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ESSAY/OPINION PIECE

How behavioral science can advance digital health

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ABSTRACT

The field of behavioral science has produced myriad data on health behavior change strategies and leveraged such data into effective human-delivered interventions to improve health. Unfortunately, the impact of traditional health behavior change interventions has been heavily constrained by patient and provider burden, limited ability to measure and intervene upon behavior in real time, variable adherence, low rates of implementation, and poor third-party coverage. Digital health technologies, including mobile phones, sensors, and online social networks, by being available in real time, are being explored as tools to increase our understanding of health behavior and to enhance the impact of behavioral interventions. The recent explosion of industry attention to the development of novel health technologies is exciting but has far outpaced research. This Special Section of Translational Behavioral Medicine, *Smartphones, Sensors, and Social Networks: A New Age of Health Behavior Change* features a collection of studies that leverage health technologies to measure, change, and/or understand health behavior. We propose five key areas in which behavioral science can improve the impact of digital health technologies on public health. First, research is needed to identify which health technologies actually impact behavior and health outcomes. Second, we need to understand how online social networks can be leveraged to impact health behavior on a large scale. Third, a team science approach is needed in the developmental process of health technologies. Fourth, behavioral scientists should identify how a balance can be struck between the fast pace of innovation and the much slower pace of research. Fifth, behavioral scientists have an integral role in informing the development of health technologies and facilitating the movement of health technologies into the healthcare system.

KEYWORDS

Digital health, mHealth, Social networks

Implications

Policy: The only opportunity for digital health innovations to affect health policy is via rigorous efficacy research.

Research: Behavioral scientists are needed to facilitate the translation of digital health innovations from commercial enterprise to research to practice.

Practice: Practitioners need guidance as to which digital health innovations are appropriate and effective for their patients.

The efficacy of traditional health behavior change interventions has long been constrained by expense, patient burden, and variable adherence. Current models of health care which limit our access to patients to face-to-face visits reduce our ability to gain an accurate understanding of the antecedents and consequences of behavior and to intervene in moments when patients most need help. Digital health technologies, including mobile phones, sensors, and online social networks, by being available in real time, are being explored as ways to enhance our ability to understand health behavior and intervene upon it more effectively.

mHealth, a segment of the digital health market that leverages mobile technologies to solve health problems, has reached its tipping point. A rapidly growing body of evidence demonstrates the efficacy of mHealth approaches across a wide range of conditions, populations, and settings. mHealth has also attracted a explosion of industry attention. An extremely diverse group of companies are capitalizing on the mHealth market, which is projected to reach over $23 billion in revenues by 2018 [1]. Sensing technologies are also being rapidly developed to gather behavioral, physiological, and contextual data that can then be used to predict behavior and/or deliver "just-in-time" interventions to improve health. Online social networks which allow individuals to interact and communicate online thereby eliminating geographical, physical, and logistical barriers are now being used for health surveillance, dissemination of information and innovations, and health behavior intervention. The potential of all of these technologies to impact health behavior change has yet to be fully realized. The purpose of this Special Issue is to collate research on the development of digital health technologies, utilization of health technology to study behavior and/or attitudes, and/or efficacy testing of technology-delivered health promotion interventions. While this early collection of research studies is exciting, digital health research is in its infancy. Many questions remain unaddressed and the proliferation of commercial technologies continues to outpace research. We propose five key questions that are integral to maximizing the impact of technology-based innovations on public health.

DO mHealth APPS WORK?

In his 2012 keynote at the mHealth Summit–a gathering of industry, academic, and nonprofit mHealth stakeholders–NIH director Francis Collins praised mHealth innovations, but argued that the field desperately needs well-designed clinical trials to establish its evidence base [2]. Take mHealth weight loss apps as an example. Tens of millions of Americans have turned to the nearly 1,000 commercial mHealth apps to help them lose weight. The top five free weight loss/fitness apps (i.e., My Fitness Pal, Map My Run, Nike+, Runkeeper, Lose It) each have over 10 million users. In terms of dissemination and reach, these mobile apps have outstanding potential, far more than traditional behavioral weight loss interventions. However, none of these apps have been evaluated in a well-designed clinical trial. This is a major scientific limitation and will impede the integration of apps into clinical care–thereby reducing their clinical and public health impact.

