Applying and advancing behavior change theories and techniques in the context of a digital health revolution: Proposals for more effectively realizing untapped potential

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Abstract

As more behavioral health interventions move from traditional to digital platforms, the application of evidence-based theories and techniques may be doubly advantageous. First, it can expedite digital health intervention development, improving efficacy, and increasing reach. Second, moving behavioral health interventions to digital platforms presents researchers with novel (potentially paradigm shifting) opportunities for advancing theories and techniques. In particular, the potential for technology to revolutionize theory refinement is made possible by leveraging the proliferation of "real-time" objective measurement and "big data" commonly generated and stored by digital platforms. Much more could be done to realize this potential. This paper offers proposals for better leveraging the potential advantages of digital health platforms, and reviews three of the cutting edge methods for doing so: optimization designs, dynamic systems modeling, and social network analysis.

130 ("recommended" 150 word limit)

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1.i. The beginning of a digital revolution in behavioral medicine

There is a sea change in technological capacity for empirically testing behavioral theories in "real-world" contexts. Cell phone use is currently near complete penetration with 96% of the global adult population having a cell-phone subscription (ITU Statistics, 2015). Internet access is rapidly growing with approximately 400 million internet users globally in 2000, rising to 3.2 billion by 2015 (ICT Data and Statistics Division: Telecommunication Development Bureau: International Telecommunication Union, 2015). Within the US, there is rapid adoption of smartphones, with current estimates of 60-64% of adults with similar penetration across socio-economic communities (Pew Research Center: Internet, 2014; Smith, 2013). These statistics demonstrate the increasing digitization of our daily lives globally.

Another technological advance relevant to behavioural science is the inferring of psychological, social, and contextual variables from "digital traces" that are passively recorded or tracked (e.g., emails exchanged, social media activity, and GPS location; Saeb et al., 2015). Currently, industry utilizes these digital traces for commercial purposes such as targeted advertising and recommendations (Resnick & Varian, 1997); there is also interest in utilizing these data streams for supporting health and behavior change via sensing of the processes and outcomes of behavioral interventions (Goldbeck, Robles, & Turner, 2011; Heckler, Klasnja, Traver, & Hendriks, 2013; Estrin, 2014; Kan-Leung, Inon, Dana, & Jennifer, 2014; Tausczik & Pennebaker, 2010; Zhou et al., 2014; Pentland, 2014; Ravichandran et al.) Such digital traces offer an effective strategy for the empirical testing of behavioral theory (e.g., inferring personality attributes from email interactions, Tausczik & Pennebaker, 2010). "Wearable" technologies (e.g., fitness tracking bands like the Fitbit or Apple Watch, or smart vision devises like Google Glass) provide new data streams and opportunities for minute-by-minute monitoring and intervening “just-in-time” (Kumar et al., 2013). Constructs that were once measurable only in a lab environment or via self-report (e.g., stress, affect, personality characteristics) are increasingly becoming possible to measure in “real-life” contexts and with more direct inference. Technologies such as smartphones and smart watches enable low-burden strategies for providing behavioral support at key times when a person has the opportunity to change and is receptive to such support (Nahum-Shani, Hekler, & Spruijt-Metz, 2015).

Beyond cell phones, smartphones, and wearables, there is an emerging movement, the “internet of things” which refers to digitally connecting the everyday appliances and devices used in our home, work, and commuting environments, such as “smart” thermostats, refrigerators and cars. The technologies we interact with everyday are increasingly connected to the internet, thus supporting an enormous explosion of interlinked data sources. This is very relevant to health. For example, sensor technologies in toilets can automatically measure biomarkers and microbiome profiles of individuals (Ratti, 2014), and bathroom mirrors can use facial recognition features to assess health problems and the monitoring of alcohol of tobacco use (Colantonio et al., 2015). Other new digital sensor technologies include ingestible smart tablets capable of gathering data on medication taking, activity, and resting patterns (Proteus Digital Health), and smart temporary tattoos capable of monitoring vital signs, skin temperature, and blood oxygen levels (Hirschberg, Betts, Emanuel, & Caples, 2014).

