holidays. By contrast, the comparison group without the glanceable visual feedback showed significantly reduced activity (19, 20). Additional studies compared the effectiveness of varying motivational frames (50) in forming online communities (82, 83) and implementing narrative (70) through a similar process of human-centered design. Employing human-centered design to develop and refine these interventions led to user engagement and improvements in target health behaviors.

Implementation. Several research teams have provided frameworks that guide users through simultaneously applying behavior change theory and human-centered approaches to the design of mobile interventions. The IDEAS (integrate, design, assess, and share) framework guides designers through a process of focusing on a specific target behavior, gaining familiarity with behavior change theory, and building an initial intervention with only the most essential features (69). The framework of Voorheis and colleagues (115) draws from a review of studies using mobile health technologies to promote health-related behavior change. They show how best practices from behavioral change theory and design thinking can be applied to mobile health intervention design in an integrated behavioral design-thinking approach.

Additional challenges remain in implementing theory-based, human-centered design. First, the technologies used in an intervention (e.g., a commercial activity tracker) may already contain behavioral change techniques (e.g., displaying step counts to promote self-monitoring) that must be accounted for when integrating additional interventions. Mercer and colleagues (64) reviewed the use of behavior change techniques and theory in activity trackers, which serves as a helpful reference for intervention designers using commercial technologies. Researchers should also clearly and consistently define all the theory and design approaches used, as well as the outcomes measured, to guide future intervention designers to the most efficacious strategies for specific populations and behaviors (25, 102). In addition, as Voorheis and colleagues (115) discuss, the guidance of behavior change theory could at times conflict with the identified preferences of users. Integrating user data is an opportunity to bridge the gap between theory and preferences by adapting interventions to individuals.

Recommendation 2: Test Emerging Health Behavior Promotion Approaches

The types of strategies used to promote engagement with mobile technology remain limited. Taj and colleagues (105) report that goal setting and self-management are most common, with Direito and colleagues (22) also noting action planning, feedback, instruction, and social comparison as strategies employed. These strategies are reviewed extensively elsewhere (18, 31, 65) and present in many commercial wearable devices (18, 64). New approaches, such as the use of citizen science and narrative, could achieve longer-term engagement while also providing new avenues to customize interventions, new insights about barriers to physical activity, and strategies to translate findings into policy change.

Citizen Science. Citizen science is the joint participation of professional scientists and the general public in research (46). The level of participation can vary from donation of data to cocreated research that is conducted "by the people" (55, 85). Technology-enabled, user-engaged citizen science provides an accessible means for capturing how people's local physical and social environments influence their ability to change their behavior. This information can then be incorporated into further intervention development and customization.

Involving laypeople in data sharing and collection is incredibly valuable. For example, the UK Biobank effort has compiled a database with half a million individuals living in the United Kingdom, including physical activity and other health behaviors, along with biological and clinical measures (24). This data set has revealed strong relationships between a greater number of available facilities for physical activity and lower adiposity (61). Althoff and colleagues (6) used step counts collected via a commercial smartphone application to quantify a new measure of population scale health-activity inequality and show that this measure is a strong predictor of body mass index in countries around the world. These are a few examples of the ways that large-scale, citizen-contributed data describing free-living behaviors and health indicators have allowed the discovery of new relationships that are challenging to study with traditional approaches alone. Cocreation of research with community members has the potential to increase engagement, accelerate translation, and identify and resolve barriers to physical activity (e.g., the Our Voice app in **Figure 3**). There is growing worldwide use of such technology-driven citizen science methods to address community health inequities across the life course (51, 52).

Narratives. Narrative-based feedback is another promising approach to increase engagement with mobile interventions for health attitudes and behaviors. Underpinning virtually all

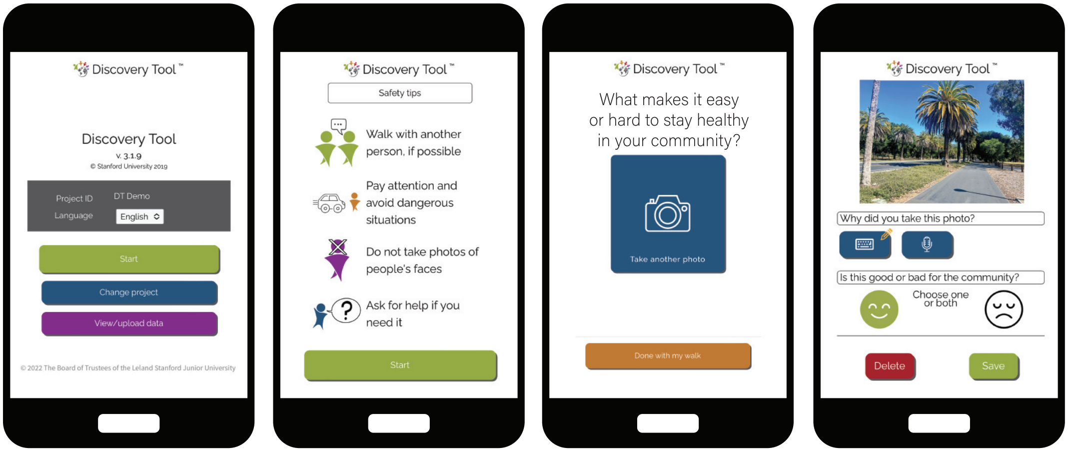

Figure 3

Our Voice app for technology-enabled citizen science. Rodriguez and colleagues (84) implemented the mobile tool as part of an elementary school Safe Routes to School program. Engaging citizen scientists to audit their environments and develop solutions through the app resulted in greater community engagement and greater levels of walking and biking to school. The Our Voice approach seeks to advance health equity by empowering individuals to advocate for local environmental changes.

communication, narratives are (*a*) a kind of embodied thought that humans perform through language; (*b*) a class of objects—such as novels, short stories, and video games—with specific characteristics that can be described; and (*c*) a specific mode of understanding by which humans cognize the world. Through the construction of a plot, and by delimiting a beginning, a middle, and an end to a story, narratives involve events arranged in time and space via relationships of cause and effect. Central to the creation of meaning, narratives help humans make sense of the complexity of their lives and are ubiquitous across cultures. Particularly salient to intervention design is the fact that when people become immersed in a story, they are transported in a way that suppresses counterargument and cognitive resistance, thus unlocking receptivity to events and ideas represented in the narrative (35, 68, 92, 97). Moreover, by leveraging behavior modeling and observational learning, narratives can further encourage positive behavior change (17, 42).