Research is not only lacking on clinical outcomes, but also on whether apps actually increase adherence to the behaviors they target. For example, studies are mixed as to whether dietary tracking apps outperform traditional tracking strategies (i.e., paper and pencil) on measures of adherence and weight loss [3, 4]. Another disconnect with the evidence base is that the behavioral strategies employed in apps have not been established as effective standalone interventions in their traditional forms. As an example, dietary tracking is a strong predictor of weight loss in randomized trials, but it has never been tested as a sole intervention strategy for weight loss. Effective weight loss interventions involve a package of behavioral and cognitive strategies designed to improve lifestyle behaviors and clinical outcomes. The efficacy of commercial apps might be limited given the narrow range of features they typically include [5]. In this special issue, we feature two systematic reviews–one for mobile apps that target obesity prevention and treatment in children and another targeting diabetes management. Both show that the use of evidence-based behavioral strategies in apps is very low relative to the strategies typically employed in traditionally delivered interventions. Schoffman and colleagues found that 61 % of mobile apps targeting childhood obesity did not include any evidence-based behavioral strategies [6]. Breland and colleagues found that 14 % of diabetes mobile apps did not include any evidence-based behavioral strategies and 33 % included only one of six possible strategies [7]. The lack of evidence is especially concerning because public opinion is beginning to coalesce in support of these apps. In a recent Consumer Reports' 2012 survey of dieting plans, MyFitnessPal received one of the highest ratings and earned higher satisfaction scores than Weight Watchers, a commercial program shown to be effective [8].

Rigorous evaluation of mHealth apps is essential not only to estimate the magnitude of their outcomes, but also to ensure that they do no harm. For example, we have strong evidence that traditional in-person weight loss interventions are not only efficacious, but do not appear to produce adverse psychosocial outcomes. Whether the same is true for mobile weight loss apps is unknown. By their very nature, mobile apps are designed to be used in a self-paced fashion. Unlike traditional interventions, which exert some control over the participant's exposure to intervention content (i.e., dose), mHealth interventions impose fewer constraints. Traditional interventions help patients navigate challenges and failures, mobile apps do not. A critical question is whether mobile weight loss app use produces deleterious impact on psychosocial functioning (e.g., mood, eating pathology).

HOW CAN ONLINE SOCIAL NETWORKS BE LEVERAGED TO POSITIVELY IMPACT HEALTH BEHAVIOR CHANGE?

Obesity [9] and tobacco [10] use have been shown to be "socially contagious," such that we are more likely to have these issues if our friends and spouses do. Social support can have a powerful impact on both unhealthy and healthy behaviors [11]. The information technology revolution of the past two decades has changed the way we interact which presents increasing opportunities and means to exchange social support. The 2012 Pew Internet Survey found that people are increasingly seeking to connect with others about health [12]. They found that 34 % of internet users have read about another's health experience on the internet and 25 % of internet users with a chronic health condition have sought out others with that condition. As these numbers rise, research is needed to explore how online social networks can best be leveraged to improve health.

Online social networks can be used to understand and promote health behavior as well as disseminate health innovations. In the current issue, Black and colleagues study how peers influence one another on online social networks in terms of their perceptions of norms about sexual behavior [13]. Other studies have shown that users of online social networks report utilizing the networks as a source of information and emotional support regarding a behavior change [14]. Online social networks have also been used to inexpensively connect participants with one another and online engagement has been shown to be associated with better outcomes in health behavior interventions. For example, Facebook has been utilized to successfully deliver weight loss intervention content [15] and in this

Special Issue, Turner-McGrievy and colleagues report that greater engagement in a Twitter social network for weight loss predicted greater weight loss [16]. Finally, hashtags, a word prefixed with a "#" and used to group messages, have also been used as a means of spreading health innovations [17]. In this issue, Vickey and colleagues developed a classification model to describe the type of information shared in tweets that contained hashtags relevant to fitness mobile apps [18].