This digital health movement involves bringing together a number of digital technologies to improve health, including wireless devices, hardware sensors and software sensing technologies, microprocessors and integrated circuits, the Internet, social networking, mobile/cellular networks and body area networks, health information technology, genomics, and personal genetic information (Topol, 2013). In this article, we confine our discussion of digital health to behavior change interventions delivered via one or more of these digital technologies.

1.ii. Advantages of applying evidence-based theories and techniques when developing digital health interventions

In the context of behavioral health interventions, the ubiquity of digital technologies and infrastructures and their adoption into day-to-day life translates into much greater potential reach than traditional interventions, and consequently greater potential for positive public health impact. However, this potential impact can only be realized to the extent that digital health interventions are effective. For all types of intervention, the development process benefits from applying evidence-based theories and techniques, as this directs attention to design characteristics (e.g., behaviour change techniques, modes of delivery) that might otherwise be ignored, and indicates conditions under which interventions and their specific characteristics are more or less likely to be effective. This may be especially important for digital health interventions given that they often require considerable initial investments in development (e.g., labor intensive software engineering). Second, application and identification of specific evidence-based techniques makes for an efficient, and therefore more rapid and less costly, process, and provides opportunities for systematic testing and refining of behavioral interventions over time

1.iii. Advantages of going digital for developing and testing theories and techniques of health behavior change

The shift from traditional to digital platforms presents researchers with significant advantages in terms of developing and testing theories and techniques of behavior change. They allow for greater specification of (i) behavioral theories and models (e.g. defining how constructs relate to one another and the predicted magnitude and direction of those relations) (Hekler et al., 2016), , (ii) dynamic temporal relationships (e.g., timescale, latency, and delay; Spruijt-Metz, Hekler, Saranummi, Intille, Korhonen, Nilsen, Rivera, Spring, Michie, & Asch, 2015) and (iii) the "threshold conditions" that clearly define when, where, for whom, and in what state of the person a mechanism of action will produce an effect (Hekler et al., 2016).

Another potential strength of digital technologies for investigating theories and techniques of behavior change is their potential for high "fidelity" of delivery (although software engineering problems and interactions with changing operating systems and hardware can undermine this in practice). A review of 342 articles evaluating intervention fidelity over 10 years and found that only 22% reported strategies to maintain provider skills, only 27% reported checking adherence to protocol, and only 35% reported using a treatment manual, cumulatively raising concerns about the fidelity of delivery of traditional interventions (Borrelli et al., 2005). Barring technical failures, digital platforms have the advantage of objectively measuring what parts of the intervention were engaged with, and therefore "received", by whom.

Because digital interventions can be delivered with high fidelity, and because they provide the possibility of very large datasets generated by valid measures of behavior, thinking, emotion and physiology in real time and everyday contexts, they provide a great potential for testing, refining and developing theories of behavior change. The digital revolution currently taking place in behavioral medicine is making these things *possible* -- but to what extent has this potential been realized thus far? To the extent that we've so far fallen short of realizing the potential power of leveraging digital health platforms, why have we fallen short? And how can we do better?

1.iv. Goals for this paper

In this paper we present strategies for embracing the digital revolution in behavioral medicine. This paper makes proposals in three areas. First, few digital health intervention developers specify how characteristics of their intervention map onto underlying evidence-based theories and techniques (Conroy, Yang, & Maher, 2014a; Crane, Garnett, Brown, West, & Michie, 2015). Improving this would be expected to increase the effectiveness of interventions and advance our understanding of underlying theory. Second, many researchers are not yet taking advantage of the richness of data generated by digital health platforms, instead over-relying on traditional self-report measures. Third, there are a range of advanced study designs and analytic methods well suited to "big data" sets generated by digital health platforms; we will introduce a selection of these that we consider should be more widely used.