Prior research has shown that narratives for health communication lead to significant persuasion for prevention (though not cessation) of behaviors (94). When culturally relevant, narratives are also a means to reach diverse groups (15, 71, 75). Sousa and colleagues (98) compared children's participation in an active video game after watching a narrative-based versus non-narrative-based video about the benefits of physical activity. The narrative group had greater immersion, as well as significantly higher physical activity levels. These results are in line with the meta-analysis by Zhou and colleagues (123) who showed that narrative game–based interventions can change behaviors, knowledge, self-efficacy, and enjoyment. Murnane and colleagues (70) are translating these narrative-based approaches to a mobile environment through the WhoIsZuki app, as well as the Perfecto app, which combines narrative feedback with culturally relevant representations (**Figure 4**) to promote physical activity.

Implementation. New tools and technologies for employing citizen science, narrative, and other emerging approaches for engagement are becoming more widely accessible. Platforms for citizen scientists to donate their mobile device data are now available (13, 36, 63) and, for example, have allowed for the rapid collection of data during the COVID-19 pandemic and the creation of models to predict infection early in the disease course (3, 32). In a perspective article, members of

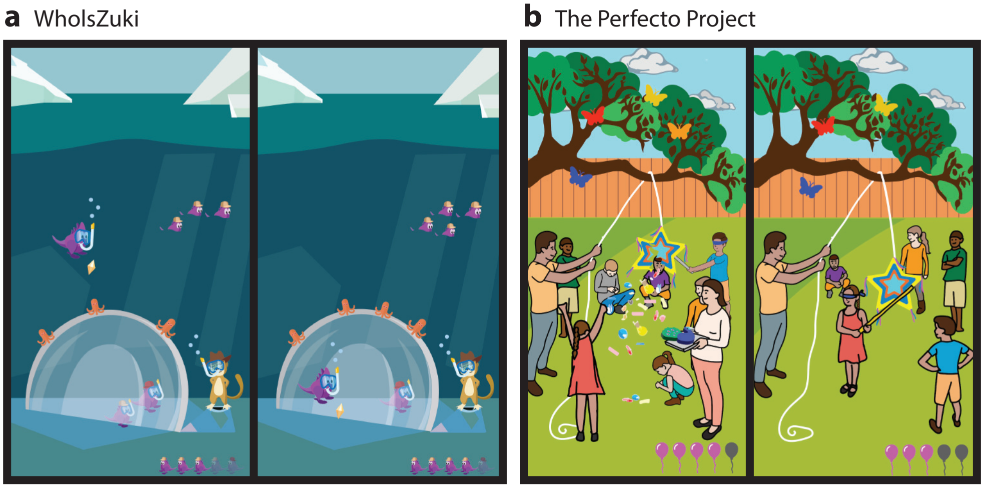

Figure 4

Example narrative-based mobile interventions. (*a*) WhoIsZuki uses a multichapter quest in which the main character's progress is driven by the user's physical activities and goals. In the pilot feasibility study, the authors explored how narrative-based smartphone interfaces can address limitations of conventional (i.e., heavily quantitative) behavioral feedback formats. (*b*) The Perfecto Project is designed to motivate physical activity and health among middle-aged and elderly Latinx people. The Perfecto project team hypothesizes that narratives with plotlines and images that draw on the values and activities of a particular group may be more motivating for that group than nonnarrative or strictly quantitative feedback. In both examples, a variety of chapter-relevant activity icons (such as sea creatures and colored butterflies in the depicted chapters) and goal-completion indicators (e.g., Zuki characters and balloons) appear in the visualization as users log physical activities. In the process, this completion of physical activity goals moves the story forward and unlocks the next chapter of the narrative. WhoIsZuki artwork by Anna Kong and Xin Jiang; Perfecto Project artwork by Sam Romero.

this author team (39) provide best practices for analyzing data sets donated or otherwise collected via commercial devices. In addition, current participatory action methods of citizen science that seek to engage community members in the fuller scientific process, as provided through the Our Voice and Galileo apps, have benefited significantly from active partnerships with researchers, technology specialists, community stakeholders, and community members worldwide (54, 76).

Several resources are available to guide the development and incorporation of narrative. Shaffer and colleagues (92) share aspects of a narrative that are most likely to create immersion. For example, stories that are coherent, temporally ordered, told in first person, or incorporate elements of humor or surprise have all been shown to create stronger immersion. Murnane and colleagues (70) also carefully detail their design process for creating the WhoIsZuki platform.

Several other potential approaches could lead to greater and longer-lasting engagement and, thus, larger improvements in health, including gamification (118) and social connection or influence (109). Additional research on the efficacy of citizen science, narrative, and these additional approaches is needed, along with investigation into how best to customize strategies to an individual or desired outcome, as discussed in more detail in the section below on personalization.

Recommendation 3: Cultivate Adaptive Mindsets that Inspire Behavior Change

Mindsets are core assumptions regarding the nature and workings of things within ourselves and in the world that work together with the properties of the body (29). Mindsets create a meaning system that aids people in making predictions, interpreting events, and taking action. Previous work has demonstrated the influence of mindsets across several domains, including intelligence (28), stress (21), and illness (124). When it comes to physical activity and health behavior, two types of mindsets are particularly relevant: (*a*) mindsets about the process of engaging in health-related behaviors, that is, the extent to which individuals associate physical activity and healthy eating with appealing versus unappealing qualities (11); and (*b*) mindsets about the adequacy of one's activity and its corresponding health consequences (121).

Mindsets are important, but often overlooked, drivers of health and behavior change that are rarely leveraged within health technology. Moreover, in some cases, well-intentioned efforts to motivate behavior change may inadvertently inspire maladaptive mindsets. For example, lofty physical activity guidelines with stringent definitions (e.g., for intense aerobic exercise and strength training) made people feel that their current activity levels were inadequate, a mindset that resulted in even less physical activity the following week (121). Conversely, teaching people that many types of activity can induce health benefits led to more adaptive mindsets, which in turn predicted self-efficacy and engagement in physical activity. Mindsets are a good target for intervention because they can be altered with brief but psychologically "wise," multimedia interventions (6, 11, 18). With a short presentation and informational pamphlet highlighting the fun and enjoyable aspects of exercise (as opposed to merely harping on the health benefits of exercise), Boles and colleagues (11) improved mindsets and increased adherence to a 10-week fitness class and motivation for future exercise.

Implementation. To establish more useful mindsets, we recommend that mobile devices help people view the process of physical activity as appealing while avoiding the demotivation that comes from feeling inadequate. As a first step, mindsets can be evaluated for their relationship to a specific outcome within the population of interest. For instance, a multipoint survey uncovered that mindset relates to future physical activity levels in individuals with knee osteoarthritis (12) and is available as part of Boswell and colleagues' supplementary materials for others to reuse. Changing mindset within an intervention can be implicit; for example, changing notifications to acknowledge the activity that people are currently doing or highlighting the appealing qualities of activities incorporates mindset change strategies into an intervention without the participant's knowledge. Mindsets can also be changed through explicit intervention to teach about the power of mindset and empower individuals with strategies for cultivating more adaptive mindsets.

