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Invited Commentary

First Steps Into the Brave New Transdiscipline of Mobile Health

Bonnie Spring, PhD; Angela Pfammatter, PhD; Nabil Alshurafa, PhD

Given substantial evidence that healthy lifestyle behaviors lessen the odds of cardiovascular disease, a guideline from the American Heart Association and American College of Cardiology[1] advises physicians to foster patients' physical activity. But how is the clinician to evaluate a patient's healthy lifestyle behaviors, let alone enhance them? Traditionally, patient self-reports supplied almost all behavioral data available to health professionals. However, whether given by free recall, structured questionnaire, or written logs, post hoc surveys inherently manifest forms of error well known to behavioral scientists. People forget. Many have no idea what moderate to vigorous activity feels like. Individuals also experience demands and motivations that distort what they report.

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For a long while, not much could be done to increase confidence in the validity of behavioral assessments. Although one could observe peoples' behavior objectively in controlled laboratory conditions or experimental tasks, legitimate questions arose about whether individuals would behave the same way in real life as they had in the laboratory. This state of affairs began to change in the 1980s, when acceleration signals from a worn sensor were first used to measure physical activity.[2]

Fast forward to the present, and sensors are everywhere, including the tiny accelerometer, gyroscope, ambient light detector, compass, and barometer inside smartphones. In this issue of *JAMA Cardiology*, McConnell and colleagues[3] are to be congratulated for pioneering efforts to examine the physical activity, sleep, and fitness data from MyHeart Counts, a launch smartphone app developed by Apple Inc's ResearchKit. The team's first aim was to evaluate the feasibility of using a smartphone to consent a large representative sample of ambulatory adults and to gather real-time sensor and survey data from them. Their second aim was to analyze those data to gain insights about associations among physical activity, well-being, and physical health.

MyHeart Counts succeeded as a proof of concept, demonstrating the potential for personally owned mobile devices to accomplish real-world ambulatory assessment. McConnell and colleagues[3] were effective at using the smartphone to implement an informed consent process, resulting in the enrollment of 48 968 study participants. As they note, the recruited sample (although large) could have been more diverse: most (82.2%) were male, young (median age, 36 years), healthy, and disproportionately from California. Serious retention difficulties arose. Although the observation period was brief, 90.7% of enrollees did not complete all 7 days. Less than 50% completed the 2 consecutive weekday and 2 consecutive weekend days that were analyzed to examine physical activity. Hence, the study did not establish the feasibility of obtaining comprehensive data from the high proportion of enrollees that would be wanted in a clinical trial. On the other hand, MyHeart Counts conveys clear object lessons for investigators aiming to learn the recruitment, retention, adherence, and engagement challenges they need to overcome in mobile health studies, particularly to maintain long-term healthy lifestyle behaviors. Surprisingly, MyHeart Counts did not use the simplest effective strategy to motivate continued engagement, namely, giving participants feedback about their behavior. Fostering engagement is about delivering value to participants by heightening the personal benefit they derive, which justifies their investment in the burden of wearing sensors and completing surveys. Learning how to optimize digital engagement is a cutting-edge scientific challenge that will become more salient as we try to place more lifestyle interventions on intelligent, technology-mediated autopilot.

Despite their intuitive appeal, caution is warranted in interpreting the findings of MyHeart Counts about physical activity and health outcomes. McConnell and colleagues[3] applied unsupervised machine-learning techniques (*K*-means and hierarchical clustering) to 10 features (eg, stationary time, walking, and driving) collected from embedded smartphone sensors. First 10 and subsequently 4 feature clusters were derived and interpreted to represent behavioral phenotypes. The types are appealing. For example, a "weekend warrior" cluster was described as those who spent approximately 25% more time in sensor-defined active than stationary states on the weekend than during the week. Being categorized as a weekend warrior was associated with not having adverse health conditions (chest pain, diabetes, heart disease, and joint pain). Hence, one might consider advising patients to accumulate more of their 150 minutes of moderate to vigorous physical activity on weekends than weekdays. However, it is unknown how the selected features relate to actual moderate to vigorous physical activity or sedentary behavior. The inference that a lack of detectable smartphone motion indexes physical inactivity rests on the assumption that people carry their devices most of the time, a presumption that is untrue for many. No less plausible than the interpretation offered is the alternative that warriors are more active on weekdays but less likely to carry their smartphone during weekday activity. It is hard to envision how clinicians could confidently apply these activity measures until they are validated against legacy measures from a worn accelerometer. Fortunately, sole reliance on the smartphone to measure physical activity is increasingly unnecessary as genuinely worn accelerometers become ubiquitous in wristbands and smartwatches.