2. Challenges to Digital Platforms

2.i. The complexity of multicomponent health interventions (digital and traditional)

Interventions to change behaviors related to health are usually complex (also referred to as ‘multi-faceted’ or ‘bundled’) in that they comprise several or many components that may interact with each other in achieving an effect. These components may be either behavior change techniques (BCTs; the potentially active ingredients of an intervention) or modes of delivery (e.g., design features of smartphone apps or communication skills in face-to-face delivery). This poses challenges for all complex interventions in identifying (i) which techniques are contributing to any effects observed and (ii) the mechanisms of action of techniques contributing to the effect.

Two methods have been successfully used to identify effective BCTs within complex interventions. The first is a statistical technique to analyze evidence syntheses using meta-regression. This enables the identification of BCTs that have strong enough effect signals that they are found to be associated with effect despite the large heterogeneity of types of intervention within the synthesis (Michie et al., 2015; Michie et al., 2014). Using this technique, Michie and colleagues have identified the BCT 'self-monitoring' to be an effective component of complex interventions in increasing physical activity and healthy eating (Michie et al., 2011), decreasing alcohol consumption (Michie et al., 2012), and in smoking cessation (West, Evans, & Michie, 2011). The same finding was replicated by Dombrowski et al. in a study of physical activity and dietary interventions for those who were overweight with co-morbidities (Dombrowski et al., 2012).

A limitation of using meta-regression for BCT identification is that it requires large numbers of studies so that there is sufficient power to test each BCT; in practice there is only sufficient power to test a handful of BCTs, so that conclusions cannot be drawn about those BCTs for which there is not sufficient power. The second limitation is that there are often many confounders (factors correlated with the presence of BCTs) so that it may be that an explanation for an effective BCT is its combination with other BCTs or with other aspects of the intervention that are not, and cannot be, factored into the analysis, either because they have not been documented or there is insufficient power for complex analyses. This is a constraint of all such secondary data analyses. A 2010 review of the association between BCTs, theoretical base and modes of delivery in 85 digital interventions suggested some interesting findings (Webb, Joseph, Yardley, & Michie, 2010), but the confounders were such that confidence in such findings were not high. It would be useful to repeat this review with the vastly larger numbers of studies we now have and using a more sophisticated analytic method, as the findings are likely to be very useful for intervention design and could be treated with more confidence.

2.ii. Lack of evidence-based theories and technique specification applied to behavioral health interventions (digital and traditional)

The need for better specification of BCTs and/or underlying theory-based mechanisms. The reporting of complex behavioral health interventions, digital and traditional, often lacks sufficient details to know exactly which BCTs were included and how they were offered. For example, an analysis of Cochrane reviews of behavioral support for smoking cessation found that less than 50% of BCTs specified in intervention protocols were mentioned in published reports (Lorencatto, West, & Michie, 2012). If we do not know exactly what the intervention consisted of, we are unable to investigate its mechanisms of action (theory defined concepts) and hence explain the effect and further improve the intervention. A further problem is that, even when interventions are well specified in terms of BCTs, the hypothesized mechanisms of action of those BCTs are frequently not stated. An analysis of 190 studies of interventions to increase physical activity and healthy eating found that only 107 (56%) explicitly reported theory or theory-derived mechanisms of action (Prestwich et al., 2014). Those that reported basing interventions on theory were further analyzed for how theory had been applied using the Theory Coding Scheme (S. Michie & Prestwich, 2010). It was found that theory was used partially and inconsistently, for example, in 90% studies, there were BCTs within the intervention that were not explicitly linked to theoretical constructs and in 91% studies, there were theoretical constructs not targeted by BCTs.