We know little how online social networking can be leveraged to promote health behavior. In some online social networks, connections are made based on a shared interest, health condition, or goal; whereas other online social networks provide a context in which existing relationships can be leveraged for health promotion efforts. We know little about the nature of relationships formed in these different types of online social networks, how loose and tight social ties can each be leveraged to promote behavior change, how socialization occurs in these venues, and how to promote engagement. Theoretical models of online social behavior are needed to understand the factors that characterize effective versus ineffective interactions and relationships on online social networks. Emerging methodologies could also be leveraged, such as semantic analysis, to help us uncover how social interactions influence individuals and behaviors in these virtual communities.

WHO SHOULD BE INVOLVED IN THE DEVELOPMENTAL PROCESS OF EMERGING TECHNOLOGIES?

Prior to efficacy testing, technology development should be guided by both evidence-based behavioral strategies and user-centered principles. Key stakeholders should be involved ranging from the target user, the providers who treat them, third-party payers, and the technology development team. Another critical consideration is how to use interface designs to best engage the target population. In this special issue, Buller and colleagues [19] provide an excellent guide for academics on the formative user-centered development process they employed to create a smart phone mobile application for sun protection. They obtained feedback from end users throughout development to ensure that the final product met user needs, was easy to use, and designed in a way that ensures users trust the product's advice. Engagement of providers and third-party payers will ensure that development takes into account the process of clinical care as well as reimbursement structures.

HOW TO STRIKE A BALANCE BETWEEN THE PACE OF RESEARCH AND THE PACE OF INNOVATION?

Research and industry operate at very different paces [20]. The procession through intervention development, feasibility testing, and efficacy testing occurs far too slowly to allow researchers to keep pace with industry. Researchers are also further slowed by the grant funding process at the front-end and the publication process at the back-end. Estimates suggest it can take up to 17 years for a research innovation to be adopted in clinical practice. By the time a research-derived digital health tool reaches clinical practice it might be obsolete.

Industry's timing advantage is a major challenge for the science of mHealth. Commercial developers excel at development. They develop mobile apps swiftly and expertly, and with products that are often more engaging and user-friendly than those developed by researchers. For industry, dissemination usually follows development. Commercial developers often rush to release a minimally viable product and "just ship" has become the mantra of modern mobile software development. They extend this advantage by enhancing their product's features, functionality, and interoperability over time–frequently in response to customer feedback and utilization. The resulting products often look attractive, function well, and are tailored to the interests of customers. In research, dissemination is the final step, following development and efficacy testing. Researcher-developed apps are often grounded in behavioral theory and evidence, but do not benefit from the customer feedback-driven iterations that fine-tune design and functionality. Researcher-developed apps suffer from the absence of a team science approach that includes experienced commercial developers and designers. On the other hand, industry-developed apps suffer from the absence of a team science approach that engages scientists in development and efficacy testing. Unless team science collaborative models begin to coalesce, the result will be products that are esthetically pleasing but result in no meaningful outcome or products that effective but not appealing. Neither outcome is likely to achieve the maximum potential impact of digital health.