Recommendation 4: Personalize to Intrinsic and Extrinsic Factors

Many interventions are generic or employ only rudimentary personalization, but interventions can be personalized in a host of ways. Both the content and delivery of an intervention can be personalized, and various factors can drive these personalizations (**Figure 5**). Some of these factors include demographic variables, physiological and biomechanical capacity (e.g., the presence of osteoarthritis), genomics, and other biochemical measurements, as well as physical, cultural, and social environments (e.g., climate or presence of a partner). The algorithm used to personalize can be based on knowledge from behavior change, biomechanical, or other models; alternately, a machine-learning model driven by past behavior can drive personalization. The desired outcomes, whether related to engagement, behavior, or health, can also be personalized.

Research on the personalization of mobile health behavior interventions is in its early stages. Meta-analyses of mobile interventions to improve health behaviors provide some evidence that personalized interventions improve physical activity and other behaviors and, in some cases, are more effective when compared directly to nonpersonalized approaches (33, 58, 110).

Personalizing to current physiological capacity, such as biomechanics, is important to the design of efficacious physical activity interventions but is currently underutilized. For example, Halilaj and colleagues (37) showed that physical activity intensity, as assessed by an activity

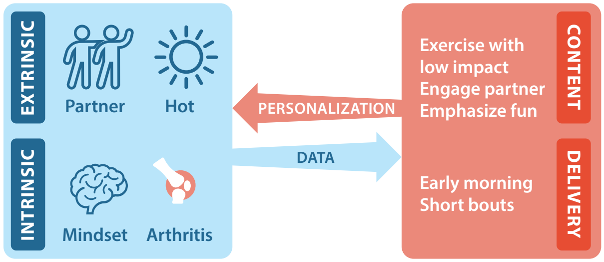

Figure 5

Examples of how personalization based on intrinsic and extrinsic factors could drive a physical activity intervention for older adults. An individual with knee osteoarthritis is recommended low-impact activities in short bouts. The content emphasizes the joy of movement to elicit an adaptive mindset. Extrinsic factors such as having a partner and living in a hot climate result in further personalization by engaging the individual's partner and suggesting activity in the early morning, respectively.

tracker, is correlated with imaging-based measures of cartilage health; in particular, sedentary and high-intensity activities are associated with degradation of cartilage, while moderate-intensity activity is associated with cartilage health. These relationships should be reflected in the physical activity goals of individuals with or at risk for osteoarthritis. Uhlrich and colleagues (113) showed that personalizing an individual's walking pattern is associated with a reduction in deleterious knee loads. These studies combine biomechanical models with data from wearable sensors to drive personalization.

Personalizing interventions to an individual's social, cultural, built, and natural environments also shows promise. Shameli and colleagues (93) show that teams entering an activity-based competition are most active when the team includes both men and women. When leveraging social connections (e.g., friends in an app's social network), same-sex friend connections had the largest influence on activity levels (5). External and internal characteristics can also be jointly personalized. For example, See and colleagues (91) review the literature to identify approaches to tailor a safe and effective physical activity intervention for older adults living in rural areas with hot climates by customizing the timing and nature of activity, along with providing hydration reminders.

Implementation. In developing a personalized intervention, a key step is gathering the required data. Advances in mobile sensor technology, along with tools to analyze the resulting data, are increasing the measures that can be used for personalization. For example, tools to quantify musculoskeletal biomechanics and metabolic energy consumption via inertial measurement units (which are included in all modern smartphones) or video (such as that collected with a smartphone) are now available (2, 47, 96). In the section on evaluating and establishing relationships, we highlight additional available sensors and apps for research on physical activity and health.

Given data about a participant, intervention developers next need an algorithm to personalize the content or delivery of the intervention. One promising approach for personalization is to combine data- and theory-driven models to personalize interventions; this approach can simultaneously leverage advances in machine learning, along with decades of knowledge from biomechanics, psychology, and health promotion. Murphy and colleagues (73) have also developed tools to aid the creation of just-in-time adaptive interventions, which aim "to provide the right type/amount of support, at the right time, by adapting to an individual's changing internal and contextual state" (p. 1). The team has published work describing the underlying theory and design principles/process (73) and shares software used in the implementation of these and other adaptive interventions (**https://d3c.isr.umich.edu/**). Researchers can also directly involve users in the design of an intervention (45, 90), for example, by guiding the user through formulating and testing hypotheses (e.g., "Do I sleep better if I exercise early in the day?").

Future work is needed to determine precisely when and how an intervention should be personalized. For example, the need for personalization increases when predictive models poorly generalize from person to person. Additional, similar guidelines, along with a better understanding of the most influential (and robust) measures to drive personalization will improve the efficacy and efficiency of personalized interventions. Finally, greater incorporation of biochemical markers, including inflammation levels, glucose levels, and other physiological measures such as stress signals, may be useful for designing personalized interventions and monitoring outcomes (e.g., 26).

Recommendation 5: Evaluate and Establish Evidence-Based Health Recommendations

Evidence for the health benefits of physical activity is strong (53); however, much remains unknown about the many relationships between intrinsic (e.g., mindset, physiological state, biomechanics, genomics) and extrinsic (e.g., natural, built, and social environments) factors, health behaviors (such as physical activity), and health outcomes. Mobile devices and wearable sensors can be valuable tools to uncover these relationships, which will, in turn, improve the personalization of interventions and guide policies to enhance health at the population scale.

Mobile health technology allows us to run large-scale studies and collect free-living, multidimensional longitudinal data. For example, accelerometer and step count data collected via wearable sensors or smartphones have helped reveal several principles that govern physical activity as it relates to health. Zahrt & Crum (120) used data from the large National Health and Nutrition Examination Survey (NHANES), including data from physical activity monitors, to show that perception of physical activity (which is related to the activity adequacy mindset discussed above), even when adjusting for measured physical activity levels, is a strong predictor of future mortality. Combining mobile technology data with other data sets (e.g., weather, environment, genetics, and economic data) is another powerful approach. For instance, Althoff and colleagues (6) connected activity data from a smartphone with information about the built environment to discover that the walkability of a city is a strong predictor of "activity inequality," the variation of activity within a population.