A further problem is that the names of evidence-based theories, theory-derived mechanisms of action, and BCTs may be specified, but inappropriately operationalized (Michie, Johnston, Francis, Hardeman, & Eccles, 2008; S. Michie & Prestwich, 2010). For example, one empirically supported mechanism of action derived from Self-Determination Theory involves the provision of autonomy support, a process that encourages participants to feel a greater sense of endorsement or ownership over their behavior change efforts (Ng et al., 2012). One technique that is used to provide autonomy support involves giving participants choices. However, some interventions have operationalized giving choices in ways that are inconsistent with the underlying theory (e.g., by providing an abundance of trivial, meaningless options, or by pressuring participants to "choose" a particular option; Moller, Deci, & Ryan, 2006).

We suggest that increasing precision in the specification and operationalization of theories and techniques of behavioral interventions has the potential of accelerating both understanding and application in behavioral medicine.

Applying evidence. Research has found that most healthcare smartphone apps do not follow evidence-based clinical guidelines and best practices, for example in obesity prevention (Breton, Fuemmeler, & Abroms, 2011; Pagoto, Schneider, Jojic, Debiasse, & Mann, 2013; Schoffman, Turner-McGrievy, Jones, & Wilcox, 2013), smoking cessation (Abroms, Lee Westmaas, Bontemps-Jones, Ramani, & Mellerson, 2013; Ubhi, Michie, Kotz, Wong, & West, 2015) and alcohol reduction. Apps for alcohol use, physical activity, and dietary behaviors have been analyzed using a taxonomy of BCTs (Conroy et al., 2014a; Crane et al., 2015); findings suggest that most apps have implemented a very limited number. For example, alcohol reduction apps implemented less than four BCTs on average (Crane et al., 2015); physical activity apps implemented less than seven BCTs on average (Yang, Maher, & Conroy, 2015), and a set of weight management apps targeting either physical activity, dietary behavior or both implemented approximately eight BCTs on average (Direito et al., 2014). In terms of the marketing of health apps, Conroy and colleagues found that online descriptions of physical activity apps in app stores also fail to highlight many of the BCTs that have been observed upon app inspection (Conroy, Yang, & Maher, 2014b). However, there are good examples of apps being well aligned with health behavior theories such as control theory and social-cognitive theory when developed within carefully controlled research studies (Lyzwinski, 2014). This is the exception and at present most people exposed to mobile health apps, the most common form of digital health intervention, will not receive help that is evidence-based.

2.iii. Challenges to applying and testing evidence-based theories and techniques on digital health platforms

Digital interventions usually have a majority of components that are not ‘tunneled’ so that there is considerable choice as to which part of the app to engage with, in which order and for how long. Thus, there is huge variation in the exposure of individuals to BCTs. For example, in a traditional behavioral intervention a lesson might be taught in-person to a group of participants; in this case, the pace, order, and content would be determined by the instructor and each participant would experience it in a uniform, or "tunneled" way. In a digital health intervention, such as an app, each participant might be free to explore different features in ways that are less rigidly determined. In face-to-face interventions, it is possible to assess exposure to BCTs by assessing the ‘fidelity’ of delivery by recording intervention sessions and recording which of the BCTs in the protocol were delivered (Lorencatto et al., 2012). We can also assess the extent to which participants respond to BCTs by investigating what they say in sessions (Michie et al., 2008). In digital interventions, we can measure ‘usage’ (i.e., the length of time that a participant spent on any particular part of the internet site or smartphone app and the sequence of visiting parts of the site/app). However, the analysis and interpretation of the vast amounts of individualized data generated are at an early stage and there are few reports of successfully using such data to identify effective BCTs, components or modules within digital interventions. For example, usage data from a digital health interventions might include whether a participant has clicked on a webpage, but tell researchers little about whether the content on the page was actually read (i.e., digital traces of "usage" may differ from usage that is likely to bring about change). The interpretation of digital trace data is a new challenge facing researchers.