Randomized controlled trials remain the foremost option for detailing the efficacy and potential harms associated with mHealth interventions. However, some argue that time, cost, and flexibility constraints of the RCT may hamper the translational process. For example, commercial mHealth applications are rarely "finished." They are frequently being enhanced and updated–often in response to user feedback and behavior. RCTs are not well suited to accommodate this type of change, but are better suited when an app is "mature." [21] Several alternative approaches for efficacy testing exist, although these have received relatively limited attention. For example, regression-incontinuity, stepped-wedge designs, SMART trials [22], and pragmatic randomized controlled trials have been proposed as study designs that could efficiently yield some efficacy data and be more amenable to handling changes in technology features [21]. In this issue, Cobb and Poirer conduct a pragmatic controlled trial that demonstrates the ability to recruit, retain, intervene, and make data-driven intervention enhancements at low cost and on a rapid timeline [23]. A major challenge with alternative designs is that data produced by them is not traditionally included in meta-analyses and systematic reviews which tend to compile efficacy data exclusively from RCTs, because historically, RCTs have been the most rigorous efficacy testing design. Meta-analyses and systematic reviews are the basis for practice guidelines and policy decisions. To the extent that mHealth research sidesteps RCTs, it may be at a disadvantage in terms of the transition from research to clinical practice. While new designs are being generated to speed the pace of research, time shall tell whether such designs will match RCTs in methodological soundness. The opportunities and challenges associated with alternative methodological options have yet to be fully explored.

WHERE DOES BEHAVIORAL SCIENCE ADD VALUE IN A CONSTANTLY EVOLVING MARKETPLACE?

The large number of apps being pumped out of fast-paced industry can lead clinicians and consumers to become overwhelmed. Science cannot move as fast as new innovations hit the market, but it may not be necessary that science match the pace as the goals of science and industry are different. The goal of science is to establish the efficacy of products that will impact clinical care and ultimately public health. As such, focusing on technology innovations that have become ubiquitous is likely to have greater impact than focusing on those that have not. For example, market share for hardware more rapidly evolves than software (e.g., Facebook has been a market leader for years). Furthermore, leaders in many app markets have held their standing for years (e.g., My Fitness Pal and Lose It weight loss apps have been market leaders since 2009). Also, a focus on basic features of technologies that could be employed across iterations would increase the applicability over time. For example, while it is conceivable that Facebook could decline in usage over the next decade, it seems less likely that online social networking in general is going to fade over that same time period given the increasing trend of usage in social networks. Studies of uses of online social networks might benefit from utilizing features that are employed broadly across social networks rather than specific to any one social network. A similar approach could be taken for mobile app research by leveraging basic features that are not likely to become obsolete. Even in the case where a technology has become obsolete, to the extent that interventions could be enacted over a range of technologies, the research would still be useful. For example, the ubiquity of smartphones might seem to make web-based interventions less relevant, but lessons learned from web-based intervention research are translatable to the mobile environment.

Behavioral scientists can develop and test evidence- and theory-based mHealth applications, but the challenge is competing in a saturated market in which design, usability, infrastructure, support, and scale have already been established based on consumer preferences by companies that have honed this expertise. For example, over 1,000 mobile apps exist for weight loss, which means that the likelihood of even the most effective app of penetrating this market is low. Indeed, there are several areas of opportunity for behavioral science to leverage skills to improve and extend mobile health interventions.

First, we can develop and test features that employ behavioral strategies that have not yet been employed in mobile apps or in online social networks. This work could then inform app development on the industry side to enhance the efficacy of mobile apps, or in the case of online social networks, inform consumers of ways they can leverage online social networks to improve health. Second, we can test currently available "mature" mobile apps for efficacy on clinical outcomes. This data would guide consumer decisions about which apps are most likely to work. Providers and healthcare systems are likely to be especially interested in outcomes data to increase their comfort in recommending apps to patients. Such research could also guide developers, giving them a clearer sense of what works and allowing them the opportunity to use data as a marketing selling point. Even if consumers do not necessarily demand efficacy data when they download apps, when efficacy data exists, it will likely influence their decisions. Third, behavioral scientists can create health promotion platforms that integrate data collected via multiple mobile applications. Tens of thousands of mobile health applications are commercially available. Mobile health devices abound–tools are widely available to measure weight, blood pressure, glucose, and a host of health indicators. Generally speaking, people use these apps and devices in isolation–there are few evidence-based forms that integrate these various data streams. The possibilities are endless. Integrative platforms might aggregate multiple distinct sources of data collected in real time, apply algorithms to inform participant feedback, and make predictions about future health outcomes, send feedback data to providers or other clinicians, link contextual data to provide real-time guidance to participants in context, and store these data for future use.