While devices to measure physical activity are most common, the available sensor and data types are also rapidly evolving, expanding the types of relationships that we can study. Continuous glucose monitors have become readily available, revolutionizing diabetic care due to the relationship between managing blood-glucose levels and reducing health risks, including microvascular and neuropathic complications (23). Mobile glucose monitors were used in research by Savikj and colleagues (88) to demonstrate that high intensity interval training (HIIT) was effective in improving blood glucose in men with diabetes when conducted in the afternoon, while morning HIIT, surprisingly, increased blood glucose, which could guide physical activity recommendations for this population. Additional sensors on the horizon measure other biomarkers such as interstitial metabolites (107) and hormones (78) and gather data about the external environment. For example, measuring biological and chemical environmental exposure (44) could be used to determine relationships between exposure to pollutants (e.g., from wildfires) and the effects of physical activity. Advances in computer vision have also expanded the information we can gain from photo and video about diet and nutrition (60, 114) and biomechanics (47). Researchers have also developed novel approaches that leverage day-to-day interactions with a mobile phone (e.g., typing accuracy and latency times in interacting with mobile apps) to assess psychomotor performance and sleep metrics (4, 77). These new physiological measures, captured over long durations and in free-living settings, have the potential to help us not only uncover associations, but also reveal causal relationships and the precise biological mechanisms by which physical activity and other health behaviors influence health.

Implementation. Uncovering relationships between physical activity and health remains an open challenge for the field. Several tools are available to aid this work, including platforms to collect, store, and analyze multimodal data from mobile technology. Depending on available resources and expertise, researchers can opt for a paid turnkey solution (79, 111) or deploy their own platform using open-source software developed by others (8, 81, 86, 100, 111). For example, the open-source Personal Health Dashboard (7) integrates wearable data with genetics and health records and allows researchers to customize workflows on their own or in collaboration with the research team.

Determining which measurements to use can be overwhelming, but databases are emerging to help evaluate the myriad choices. The Feasibility Studies Database (**https://feasibility-studies.ctti-clinicaltrials.org/**) is a freely accessible database of mobile technologies drawn from the scientific literature, searchable by participant demographics, therapeutic area, sensor technology, outcome measurement, and other parameters. The Digital Medicine Society's Library of Digital Endpoints (**https://www.dimesociety.org/communication-education/library-of-digital-endpoints/**) captures wearables-based outcome measurements used in industry-sponsored studies of medical products.

Large-scale, retrospective data sets (e.g., from commercial devices) are another promising resource for large-scale free-living data about activity and health. In addition to helping reveal relationships, these data sets can provide a valuable baseline for typical, free-living variation of activity and related behaviors and health measures within a population. Hicks and colleagues (39) share best practices for conducting research with large-scale wearable data sets and review potential approaches to move toward causal relationships using natural experiments. They also share lessons learned to help overcome challenges with data sharing between academia and industry (e.g., identifying questions of mutual interest). Another means of generating large-scale data sets is via the citizen science approach, where anyone—not just researchers—can collect data to answer research questions important to them. For all analyses, it is vital to define specific research questions prior to analysis rather than blindly searching for associations in a given data set.

CONCLUSIONS

Disseminating mobile technology in public health promotion offers several overarching challenges and opportunities (also summarized in Future Issues, below). Protecting the privacy of participants and ensuring ethical use of data are essential. In addition to ensuring compliance with all regulatory and ethics requirements, researchers should share goals, intended data uses, and results with participants (67). New tools and regulations for conducting research and handling data are also needed (27, 112), for example to prevent users from being reidentified (72), to ensure informed consent (89), and to support the participation of underrepresented groups (43). Broader engagement of biomedical ethicists in the design and implementation of mobile health interventions will facilitate these efforts (59).

Translating mobile health research into practice in clinical and public health remains a challenge (56). The combined effort of many groups, such as governmental agencies, insurance companies, scientists and researchers, and private companies, could help meet this challenge. Partnerships across these groups should create motivation and incentives for translational work (e.g., focused funding opportunities). Tomlinson and colleagues (108) discuss this cooperation, and other recommendations, as essential for scaling mobile health technology. Additional work to expand on existing research platforms for mobile health interventions would also aid translation. The start-up cost for current platforms can be high, and a richer feature set (e.g., incorporating narrative or citizen science approaches) would make these tools more broadly applicable. Expanding these platforms for multimodal mobile health research would not only speed translation but also accelerate research, eliminating the need for researchers to recreate similar technology with each new study and increasing the interoperability of different types of data. Integrating into the platforms tools for data sharing that protect participant privacy will also help reverse the current status quo where much of the data are not shared.

Most existing interventions focus on preventing disease. We suggest that interventions also focus on performance goals such as finishing a race, playing with grandkids, or independently completing activities of daily living such as food preparation.

Research should also consider public health interventions at population scale, rather than solely on the individual level. While we encourage giving an individual personalized feedback and interventions to spur them to change their behavior, mobile interventions could have an even broader impact by uncovering the drivers of and barriers to health behaviors and providing evidence to improve health care practice and public policy. To support this effort, more work is needed to quantify and report the economic and health benefits of mobile interventions, such as preventing disease and reducing years lost due to disability, and determine the equity implications of mobile interventions through epidemiological and economic models (43).

With the increased emergence of mobile health tools and technologies, standardizing their evaluation and the associated reporting of research results is essential to ensure quality evidence. Checklists such as the mobile health evidence reporting and assessment developed by the World Health Organization mHealth Technical Evidence Review Group (1) and the Consolidated Standards of Reporting Trials-eHealth (30) can provide a basis for this work. We further recommend that researchers and consumers select mobile technologies whose efficacy has been demonstrated in the peer-reviewed literature, with evaluation results reported using these standardized approaches.

In providing the recommendations in this perspective, we hope to spur new basic science research on the relationships between physical activity and health, as well as new translational research on the design of effective mobile interventions to promote health and ultimately more efficacious interventions to help reduce the global burden of disease.

FUTURE ISSUES

1. Best practices are needed to protect the privacy of participants and ensure ethical use and sharing of data.
2. Mobile health research must be translated to practice in clinical and public health.
3. Expanding from disease prevention to improving and maintaining performance in ways that are meaningful across the population and across the life span is a key opportunity.
4. Public health interventions at population scale are needed to address barriers and drivers of health behaviors.
5. Quantifying the economic and health benefits and equity implications of mobile interventions will support prioritization and scaling.
6. All interventions must be evaluated and results shared in a standardized manner to ensure reproducibility and high-quality evidence.

DISCLOSURE STATEMENT

M.P.S. is a cofounder and scientific advisor of Personalis, SensOmics, Qbio, January AI, Fodsel, Filtricine, Protos, RTHM, Iollo, Marble Therapeutics, and Mirvie. He is a scientific advisor of Genapsys, Jupiter, Neuvivo, Swaza, and Mitrix. The other authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

AUTHOR CONTRIBUTIONS

J.L.H., M.A.B., and S.L.D. led the overall article and literature review, were the primary writers of the manuscript, and led the conception and design of the figures. A.C.K., J.A.L., E.L.M., J.L.H., M.A.B., and S.L.D. drafted the section on theory-driven design. T.A., J.A.L., P.M.L.M., E.L.M., A.C.K., J.L.H., and M.A.B. drafted the section on emerging approaches. A.J.C. and M.A.B. drafted the section on mindset. T.A., M.P.S., J.L.H., M.A.B., and S.L.D. drafted the section on personalization. T.A., M.P.S., J.P.K., J.L.H., and S.L.D. drafted the section on causal relationships. All authors contributed to the development of the recommendations and overall framework depicted in **Figure 1**, contributed to writing and finalizing the article, and approved the final version of the article.

