Published in final edited form as:

JAMA Cardiol. 2017 January 01; 2(1): 76–78. doi:10.1001/jamacardio.2016.4440.

First Steps into the Brave New Transdiscipline of Mobile Health

Bonnie Spring, PhD*, Angela Pfammatter, PhD*, and Nabil Alshurafa, PhD*

* Behavioral Medicine Division, Department of Preventive Medicine, Northwestern University, Feinberg School of Medicine

Given substantial evidence that healthy lifestyle behaviors lessen the odds of cardiovascular disease, the AHA/ACC¹ Guidelines advise physicians to foster patients' physical activity. But how is the clinician to evaluate the patient's healthy lifestyle behaviors, let alone enhance them? Traditionally, patient self-reports supplied nearly all behavioral data available to health professionals. Whether given by free recall, structured questionnaire, or written logs, however, *post hoc* surveys suffer from 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.

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 people 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 first were 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. Dr. McConnell and colleagues are to be congratulated for pioneering efforts to examine the physical activity, sleep, and fitness data from MyHeart Counts, a launch Apple Research Kit application. 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 relationships among physical activity, wellbeing, and physical health.³

MyHeart Counts succeeded as a proof of concept demonstrating the potential for personally owned mobile devices to accomplish real world ambulatory assessment. The investigators were effective at using the phone 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 were male (82%), young (median age 36 years), healthy, and disproportionately from California. Serious retention difficulties arose: although the observation period was quite brief, 90% of enrollees did not complete all 7 days. Fewer than 50% completed the two consecutive weekday and two consecutive weekend days that

Financial Disclosure: Dr. Spring serves on the Scientific Advisory Board for Actigraph. Drs. Pfammatter and Alshurafa have nothing to disclose.

Author Manuscript

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 wishing to learn the recruitment, retention, adherence, and engagement challenges they need to overcome in mobile health studies, particularly to maintain healthy lifestyle behaviors long-term. Surprisingly, MyHeart Counts did not use the simplest, effective strategy to motivate continued engagement – giving participants feedback about their behavior. Fostering engagement is about delivering value to participants: heightening the personal benefit they derive that 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.

Author Manuscript

Despite their intuitive appeal, caution is warranted in interpreting MyHeart Counts' findings about physical activity and health outcomes. The researchers applied unsupervised machine learning techniques (k-means and hierarchical clustering) to 10 features (e.g., driving, walking, stationary time) 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 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, joint pain, heart condition). Hence, one might consider advising patients to accumulate more of their 150 minutes of moderate-vigorous physical activity (MVPA) on weekends than weekdays. Note, though, that it is unknown how the selected features relate to actual MVPA or sedentary behavior. The inference that lack of detectable phone motion indexes physical inactivity rests on the assumption that people carry their phones 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 the phone 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 phone to measure physical activity is increasingly unnecessary as genuinely worn accelerometers become ubiquitous in wristbands and smartwatches.

Author Manuscript

Perhaps the study's greatest contribution 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 pre-specified predictions. Another lies in the different cultural traditions of data modeling applied in medical statistics versus 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 (e.g., regression, 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 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 phone use patterns emerged, but will be difficult for health professionals to comprehend, trust, or act upon in the absence of legacy measures or familiar data models. Frank acknowledgement of such gaps in comprehension across mHealth's component disciplines is what ultimately will push mHealth 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 creates 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 (e.g., stress), environmental context (e.g., location, light), and intervention receptivity (e.g., not asleep, in class, 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.

Acknowledgments

Funding Source: Supported in part by NIH grants R01DK108678, DK097364, U54EB020404, NSF grant 1545751, and American Heart Association Strategically Focused Prevention Research Network Project 14SFRN20740001 to Dr. Spring

References

1. Eckel RH, Jakicic JM, Ard JD, et al. 2013 AHA/ACC Guideline on Lifestyle Management to Reduce Cardiovascular Risk: A Report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines. *J Am Coll Cardiol*. 2014;63(25_PA):. doi:10.1016/j.jacc.2013.11.003.
2. Troiano RP, McClain JJ, Brychta RJ, Chen KY Evolution of accelerometer methods for physical activity research. *J Sports Med*. 2014 7; 48(13): 1019–1023.
3. McConnell MV, Schcherbina A, Pavlovic A, Homburger JR, Goldfeder RL et al. MyHeart Counts: A cardiovascular mobile health study. 2016, *JAMA Cardiology*.
4. Breiman L Statistical modeling: The two cultures. *Statistical Science*. 2001, Vol. 16, No. 3, 199–231
5. Spring B, Gotsis M, Paiva A, Donna Spruijt-Metz D Healthy Apps: Technology Enabled Continuous Observation. *IEEE Pulse*. 2013, 9(November/December), 34–40. PMID: [PubMed: 24233190]
6. Kumar S, Abowd G, Abraham WT, al' Absi M, Beck JG, Chau DHP, Condie T, Ganesan D, Ertin E, Estrin D, Lam C, Marlin B, Marsh C, Murphy S, Patrick K, Rehg J, Nahum-Shani I, Sharmin M, Shetty V, Sim I, Spring B, Srivastava M, Wetter D Center of Excellence for Mobile Sensor Data-to-Knowledge (MD2K) *Journal of the American Medical Internet Association*. 2015, 22(6), 1137–1142

7. Nahum-Shani I, Smith SN, Spring B, Collins LM, Witkiewitz K, Tewari A, Murphy SA. (in press) Just-in-Time Adaptive Interventions (JITAIs): Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine*, 2017