A further complexity arises when interventions are ‘adaptive’ in that they change over time and potentially in continuous fashion according to feedback from the user (Almirall, Nahum-Shani, Sherwood, & Murphy, 2014; Lagoa, Bekiroglu, Lanza, & Murphy, 2014). Adaptive changes to interventions are more common and complex on digital platforms, as when algorithmic content delivery is incorporated using real-time data from sensors within an app and surrounding context as well as data inputted by the user. Additionally, in many cases, the technology itself (hardware and software) tied to a digital health interventions is continuously updated. The question as to what exactly is being offered, delivered and evaluated is therefore not straightforward. Researchers struggling with these challenges have suggested that the solution may lie in defining digital interventions not so much as static ‘things,’ but as a set of underlying principles (theory-derived concepts or mechanisms of action) related to BCTs and delivery methods (Mohr et al., 2015).

3. Emerging methods for capitalizing on the digital health revolution

Researchers and digital intervention developers have so far barely scratched the surface of the potential of the digital health revolution for advancing and refining theory. Most of our current theories of behavior change are static and have been developed on the basis of group differences and cross-sectional designs rather than on the basis of change within individuals (Davies, Morriss, & Glazebrook, 2014; Michie, Atkins, & West, 2014; Riley et al., 2011). In this section, we review a number of emerging research methods facilitated by digital platforms and "big data," which have the potential to advance and refine our theories of behavior change in ways that were previously impossible. These methods include multiphase optimization designs, dynamic system modeling, and social network analysis. In each case, we briefly describe how these methods work (citing sources with more in-depth coverage), and provide illustrative examples of cutting edge work being done using digital health data.

3.i. Multiphase optimization designs, digital health data, & theory refinement

The multiphase optimization strategy (MOST) is an engineering-inspired framework for systematically, incrementally, and efficiently improving behavioral interventions (Collins et al., 2011; Collins et al., 2015; Collins, Murphy, & Strecher, 2007). Although this framework is still fairly novel, MOST has been applied to a wide range of interventions targeting health behaviors, including smoking cessation (Collins et al., 2011; Strecher et al., 2008), weight loss (Pellegrini, Hoffman, Collins, & Spring, 2014), and drug use prevention among NCAA athletes (Wyrick, Rulison, Fearnow-Kenney, Milroy, & Collins, 2014), with a few applications using web- and app-based technologies (Pellegrini et al., 2014; Strecher et al., 2008; Wyrick et al., 2014). Although relatively efficient, historically, a limitation of MOST is that it requires relatively large sample sizes, and data collected across multiple waves. Using traditional intervention delivery channels, using MOST designs is possible, but very expensive; however, as interventions move to digital platforms, the cost of data collection needed for running MOST designs can be cut substantially, making these techniques accessible to far more researchers; that is, if they are familiar with this method and trained to use it.

MOST consists of three phases: preparation, optimization, and evaluation (Collins et al., 2015). The preparation and evaluation phases are similar to the traditional approach of developing and testing behavioral interventions via the use of a 2-arm randomized controlled trial; however, MOST employs an additional phase of optimization, to empirically examine the independent and combined effects of potential intervention components prior to evaluation (an intervention component being any aspect of an intervention that can be separated out for examination). This additional phase not only contributes to the development of interventions that are more effective, economical, efficient, and scalable, but simultaneously enables behavior change theories and techniques to be empirically examined and refined throughout the intervention development process. A more detailed description of MOST can be found in Collins et al. (2015).

