

mHealth's Revolution: Balancing Help and Harm

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Recent advances in mobile technology have opened up enormous opportunities to improve patients' health and well-being. In this paper mobile technology is defined as wireless devices and sensors (including mobile phones) that are intended to be worn, carried, or accessed with the person during normal daily activities. mHealth is the application of these technologies either by consumers or providers, for monitoring health status or improving health outcomes, including wireless diagnostic and clinical decision support. mHealth technologies offer real-time monitoring and detection of changes in health status, support the adoption and maintenance of a healthy lifestyle, provide rapid diagnosis of health conditions, and facilitate the implementation of interventions ranging from promoting patient self-care to providing remote healthcare services.

Although mHealth is a new area of scientific development, the transition to remote healthcare and support for prevention has been developing for decades. Medical practice and healthcare originated as a system to treat infectious diseases (such as smallpox) and traumatic injuries. As life expectancy increased, by the mid-1900s, attention had shifted to managing chronic illnesses such as diabetes and heart disease. By definition, chronic illnesses are not expected to be resolved through treatment. This transition from acute to chronic treatment, paired with an extended lifespan, resulted in a healthcare system that is growing with unsustainable levels of cost. While this problem is evident in the US, it is also an issue in developing countries.¹

In tandem with these changes, high-quality, user-friendly wireless consumer devices, such as mobile phones, have become ubiquitous around the world. These devices provide not only mobile communication, but also sensing, analytic, and visual capabilities, as well as access to the cloud. Sensors embedded in a mobile phone, complemented by sensors on and in a body, can provide an unprecedented view of the person's health status and behavior patterns.

mHealth builds upon earlier work in telehealth, mobile computing, and persuasive technology in healthcare settings.² It has the potential to turn mobile devices into personal labs that continuously assess a person's physiology, behavior, social context, and environmental exposure. For example, a personal therapist application on a mobile device could mine the Internet for information about the latest health research and apply it while continuously collecting personal health data to make inferences about the user's health, and then share these results with caregivers so they can provide appropriate treatments. Persuasive user interfaces on the mobile device could facilitate compliance with the prescribed treatment protocol by applying just-in-time intervention. In addition to directly improving healthcare, mHealth could also accelerate health research and the formulation of public health policies.

MOBILE HEALTH SYSTEMS RESEARCH

Mobile technology can simultaneously acquire information, process the data, make inferences, mediate a range of interventions, and provide communications with other devices and systems. At the lowest layer, sensors collect raw data that is processed to make inferences on individuals. These inferences can then be used to inform the design or delivery of interventions and to make health inferences at the population level to inform health research, practice, delivery, and policy formulation.

Sensing in mHealth

To reach its potential, mHealth technology must be able to capture diverse personal and environmental signals relevant to the health of both individuals and communities. Researchers are repurposing a variety of sensors already included in mobile phones, such as accelerometers and GPS, via sophisticated algorithms for use in mHealth applications, resulting in many innovative health-, wellness-, and fitness-related applications. However, the measured signals from these sensors often lack clinical relevance and fall short of the specificity needed to allow definitive diagnosis and treatment of complex health conditions.

As interest in mHealth grows, we anticipate the increasing availability of sensors that are specifically

targeted at and optimized for mHealth. In the short term, factors such as cost, market size, mass, volume, and placement constraints might necessitate using external sensors that are wirelessly connected to a smartphone. Over the long term, however, the need for a better user experience is likely to require integrating such sensing into smartphones or other emergent cellular-connected wearable devices such as smart watches or eyeglasses.

The core challenge lies in developing new sensors that are compatible with a smartphone from a cost and size perspective, can be used for continuous real-time sensing without much burden on the user, and enable various tests that can only be done in a clinical setting. Biomolecular sensing, imaging, and bioelectric sensing are particularly important.

Biomolecular sensing. With their high selectivity, ultra sensitivity, and energy efficiency, solid-state sensors can turn a common smartphone into a powerful and easy-to-use diagnostic tool.

Assessing biomarkers and pathogens in body fluids and human breath to detect diseases, their progression, and therapy effectiveness is essential in healthcare. Such sensing, however, typically relies on sample preparation and laboratory analysis, which are not usually available in a mobile setting. Advancements in nanotechnology, microfluidics, and solid-state sensors, however, offer the promise of miniature low-cost chip-sized sensors that can provide “lab-on-chip” capabilities.