Tailoring to improve feedback–For most health apps, feedback is not more sophisticated than a series of "atta-boys" and "atta-girls"–current formulations are unlikely to promote long-term engagement or behavior change. Behavioral science excels at devising effective feedback approaches and we have a wealth of evidence that could be leveraged to create feedback algorithms that consider a range of psychosocial, emotional, behavioral, and/or contextual circumstances. Feedback algorithms like these would be of great utility–in both the commercial and research realms–to improve participant engagement and behavior change outcomes, while reducing attrition.

Strategies to improve participant engagement/utilization–Patient engagement has been called "the blockbuster drug of the century." [24] Patient engagement is central to a range of health system reforms and is a primary target for most mobile health applications. Unfortunately, patient engagement remains a challenge for developers–both commercial and academic. However, behavioral scientists are well-positioned to make improvements on this important outcome. Despite declining engagement being a characteristic component of most mobile health application trials, our rates of engagement and attrition often outperform those of our commercial colleagues (e.g., [25]). With directed attention, use of more advanced feedback strategies and engagement strategy interfaces the research community might be positioned to make major improvements in engagement. This would be a boon for commercial-academic partnerships and likely improve outcomes.

Application rating schemes–At present there is no straightforward way for consumers or providers to choose among the myriad choices of mHealth apps. With so many health apps to choose from and pricing strategies that disallow free evaluations, consumers and providers have very little data with which to guide their app selections. Rating schemes are popular online for most services, but few such offerings exist for health applications. Organizations like Happtique have begun the process of collating and rating mobile health apps, but these do not yet include what is arguably most important to behavioral scientists–evidence. We need application rating schemes that can help guide consumers and providers selection of applications based on their efficacy and/or use of evidence-based strategies. No consensus exists as to the optimal means for rating apps. Given the absence of RCTs, apps can be rated by the degree to which they incorporate evidence-based strategies [5, 26], incorporate health behavior theory [27], or reflect behavior change taxonomies [28]. Such a rating system might also inform researchers as to which apps would make the best candidates for rigorous testing. At present, the most popular apps might be selected for testing, but as one review of weight loss mobile apps showed, the app that had the highest number of evidence-based strategies was not the most popular app in the marketplace which suggests that selection by popularity and/or evidence alone might not be ideal [5].

Enhancing our impact–Many of the "innovations" in the burgeoning digital health market are built squarely on long-standing behavioral science findings. Among many examples–commercial smartphone apps are almost exclusively reliant on principles of self-monitoring, and social support. However, the range of behavioral strategies employed is narrow and oversimplified versions of behavioral strategies are often used. As the studies in this special issue illustrate, behavioral science is well-positioned to enhance its digital health impact. However, it will need to consider how to best contend with the industry's increasing involvement in the digital health market. Given the challenges of time, funding, and expertise, behavioral science and industry cannot afford to compete or work exclusively in parallel to one another. We have proposed four areas that might move behavioral science toward better clarity in its value proposition and shape its digital health research mission. The studies in this special issue illustrate many of the exciting areas for the next generation of behavioral science in digital health–industry partnerships, trial designs that match industry's speed, evaluation studies, and rating schemes, among many others. As these studies show, behavioral science can enhance its impact when we retool, partner, and adapt our questions and methods to match the demands of this market–and we can do this in a manner that upholds our scientific principles.

Conflicts of interest: Dr. Pagoto is on the advisory board of Mobile Wellbeing, Inc.

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