A strong theory-derived conceptual model should inform the process whereby proximal (near-term) outcomes, which represent mediating mechanisms (e.g., adherence to diary or physical activity goals, as opposed to longer term weight change), can be used to make decisions about which candidate intervention components to include in an optimized intervention. This strategy potentially shortens the amount of time needed to conduct the study and is well-suited to digital interventions which often rely on technologies that are rapidly changing (Riley & Rivera, 2014). For example, in a hypothetical intervention to increase antiretroviral therapy (ART) among alcohol using injection drug users, Collins and colleagues (2015) use a conceptual model of the ART adherence to identify and directly map five candidate intervention components to their corresponding proximal mediator. In this hypothetical example, one intervention component included a strategy of sending text messages (SMS) to increase participant’s perceived social support (a proximal mediator) to reduce alcohol consumption and/or ART adherence intentions (a proximal outcome), thereby reducing alcohol consumption and improving ART adherence behavior (a behavioral outcomes), and decreasing HIV viral load (a long-term outcome). To screen the components, the use of a highly efficient experiment, most often a factorial experiment, during the *optimization* phase, enables the examination of the individual and combined effects of multiple candidate intervention components. Given that each intervention component can be mapped onto proximal mediators (mechanisms of action based on a conceptual model or theory), the relative contributions of specific constructs from different behavioral change theories can be examined individually.

Optimization phase research can also be used to produce more effective and efficient digital health interventions, as the results from "screening" experiment (designed to test the individual effects of candidate intervention components) informs subsequent decisions about which candidate components to include in future "optimized" versions of the intervention (Collins et al., 2014). For example, in one ongoing remotely-delivered weight loss intervention, five candidate intervention components are being tested, in this case a mixture of digital and traditional components (i.e., telephone coaching, letters from a physicians, text messages, meal replacement recommendations, and buddy training). Analysis of this fractional factorial design will be used to evaluate whether each component independently or in combination increase social accountability and adherence to weight management practices (Pellegrini et al., 2014). If a candidate component does not perform well, it may not be as relevant to the behavior change process as originally thought. Alternatively, it could mean that the technique employed to impact the targeted mediators (e.g., social accountability) was not effective. To address this potential ambiguity, post-hoc secondary data analyses can be performed to explore the underlining conceptual mechanisms of behavior change. Advanced mediation analyses derived from these large factorial designs can test a wide variety of paths, such as whether social accountability mediates the relation between telephone coaching (a single intervention component) and adherence to weight management practices. Traditional mediation analyses of bundled interventions are unable to disentangle an individual component's effect on the mediator (MacKinnon, 2008), thus the use of a factorial design has the potential to shed light on the mechanisms of how both the intervention and the behavioral change theory being applied work.

3.ii. Dynamical systems modeling, digital health data, & theory refinement

Another emerging method for making the most of "big data" in order to predict and understand human behavior involves the application of dynamic systems modeling (see: (Spruijt-Metz et al., 2015)). Dynamic systems modeling is closely related to control systems engineering, a suite of methods that can be used for the development of highly personalized digital health interventions. These methods include strategies such as system identification (Ljung, 1999), and model-predictive control (Nandola & Rivera, 2013). System identification is an analytical technique that examines the dynamic relationships between manipulated inputs (i.e., BCTs, such as goal-setting), disturbance variables (i.e., factors that vary over time that are external to the person, such as weather), and outputs (i.e., the target of an intervention, such as physical activity or weight loss) within a single-case, time-series context. This analytic technique builds on the logic of regression to understand the dynamic inter-relations between these constructs. This modeling strategy has been used to develop a mathematically specified version of social cognitive theory (Timms, Martin, Rivera, Hekler, & Riley, 2014; Riley et al., 2016), and has been applied to the development of an intensively adaptive intervention to support increased walking. Current work is exploring if dynamical system models of behavior can be used to define dynamic concepts such as "ambitious but doable" daily step goals that take into account past behavioral patterns (e.g., previous ability to meet step goals), daily variations in individual characteristics (e.g., stress, busyness), and contextual characteristics (e.g., location, weather, busyness based on calendar) to define what an appropriate "ambitious but doable" step goal would be for a particular individual at a particular time.