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LITERATURE CITED

1. Agarwal S, LeFevre AE, Lee J, L'Engle K, Mehl G, et al. 2016. Guidelines for reporting of health interventions using mobile phones: mobile health (mHealth) evidence reporting and assessment (mERA) checklist. *BMJ* 352:i1174
2. Al Borno M, O'Day J, Ibarra V, Dunne J, Seth A, et al. 2022. OpenSense: an open-source toolbox for inertial-measurement-unit-based measurement of lower extremity kinematics over long durations. *J. Neuroeng. Rehabil.* 19(22):22
3. Alavi A, Bogu GK, Wang M, Rangan ES, Brooks AW, et al. 2022. Real-time alerting system for COVID-19 and other stress events using wearable data. *Nat. Med.* 28(1):175–84
4. Althoff T, Horvitz E, White RW. 2018. Psychomotor function measured via online activity predicts motor vehicle fatality risk. *npj Digit. Med.* 1(1):20173
5. Althoff T, Jindal P, Leskovec J. 2017. Online actions with offline impact: how online social networks influence online and offline user behavior. *Proc. Int. Conf. Web. Search Data Min*. 2017:537–46
6. Althoff T, Sosič R, Hicks JL, King AC, Delp SL, Leskovec J. 2017. Large-scale physical activity data reveal worldwide activity inequality. *Nature* 547(7663):336–39
7. Attig C, Franke T. 2020. Abandonment of personal quantification: a review and empirical study investigating reasons for wearable activity tracking attrition. *Comput. Hum. Behav.* 102:223–37
8. Bahmani A, Alavi A, Buergel T, Upadhyayula S, Wang Q, et al. 2021. A scalable, secure, and interoperable platform for deep data-driven health management. *Nat. Commun.* 12:5757
9. Bandura A. 2001. Social cognitive theory: an agentic perspective. *Annu. Rev. Psychol.* 52:1–26

10. Bennett JE, Stevens GA, Mathers CD, Bonita R, Rehm J, et al. 2018. NCD Countdown 2030: worldwide trends in non-communicable disease mortality and progress towards Sustainable Development Goal target 3.4. *Lancet* 392(10152):1072–88
11. Boles DZ, DeSousa M, Turnwald BP, Horii RI, Duarte T, et al. 2021. Can exercising and eating healthy be fun and indulgent instead of boring and depriving? Targeting mindsets about the process of engaging in healthy behaviors. *Front. Psychol.* 12(Oct.):745950
12. Boswell MA, Evans KM, Zion SR, Boles DZ, Hicks JL, et al. 2022. Mindset is associated with future physical activity and management strategies in individuals with knee osteoarthritis. *Ann. Phys. Rehabil. Med.* 65(6):101634
13. Bot BM, Suver C, Neto EC, Kellen M, Klein A, et al. 2016. The mPower study, Parkinson disease mobile data collected using ResearchKit. *Sci. Data* 3:160011
14. Boulton ER, Horne M, Todd C. 2018. Multiple influences on participating in physical activity in older age: developing a social ecological approach. *Health Expect*. 21(1):239–48
15. Briant KJ, Halter A, Marchello N, Escareño M, Thompson B. 2016. The power of digital storytelling as a culturally relevant health promotion tool. *Health Promot. Pract.* 17(6):793–801
16. Buckingham SA, Williams AJ, Morrissey K, Price L, Harrison J. 2019. Mobile health interventions to promote physical activity and reduce sedentary behaviour in the workplace: a systematic review. *Digit. Health* 5:2055207619839883
17. Cohen J. 2001. Defining identification: a theoretical look at the identification of audiences with media characters. *Mass Commun. Soc.* 4(3):245–64
18. Conroy DE, Yang C-H, Maher JP. 2014. Behavior change techniques in top-ranked mobile apps for physical activity. *Am. J. Prev. Med.* 46(6):649–52
19. Consolvo S, Klasnja P, McDonald DW, Avrahami D, Froehlich J, et al. 2008. Flowers or a robot army?: Encouraging awareness & activity with personal, mobile displays. *Proc. Int. Conf. Ubiquitous Comput*. 2008:54–63
20. Consolvo S, Klasnja P, McDonald DW, Landay JA. 2012. Designing for healthy lifestyles: design considerations for mobile technologies to encourage consumer health and wellness. *Found. Trends Hum.-Comput. Interact.* 6(3–4):167–315
21. Crum AJ, Akinola M, Martin A, Fath S. 2017. The role of stress mindset in shaping cognitive, emotional, and physiological responses to challenging and threatening stress. *Anxiety Stress Coping* 30(4):379–95
22. Direito A, Carraça E, Rawstorn J, Whittaker R, Maddison R. 2017. mHealth technologies to influence physical activity and sedentary behaviors: behavior change techniques, systematic review and meta-analysis of randomized controlled trials. *Ann. Behav. Med.* 51(2):226–39
23. Dis. Control Complic. Trial Res. Group, Nathan DM, Genuth S, Lachin J, Cleary P, et al. 1993. The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. *N. Engl. J. Med.* 329(14):977–86
24. Doherty A, Jackson D, Hammerla N, Plötz T, Olivier P, et al. 2017. Large scale population assessment of physical activity using wrist worn accelerometers: the UK Biobank study. *PLOS ONE* 12(2):e0169649
25. Domin A, Spruijt-Metz D, Theisen D, Ouzzahra Y, Vögele C. 2021. Smartphone-based interventions for physical activity promotion: scoping review of the evidence over the last 10 years. *JMIR mHealth uHealth* 9(7):e24308
26. Dunn J, Kidzinski L, Runge R, Witt D, Hicks JL, et al. 2021. Wearable sensors enable personalized predictions of clinical laboratory measurements. *Nat. Med.* 27(6):1105–12
27. Dunseath S, Weibel N, Bloss CS, Nebeker C. 2018. NIH support of Mobile, Imaging, Pervasive Sensing, Social Media and Location Tracking (MISST) research: laying the foundation to examine research ethics in the digital age. *npj Digit. Med.* 1:20171
28. Dweck CS, Hong Y-Y, Chiu C-Y. 1993. Implicit theories: individual differences in the likelihood and meaning of dispositional inference. *Pers. Soc. Psychol. Bull.* 19(5):644–56
29. Dweck CS, Yeager DS. 2019. Mindsets: a view from two eras. *Perspect. Psychol. Sci.* 14(3):481–96
30. Eysenbach G, CONSORT-EHEALTH Group. 2011. CONSORT-EHEALTH: improving and standardizing evaluation reports of Web-based and mobile health interventions. *J. Med. Internet Res.* 13(4):e126