Examples include

- Nanowire sensors, which are fabricated at low cost in high-yield semiconductor foundries and packaged into disposable electronic strips.³ These embedded sensors can detect the presence of specific molecules such as cardiac troponins in a mobile setting to facilitate the diagnosis, monitoring, and risk stratification of suspected acute myocardial infarction in cardiovascular patients.
- All-electronic digital microfluidic devices operated by electrowetting-on-dielectric actuators, which can stimulate highly precise programmable microreactions to allow performing a wide range of assays in a mobile setting.
- DNA microarrays, which can capture the epigenetic information necessary to understand the protein-DNA interactions that underlie many biological processes and disease states.
- Low-power solid-state chemical sensors, which use inorganic materials for potentiometric and resistive sensing of trace gases in human breath in real-time and at low parts per billion (ppb) concentrations. Research has associated the presence of trace gases with various diseases, such as nitric oxide for asthma, acetone for diabetes, and hydrogen for gastroenteric ailments.

Imaging. Passive and active imaging methods such as ultrasound, x-rays, MRI, and CT scans are mainstays of modern healthcare. However, factors such as optical pathway impose size constraints and the need to generate powerful or even dangerous signals (e.g., x-ray) or fields (e.g., MRI), make it impossible to embed them in a smartphone. Indeed, cameras are the only imaging devices widely available in a mobile environment. Using computer vision methods, researchers have incorporated smartphone cameras in mHealth applications to perform tasks such as detecting the heart rate from microblushes and estimating refractive errors in the eye. For imaging to scale in mHealth, it must move beyond the current human-in-the-loop approach for interpreting images to perform computational triage. Two solutions are emerging that provide complementary capabilities.

The first one is lens-free computational microscopy and tomography⁴ running on a smartphone that can algorithmically overcome optical constraints to provide high-resolution 3D imaging of biological samples with a wide field of view and a large depth of field. These methods have been shown to assay blood samples for malaria.

The second solution is Radio Frequency (RF) imaging, which is an attractive option for smartphones as they already have several built-in radio transmitters and receivers—for example, cellular, Wi-Fi, and Bluetooth—that researchers can potentially repurpose. Wideband signals from an RF transmitter can penetrate and illuminate the interior of the human body, and the mobile device can analyze the interferogram image resulting from the reflected signal waveforms to infer a variety of internal variables, such as heart motion, blood flow, respiration, and fluid accumulation. Because RF imaging is inherently contactless—that is, it does not require coupling transducers to the body via gels or fixed electrodes—it allows unobtrusive real-time physiological sensing.

Bioelectric sensing. The measurement and analysis of surface biopotentials is a powerful, and often the only, sensing modality for diagnosing and monitoring many disorders. Examples include electrocardiography (ECG) for the heart, electroencephalography (EEG) for the brain, and electromyography (EMG) for muscles.

Although devices for measuring surface bioelectric signals in mobile environments have been available for many years (Holter monitors, for example), they are too cumbersome for long-term monitoring, which requires affixing multiple electrodes to the body. With ongoing developments in low-power electronics, smarter and compressive sampling, and energy harvesting, battery-less wireless patches could offer a less obtrusive bioelectric sensing approach that eliminates the tangle of wires and electrodes.⁵ For sporadic monitoring, emerging contactless bioelectric sensors that use through-the-clothing capacitive coupling could allow building the entire sensor into a smartphone.

mHealth Hype or Hope

An effective mHealth computing platform must be able to efficiently make semantically rich and medically trusted inferences about physical, physiological, psychological, cognitive, and behavioral states from sensor information, and correlate these inferences with environmental, social, and other factors. Unfortunately, research to date has not supported the vast hype associated with mHealth. Multiple reviews have suggested that the most of the work done in mHealth apps does not meet best practice standards (Pagota et al., 2014, Abrams et al., 2011). Other research has suggested that some mHealth tools may mislead consumers, such a recent exploration of four dermatology apps that missed 30% of skin cancer cases (Ferris et al., 2013) or a recent review that found a majority of insulin dose calculator apps provided no protection against or may actively contribute to incorrect or inappropriate dose recommendations (Huckvale et al 2015). Finally, reviews of the clinical trials in mHealth have shown some success, although the studies that show significant positive effects for mHealth are still not in the majority (Free et al., 2013; Kaplan and Stone, 2013). Thus, the flood of mHealth tools may not be actually improving people's health and some may actually be harming it. One exception to these trends, is the fact the number of clinical trials registered in Clinicaltrials.gov has been increasing, suggesting that science in this burgeoning area is growing.