Perhaps the greatest contribution of the study by McConnell and colleagues[3] lies in highlighting the type of dialogue across disciplines that is needed to press forward the mobile health frontier. Conducting the study required engineers to develop sensors, design specialists to create an appealing form factor, computer scientists to apply machine learning, and behavioral scientists to speculate about how the novel clusters that emerged might represent people with habitually different physical activity patterns. Beneath this apparently smooth surface of collaboration, a great diversity of disciplinary assumptions, mental models, methods, and analytics is at play. One point of divergence comes in the computer scientist's comfort with research that generates novel hypotheses, relative to the biomedical scientist's stronger preference for science that tests prespecified predictions. Another lies in the different cultural traditions of data modeling applied in medical statistics vs computer science.[4] A common assumption in statistics is that nature can be reasonably characterized by a finite set of data models. These models have spawned a set of familiar analytic techniques (eg, regression and discriminant function) based on distributional assumptions that fit data imperfectly but have the advantage of yielding simple, comprehensible results. A legitimate alternative viewpoint is that accuracy trumps simplicity when modeling a complex natural world whose data mechanisms are unknown or unknowable. In modeling complex data that could not be fit by conventional statistics, engineers, physicists, and computer scientists developed new algorithmic models that treat the data mechanism as unknown. These developments can provide more accurate, data-driven models of behavior than statistical models but at the expense of simple interpretability. And therein lies the MyHeart Counts dilemma. Novel individual differences in smartphone use patterns emerged but will be difficult for health professionals to comprehend, trust, or act on in the absence of legacy measures or familiar data models. Frank acknowledgment of such gaps in comprehension across mobile health's component disciplines is what ultimately will push mobile health forward, opening the health sciences to innovative, actionable insights from computer science.

When accessed comprehensively, the dense continuous data transmitted by smartphones and wearable sensors create capabilities for health promotion intervention that have never previously existed.[5] Sensor data can be analyzed in real time to reveal fluctuations in a person's internal state (eg, stress), environmental context (eg, location and light), and intervention receptivity (eg, not asleep, in class, or driving).[6] For the first time, intervention can be adapted to offer help just in time when it is needed and when timing is optimal for the person to process treatment most effectively.[7] In the brave new transdiscipline of mobile health, the future is now.

ARTICLE INFORMATION

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Editor's Note

Making Every Mobile Heart Count!

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In this issue of *JAMA Cardiology*, McConnell et al[1] present the initial results from MyHeart Counts, a new model for participant engagement and clinical research using mobile health technology. During the past 2 decades, the world has continued to accelerate from an infrastructure of brick-and-mortar buildings to conduct everyday business and social activities to one that is full of virtual buildings, homes, and social networks. However, the last frontier in this digital transformation appears to be health care and clinical research. There are many theoretical possibilities on how "e-anything" may bring research closer to home that is more convenient, participant-centered, and integrated to daily lives, as MyHeart Counts shows. But there is much work to be done to realize those dreams.

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Also in this issue, the Invited Commentary by Spring et al[2] highlights the promise of this brave new transdisciplinary approach of research joining the digital revolution but also notes that simply signing up for a mobile health application is not enough. For research to matter and have an effect, we will need to quickly learn how to keep participants fully engaged to obtain complete data and how to provide value back to participants for donating their data in a seamless manner. Also notable is the need to ensure that the digital divide, as seen in health care, improves as it becomes more integrated in clinical research.

Moving forward, we should share our experiences, the methodological challenges, and new opportunities to do research differently but with quality and convenience as an open, trustworthy, learning model. In this vein, the editors of *JAMA Cardiology* encourage the community to share their research leveraging mobile health technologies so that clinical research can catch up and join the digital world.

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