31. French DP, Olander EK, Chisholm A, McSharry J. 2014. Which behaviour change techniques are most effective at increasing older adults' self-efficacy and physical activity behaviour? A systematic review. *Ann. Behav. Med.* 48(2):225–34
32. Gadaleta M, Radin JM, Baca-Motes K, Ramos E, Kheterpal V, et al. 2021. Passive detection of COVID-19 with wearable sensors and explainable machine learning algorithms. *npj Digit. Med.* 4(1):166
33. Ghanvatkar S, Kankanhalli A, Rajan V. 2019. User models for personalized physical activity interventions: scoping review. *JMIR mHealth uHealth* 7(1):e11098
34. Gourlan M, Bernard P, Bortolon C, Romain AJ, Lareyre O, et al. 2016. Efficacy of theory-based interventions to promote physical activity. A meta-analysis of randomised controlled trials. *Health Psychol. Rev.* 10(1):50–66
35. Green MC, Brock TC. 2000. The role of transportation in the persuasiveness of public narratives. *J. Pers. Soc. Psychol.* 79(5):701–21
36. Greshake Tzovaras B, Angrist M, Arvai K, Dulaney M, Estrada-Galiñanes V, et al. 2019. Open Humans: a platform for participant-centered research and personal data exploration. *Gigascience* 8(6):giz076
37. Halilaj E, Hastie TJ, Gold GE, Delp SL. 2018. Physical activity is associated with changes in knee cartilage microstructure. *Osteoarthr. Cartil.* 26(6):770–74
38. Hekler EB, Michie S, Pavel M, Rivera DE, Collins LM, et al. 2016. Advancing models and theories for digital behavior change interventions. *Am. J. Prev. Med.* 51(5):825–32
39. Hicks JL, Althoff T, Sosic R, Kuhar P, Bostjancic B, et al. 2019. Best practices for analyzing large-scale health data from wearables and smartphone apps. *npj Digit. Med.* 2:45
40. Hintze D, Findling RD, Muaaz M, Scholz S, Mayrhofer R. 2014. Diversity in locked and unlocked mobile device usage. *Proc. ACM Int. Jt. Conf. Pervasive Ubiquitous Comput*. 2014:379–84
41. Hintze D, Hintze P, Findling RD, Mayrhofer R. 2017. A large-scale, long-term analysis of mobile device usage characteristics. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1(2):13
42. Hinyard LJ, Kreuter MW. 2007. Using narrative communication as a tool for health behavior change: a conceptual, theoretical, and empirical overview. *Health Educ. Behav.* 34(5):777–92
43. Holko M, Litwin TR, Munoz F, Theisz KI, Salgin L, et al. 2022. Wearable fitness tracker use in federally qualified health center patients: strategies to improve the health of all of us using digital health devices. *npj Digit. Med.* 5(1):53
44. Jiang C, Wang X, Li X, Inlora J, Wang T, et al. 2018. Dynamic human environmental exposome revealed by longitudinal personal monitoring. *Cell* 175(1):277–91.e31
45. Karkar R, Zia J, Vilardaga R, Mishra SR, Fogarty J, et al. 2016. A framework for self-experimentation in personalized health. *J. Am. Med. Inform. Assoc.* 23(3):440–48
46. Kelty C, Panofsky A. 2014. Disentangling public participation in science and biomedicine. *Genome Med*. 6(1):8
47. Kidziński Ł, Yang B, Hicks JL, Rajagopal A, Delp SL, Schwartz MH. 2020. Deep neural networks enable quantitative movement analysis using single-camera videos. *Nat. Commun.* 11(1):4054
48. King AC, Campero I, Sheats JL, Castro Sweet CM, Garcia D, et al. 2017. Testing the comparative effects of physical activity advice by humans versus computers in underserved populations: the COMPASS trial design, methods, and baseline characteristics. *Contemp. Clin. Trials* 61(April):115–25
49. King AC, Campero MI, Sheats JL, Castro Sweet CM, Hauser ME, et al. 2020. Effects of counseling by peer human advisors vs. computers to increase walking in underserved populations: the COMPASS randomized clinical trial. *JAMA Intern. Med.* 180(11):1481–90
50. King AC, Hekler EB, Grieco LA, Winter SJ, Sheats JL, et al. 2016. Effects of three motivationally targeted mobile device applications on initial physical activity and sedentary behavior change in midlife and older adults: a randomized trial. *PLOS ONE* 11(6):e0156370
51. King AC, King DK, Banchoff A, Solomonov S, Ben Natan O, et al. 2020. Employing participatory citizen science methods to promote age-friendly environments worldwide. *Int. J. Environ. Res. Public Health* 17(5):1541
52. King AC, Odunitan-Wayas FA, Chaudhury M, Rubio MA, Baiocchi M, et al. 2021. Community-based approaches to reducing health inequities and fostering environmental justice through global youth-engaged citizen science. *Int. J. Environ. Res. Public Health* 18(3):892