The reasons for the potential challenges to mHealth are numerous. Some of the issues are in the quality of the data, the quality of the inferences derived the data, the inherent variability of people in their natural habitat, poor design of mHealth tools or, as noted earlier, a failure to integrate science and best practice into mHealth development.

Data collection in mHealth sensing introduces various data quality challenges. Sensors such as ECG electrodes might be placed incorrectly on the body, or, even if initially placed at the correct location, could subsequently slip or become detached. Sensor measurements might be noisy not only because of placement and attachment errors, but also because of the variability inherent in a patient's daily activities and the mobile environment. Wearable wireless communication devices are convenient, but can be another source of signal distortion. Finally, device might intentionally degrade data quality to conserve battery life. Thus, we need metrics to characterize the distortions and uncertainties associated with collecting the data and the resulting inaccuracy because decisions are based on that data. The decisions will only be as good as the data collected. Poor data quality can result in suboptimal outcomes, including missed opportunities for effective intervention or even wrong information to guide health decisions.

Additionally, for mHealth data to be usable in making health-related decisions, mHealth tools will need accurate inferences regarding health status, behavior, and context. For example, to best help people manage their diet in diabetes, we should know current glucose, activity level and food intake and timing. Researchers are currently, making progress in inferring physical state (such as posture and activity using accelerometers⁷), psychological state (such as stress using sensory measurements⁸), social context (such as conversation based on respiratory patterns⁹), and environment (such as place and commuting status using GPS). Significant work, however, is required to make these models and inferences reliable enough to use in the real world with a diverse sample of participants, so they can provide the basis for real-time inferences, decisions, and actions. A key concern is the potential for high false alarms rates that can render the entire system annoying, ineffective and even potentially harmful.

Although data collected in the lab may have valid labels, it may not represent the natural environment in which mHealth systems ultimately need to work.¹¹ Labels collected in a mobile environment represent the natural environment, but they can be noisy, uncertain, biased, missing, or spurious. For example,

researchers could use self-reported times of smoking to develop a model for automated detection of smoking, but these labels may not accurately represent the actual start and end times of the smoking episodes. Subjects might forget to report an episode or might even falsely report it to earn compensation. Without knowing if the labels are valid, inferences again may be inaccurate, poorly timed or even completely incorrect resulting in providers or consumers having timely, needed information.

Design of mHealth tools may also contribute to their effectiveness and potential for help or harm. Recently, multiple articles have appeared in the popular press noting that mHealth fails those who most need it; that is, mHealth has to move away from being just exciting technology for a select group of tech savvy individuals. Instead, it must become a product that understands the needs of the population and merges an understanding of science and consumer behavior to create tools that are useful. The usefulness component is key, because those who are most in need are not going to tolerate buggy technology. People who most need mHealth are those who are trying to maximize their health as one of many competing demands. For example, a pulse oximeter that repeatedly unsyncs from a phone, or an app that becomes buggy with each operating system update will only discourage people from using mHealth interventions. For many potential users, especially, the underserved, stigmatized, and those with limited health literacy, a device that assumes you have nothing more to do than think about your mHealth technology may have little or no chance. As Patel, Ash and Volpp (2015) noted in a recent article in JAMA, mHealth is no more than a tool. Incorrectly developed tools will yield little benefit and may even cause harm to those with less health literacy or resources. The technology itself is not magic, and for it to be successful, we will need our best science so that these tools provide useful information in a way that will fit into people's lives.

mHEALTH Help or Harm

Unlike other human-cyber-physical systems, where the human is just an operator, a sensor, or an actuator (as in other areas of technology, such as aviation or cars), in mHealth systems, humans are the center of the system and whose health and well-being is to be affected and controlled. The life-and-death implications and the associated economic and legal burdens place a high degree of responsibility on mHealth system designers. Moreover, the human body is complex, highly variable, and not well understood. Without evaluation, people may receive mHealth devices that are ineffective or harmful. Additionally, those that are ineffective may also have an adverse effect if they delay appropriate treatment seeking. Conversely, those that are effective will not receive the dissemination that should. Thus, the issues around verification, evaluation and safety are considerable.