53. King AC, Whitt-Glover MC, Marquez DX, Buman MP, Napolitano MA, et al. 2019. Physical activity promotion: highlights from the 2018 Physical Activity Guidelines Advisory Committee systematic review. *Med. Sci. Sports Exerc.* 51(6):1340–53
54. King AC, Winter SJ, Chrisinger BW, Hua J, Banchoff AW. 2019. Maximizing the promise of citizen science to advance health and prevent disease. *Prev. Med.* 119:44–47
55. King AC, Winter SJ, Sheats JL, Rosas LG, Buman MP, et al. 2016. Leveraging citizen science and information technology for population physical activity promotion. *Transl. J. Am. Coll. Sports Med.* 1(4):30–44
56. Ku JP, Sim I. 2021. Mobile health: making the leap to research and clinics. *npj Digit Med*. 4(1):83
57. Kunst A. 2022. Consumer electronics ownership in the United States 2022. *Statista*, April 21. **https://www.statista.com/forecasts/997201/consumer-electronics-ownership-in-the-us**
58. Laranjo L, Ding D, Heleno B, Kocaballi B, Quiroz JC, et al. 2021. Do smartphone applications and activity trackers increase physical activity in adults? Systematic review, meta-analysis and metaregression. *Br. J. Sports Med.* 55(8):422–32
59. Lucivero F, Jongsma KR. 2018. A mobile revolution for healthcare? Setting the agenda for bioethics. *J. Med. Ethics* 44(10):685–89
60. Manoogian ENC, Wei-Shatzel J, Panda S. 2022. Assessing temporal eating pattern in free living humans through the myCircadianClock app. *Int. J. Obes.* 46(4):696–706
61. Mason KE, Pearce N, Cummins S. 2018. Associations between fast food and physical activity environments and adiposity in mid-life: cross-sectional, observational evidence from UK Biobank. *Lancet Public Health* 3(1):e24–33
62. Matheson GO, Klügl M, Engebretsen L, Bendiksen F, Blair SN, et al. 2013. Prevention and management of non-communicable disease: the IOC consensus statement, Lausanne 2013. *Sports Med*. 43(11):1075–88
63. McConnell MV, Shcherbina A, Pavlovic A, Homburger JR, Goldfeder RL, et al. 2017. Feasibility of obtaining measures of lifestyle from a smartphone app: the MyHeart Counts Cardiovascular Health study. *JAMA Cardiol*. 2(1):67–76
64. Mercer K, Li M, Giangregorio L, Burns C, Grindrod K. 2016. Behavior change techniques present in wearable activity trackers: a critical analysis. *JMIR mHealth uHealth* 4(2):e40
65. Michie S, Ashford S, Sniehotta FF, Dombrowski SU, Bishop A, French DP. 2011. A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: the CALO-RE taxonomy. *Psychol. Health* 26(11):1479–98
66. Michie S, van Stralen MM, West R. 2011. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implement. Sci.* 6(42):42
67. Michie S, Yardley L, West R, Patrick K, Greaves F. 2017. Developing and evaluating digital interventions to promote behavior change in health and health care: recommendations resulting from an international workshop. *J. Med. Internet Res.* 19(6):e232
68. Moyer-Gusé E. 2008. Toward a theory of entertainment persuasion: explaining the persuasive effects of entertainment-education messages. *Commun. Theory* 18(3):407–25
69. Mummah SA, Robinson TN, King AC, Gardner CD, Sutton S. 2016. IDEAS (integrate, design, assess, and share): a framework and toolkit of strategies for the development of more effective digital interventions to change health behavior. *J. Med. Internet Res.* 18(12):e317
70. Murnane EL, Jiang X, Kong A, Park M, Shi W, et al. 2020. Designing ambient narrative-based interfaces to reflect and motivate physical activity. *Proc. Conf. Hum. Factors Comput. Syst.* 2020:1–14
71. Murphy ST, Frank LB, Chatterjee JS, Baezconde-Garbanati L. 2013. Narrative versus nonnarrative: the role of identification, transportation, and emotion in reducing health disparities. *J. Commun.* 63(1):116–37
72. Na L, Yang C, Lo C-C, Zhao F, Fukuoka Y, Aswani A. 2018. 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.* 1(8):e186040
73. Nahum-Shani I, Smith SN, Spring BJ, Collins LM, Witkiewitz K, et al. 2018. Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Ann. Behav. Med.* 52(6):446–62

74. Norman DA, Draper SW. 1986. *User Centered System Design: New Perspectives on Human-Computer Interaction*. Mahwah, NJ: Erlbaum
75. Ochoa CY, Murphy ST, Frank LB, Baezconde-Garbanati LA. 2020. Using a culturally tailored narrative to increase cervical cancer detection among Spanish-speaking Mexican-American women. *J. Cancer Educ.* 35(4):736–42
76. Pandey V, Koul T, Yang C, McDonald D, Price Ball M, et al. 2021. Galileo: citizen-led experimentation using a social computing system. *Proc. CHI Conf. Hum. Factors Comput. Syst.* 2021:565
77. Park C, Arian M, Liu X, Sasson L, Kahn J, et al. 2021. Online mobile app usage as an indicator of sleep behavior and job performance. *Proc. World Wide Web Conf.* 2021:2488–500
78. Parlak O, Keene ST, Marais A, Curto VF, Salleo A. 2018. Molecularly selective nanoporous membrane-based wearable organic electrochemical device for noninvasive cortisol sensing. *Sci. Adv.* 4(7):eaar2904
79. Peyser ND, Marcus GM, Beatty AL, Olgin JE, Pletcher MJ. 2022. Digital platforms for clinical trials: the Eureka experience. *Contemp. Clin. Trials* 115:106710
80. Prochaska JO. 2020. Transtheoretical model of behavior change. In *Encyclopedia of Behavioral Medicine*, ed. MD Gellman, pp. 2266–70. Cham, Switz.: Springer Int.
81. Ranjan Y, Rashid Z, Stewart C, Conde P, Begale M, et al. 2019. RADAR-base: open source mobile health platform for collecting, monitoring, and analyzing data using sensors, wearables, and mobile devices. *JMIR mHealth uHealth* 7(8):e11734
82. Resnick PJ, Janney AW, Buis LR, Richardson CR. 2010. Adding an online community to an Internet-mediated walking program. Part 2: strategies for encouraging community participation. *J. Med. Internet Res.* 12(4):e72
83. Richardson CR, Buis LR, Janney AW, Goodrich DE, Sen A, et al. 2010. An online community improves adherence in an internet-mediated walking program. Part 1: results of a randomized controlled trial. *J. Med. Internet Res.* 12(4):e71
84. Rodriguez NM, Arce A, Kawaguchi A, Hua J, Broderick B, et al. 2019. Enhancing safe routes to school programs through community-engaged citizen science: two pilot investigations in lower density areas of Santa Clara County, California, USA. *BMC Public Health* 19(1):256
85. Rowbotham S, McKinnon M, Leach J, Lamberts R, Hawe P. 2019. Does citizen science have the capacity to transform population health science? *Crit. Public Health* 29(1):118–28
86. Sage Bionetworks. 2019. Bridge platform. *Sage Bionetworks*. **https://sagebionetworks.org/tools_resources/bridge-platform/**
87. Sakaniwa R, Noguchi M, Imano H, Shirai K, Tamakoshi A, et al. 2022. Impact of modifiable healthy lifestyle adoption on lifetime gain from middle to older age. *Age Ageing* 51(5):afac080
88. Savikj M, Gabriel BM, Alm PS, Smith J, Caidahl K, et al. 2019. Afternoon exercise is more efficacious than morning exercise at improving blood glucose levels in individuals with type 2 diabetes: a randomised crossover trial. *Diabetologia* 62(2):233–37
89. Schneble CO, Elger BS, Shaw DM. 2020. All our data will be health data one day: the need for universal data protection and comprehensive consent. *J. Med. Internet Res.* 22(5):e16879
90. Schraefel MC, Muresan GC, Hekler E. 2021. Experiment in a box (XB): an interactive technology framework for sustainable health practices. *Front. Comput. Sci.* 3:661890
91. See L, Rasiah RL, Laing R, Thompson SC. 2021. Considerations in planning physical activity for older adults in hot climates: a narrative review. *Int. J. Environ. Res. Public Health* 18(3):1331
92. Shaffer VA, Focella ES, Hathaway A, Scherer LD, Zikmund-Fisher BJ. 2018. On the usefulness of narratives: an interdisciplinary review and theoretical model. *Ann. Behav. Med.* 52(5):429–42
93. Shameli A, Althoff T, Saberi A, Leskovec J. 2017. How gamification affects physical activity: large-scale analysis of walking challenges in a mobile application. *Proc. Int. World Wide Web. Conf.* 2017:455–63
94. Shen F, Sheer VC, Li R. 2015. Impact of narratives on persuasion in health communication: a meta-analysis. *J. Advert.* 44(2):105–13
95. Short CE, James EL, Plotnikoff RC, Girgis A. 2011. Efficacy of tailored-print interventions to promote physical activity: a systematic review of randomised trials. *Int. J. Behav. Nutr. Phys. Act.* 8:113
96. Slade P, Habib A, Hicks JL, Delp SL. 2022. An open-source and wearable system for measuring 3D human motion in real-time. *IEEE Trans. Biomed. Eng.* 69(2):678–88