When assessing health products, the first question evaluators ask is whether the device, medication, or treatment is safe. Likewise, researchers must ask whether an overall mHealth system is safe from both a health and an engineering perspective. From a health perspective, safety means the mHealth system produces information that is valid and of adequate quality for critical decision making. For example, given the rapid onset of a heart failure event and the potentially catastrophic impact of a missed detection, an mHealth system that predicts heart failure in patients with congestive heart disease must maintain high-quality information continuously over an extended time period. For more advanced mHealth systems that might also trigger autonomous physiological and behavioral interventions, safety from a health perspective means that the interventions are medically safe and appropriate.

From an engineering perspective, safety means that devices, such as sensors, used in mHealth systems will not cause their users unanticipated harm or discomfort because of design or manufacturing errors. For example, a wearable sensor with poor circuit and thermal design could lead to excessive heating or a battery fire. Engineering safety is not just a hardware matter—errors in the embedded software are also a source of concern about safety. For example, faulty firmware in a defibrillator can cause unintended shocking, and an ill-designed user interface might confuse the user and elicit incorrect responses. Even when a device is functioning as engineered, the human body's variability combined with ambient conditions can result in safety issues in unexpected contexts, such as in extreme environmental conditions. For a device to be safe, designers must address all of these factors.

Efficacy—the evaluation of whether the device does what it claims, as well as for whom and in what context—is crucial for devices used in health applications. Health researchers ask whether the device is valid, i.e. it measures what it claims, and reliable, i.e. it generates reproducible measurements. Although these are common healthcare issues, defining and assessing such metrics is difficult in a mobile environment. For example, what's the best way to test the reliability of a device that is designed to assess temporal variability or address a concept's validity for which there is no ground truth (stress, for example)?

These issues call for new research and specific metrics.

The evaluation of health interventions usually occurs in multiple phases. Early in development, carefully designed studies with individual patients or small groups are useful. Researchers can use these studies to assess safety, feasibility, and usability and determine the interventions' potential effect. Later in development, when an intervention is mature, the use of randomized clinical trials (RCTs) is common. To minimize biases, RCTs involve randomly assigning a large number (perhaps thousands) of potential participants to a treatment group and a control group, in which some participants receive a placebo. The RCT lets researchers estimate the treatment effects' statistical significance and size. Although statistically sound, RCTs are generally expensive, inefficient, and lengthy. They also are a challenge in ever-changing technology development.

These designs are well-known in the research world, but are not common in the mobile health app world. Evaluation is often based on downloads and ratings, rather than efficacy or effectiveness. To address the issues highlighted here, a new world of development and evaluation will need to be developed that allows app developers and industry leaders to evaluate aspects of their products quickly and efficiently. New methods of rapid evaluation would allow novel models and concepts to enter the mHealth world in a way that will be safe and not stifle creativity. Examples of some of the new systems being developed to address these issues includes Apple's ResearchKit and NIH's Mobilizing Research. Both systems are being developed to rapidly evaluate mobile tools to increase efficacy and ultimately safety. Additionally, systems like Open mHealth are useful to propagating efficacious mHealth tools and sharing of components. These and other developing systems will allow researchers and developers to work cooperatively to optimize mHealth tools.

Conclusion

In conclusion, mHealth heralds an exciting new era in health with a shifting focus of healthcare to wellness and prevention. These devices also portend a transformed health research environment, where most data are collected remotely and entire clinical trials may be run without the researcher and the participant ever meeting face to face. The data following from these systems, in combination with the multiple fixed sensors in the community, will also create a rich database for exploration into new ways of understanding health. Thus, as mHealth systems become more prevalent and versatile, their use will not only enable myriad disruptive transformations in healthcare delivery and medical research, but will also present many scientific, liability, and regulatory challenges. mHealth's success will therefore depend on successful transdisciplinary research collaborations and partnerships between science and industry.

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