97. Slater MD, Rouner D. 2002. Entertainment? Education and elaboration likelihood: understanding the processing of narrative persuasion. *Commun. Theory* 12(2):173–91
98. Sousa CV, Fernandez A, Hwang J, Lu AS. 2020. The effect of narrative on physical activity via immersion during active video game play in children: mediation analysis. *J. Med. Internet Res.* 22(3):e17994
99. Spring B, Gotsis M, Paiva A, Spruijit-Metz D. 2013. Healthy apps: mobile devices for continuous monitoring and intervention. *IEEE Pulse* 4(20):34–40
100. Stanford Byers Cent. Biodesign. 2022. CardinalKit. *Stanford Biodesign*. **http://cardinalkit.org**
101. Stanford Byers Cent. Biodesign. 2022. How patients inspire our innovators. *Million+ Patients Helped*. **https://biodesign.stanford.edu/our-impact/million-plus-patients-helped.html**
102. Stephenson A, McDonough SM, Murphy MH, Nugent CD, Mair JL. 2017. Using computer, mobile and wearable technology enhanced interventions to reduce sedentary behaviour: a systematic review and meta-analysis. *Int. J. Behav. Nutr. Phys. Act.* 14(1):105
103. Stockwell S, Schofield P, Fisher A, Firth J, Jackson SE, et al. 2019. Digital behavior change interventions to promote physical activity and/or reduce sedentary behavior in older adults: a systematic review and meta-analysis. *Exp. Gerontol.* 120(March):68–87
104. Stolley MR, Fitzgibbon ML, Schiffer L, Sharp LK, Singh V, et al. 2009. Obesity Reduction Black Intervention Trial (ORBIT): six-month results. *Obesity* 17(1):100–6
105. Taj F, Klein MCA, Van Halteren A. 2019. Digital health behavior change technology: bibliometric and scoping review of two decades of research. *JMIR mHealth uHealth* 7(12):e13311
106. Taylor K, Silver L. 2019. *Smartphone ownership is growing rapidly around the world, but not always equally*. Rep., Pew Res. Cent., Washington, DC. **https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/**
107. Tehrani F, Teymourian H, Wuerstle B, Kavner J, Patel R, et al. 2022. An integrated wearable microneedle array for the continuous monitoring of multiple biomarkers in interstitial fluid. *Nat. Biomed. Eng.* **https://doi.org/10.1038/s41551-022-00887-1**
108. Tomlinson M, Rotheram-Borus MJ, Swartz L, Tsai AC. 2013. Scaling up mHealth: Where is the evidence? *PLOS Med*. 10(2):e1001382
109. Tong HL, Laranjo L. 2018. The use of social features in mobile health interventions to promote physical activity: a systematic review. *npj Digit. Med.* 1:43
110. Tong HL, Quiroz JC, Kocaballi AB, Fat SCM, Dao KP, et al. 2021. Personalized mobile technologies for lifestyle behavior change: a systematic review, meta-analysis, and meta-regression. *Prev. Med.* 148:106532
111. Torous J, Kiang MV, Lorme J, Onnela J-P. 2016. New tools for new research in psychiatry: a scalable and customizable platform to empower data driven smartphone research. *JMIR Ment. Health* 3(2):e16
112. Tovino SA. 2020. Privacy and security issues with mobile health research applications. *J. Law Med. Ethics* 48:154–58
113. Uhlrich SD, Silder A, Beaupre GS, Shull PB, Delp SL. 2018. Subject-specific toe-in or toe-out gait modifications reduce the larger knee adduction moment peak more than a non-personalized approach. *J. Biomech*. 66:103–10
114. van Asbroeck S, Matthys C. 2020. Use of different food image recognition platforms in dietary assessment: comparison study. *JMIR Form. Res.* 4(12):e15602
115. Voorheis P, Zhao A, Kuluski K, Pham Q, Scott T, et al. 2022. Integrating behavioral science and design thinking to develop mobile health interventions: systematic scoping review. *JMIR mHealth uHealth* 10(3):e35799
116. Wall J, Hellman E, Denend L, Rait D, Venook R, et al. 2017. The impact of postgraduate health technology innovation training: outcomes of the Stanford Biodesign Fellowship. *Ann. Biomed. Eng.* 45(5):1163–71
117. Webb TL, Joseph J, Yardley L, Michie S. 2010. Using the Internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. *J. Med. Internet Res.* 12(1):e4
118. Xu L, Shi H, Shen M, Ni Y, Zhang X, et al. 2022. The effects of mHealth-based gamification interventions on participation in physical activity: systematic review. *JMIR mHealth uHealth* 10(2):e27794

119. Yang Q, Van Stee SK. 2019. The comparative effectiveness of mobile phone interventions in improving health outcomes: meta-analytic review. *JMIR mHealth uHealth* 7(4):e11244
120. Zahrt OH, Crum AJ. 2017. Perceived physical activity and mortality: evidence from three nationally representative U.S. samples. *Health Psychol*. 36(11):1017–25
121. Zahrt OH, Crum AJ. 2020. Effects of physical activity recommendations on mindset, behavior and perceived health. *Prev. Med. Rep.* 17:101027
122. Zhang T, Dong H. 2009. *Human-centered design: an emergent conceptual model*. Presented at Include2019 Royal College of Art, London, April 8–10
123. Zhou C, Occa A, Kim S, Morgan S. 2020. A meta-analysis of narrative game-based interventions for promoting healthy behaviors. *J. Health Commun.* 25(1):54–65
124. Zion SR, Louis K, Horii R, Leibowitz K, Heathcote LC, Crum AJ. 2022. Making sense of a pandemic: Mindsets influence emotions, behaviors, health, and wellbeing during the COVID-19 pandemic. *Soc. Sci. Med.* 301:114889