Model-predictive control provides a mechanism for translating knowledge about the dynamics of behavior into dynamic decision-rules that can be utilized "on the fly" within a digital health intervention. A model-predictive controller functions by utilizing a dynamical systems model to run simulations and predictions on what might plausibly happen for the specific person being helped, particularly with variations on factors that the system can actively manipulate. In the "ambitious but doable" step goal example described above, the model-predictive controller can examine plausible outcomes depending on variations on suggested step goals and the number of points conferred for meeting that step goal (which, in the current system, translated into gift cards). The system then utilizes these predictions for the next day or longer-term to determine target goals and associated points that would be most useful for supporting a person in achieving a meaningful long-term target, such as maintaining 10,000 steps per day over 6 months or a year. In this way, the model-predictive controller runs predictions that are akin to meteorology (step 1) but then goes a step further, utilizing that information to make decisions (step 2) in order to "close the loop." This iterative process of predicting and testing supports both improved intervention development and theory testing.

Using this framework, a theory can be tested on the quality of its prediction for a specific person as well as relationships between constructs in general (for the average person) For example, a model-predictive controller may make the prediction that a person will walk 6,000 steps tomorrow plus or minus 500 steps if a goal of 5,500 steps and 500 points were provided. At the end of that day, the model-predictive controller can then compare how well that prediction was to the actual steps achieved by that individual. In this way, the model is constantly tested and refined for its predictive utility for a specific person. This results in a significant advancement from current practices for the rapid empirical testing and refinement of behavior change theories as represented via well-specified mathematical models.

3.iii. Social networks, digital health data, & theory refinement

The third emerging research method we review, participants' social networks, and their relative position and influence within such networks, offers researchers ways to "zoom out" and consider system-level features driving intervention success. Social network analysis can be used to help understand how individuals are influenced by friends, and how behavioral health interventions influence not only the targets of interventions but also their friends and other in their networks. social network analytic methods are being used to model wide-ranging social networks, including digitally networked communities dedicated to a specific health behavior (e.g., PatientsLikeMe.org) and online communities that are more generally defined (e.g., Facebook and Twitter).

Prior to the current widespread adoption of internet connected technologies, several decades of research using network analytic methods have established that individuals’ behavior and health status are heavily influenced by their "real world" social relationships and the social conditions guiding interpersonal interactions (see Berkman & Syme, 1979; Christakis & Fowler, 2007). However, collecting data for the purpose of modeling the influence of an individuals' social network was prohibitively expensive for most behavioral health researchers. For example, the seminal work conducted by Christakis and Fowler (2007) used data from the famous and costly Framingham Heart Study, which involved hundreds of participants reporting the important members of their social networks at multiple time points over several decades. As the general public embrace large, online social networking sites like Twitter and Facebook, and as digital health interventions incorporate these sites or provide access to their own dedicated online networking tools, collecting and modeling network data is becoming more affordable and feasible. Social network research has grown in popularity over the past few decades, and behavioral health interventions are increasingly acknowledging the importance of social influence on intervention success.

Social network analysis is defined here as the empirical study of how social networks influences individuals' health behavior and outcomes, and it involves characterizing social relations around the individual (i.e., ties), and how properties of these connections (e.g., tie strength) and characteristics of friends/alters affect the individual/ego. Social network analysis may also involve studying how structural properties of the network (e.g., network density) influence individuals' health (Latkin & Knowlton, 2015). Social networks are rarely considered in relation to the behavior change pathway, as illustrated in a review of obesity treatment interventions considering social relational constructs see Leroux, Moore, & Dubé, 2013). Among those that do, the pathway under study is most often social support, which is just one of many ways in which social networks exert their influence on individuals' health (Berkman, Glass, Brissette, & Seeman, 2000). Furthermore, although many interventions may be described as having taken a social network approach, most study the mechanisms connecting social networks to health, and do not conduct true social network analyses (see Smith & Christakis, 2008).

Digital health interventions are especially well suited to true network analysis because they enable the collection of large quantities of social interaction data over time. These data can include participants' interactions with their existing online connections/friends and/or interactions with others in the intervention. Capturing the digital traces that define online social network interactions enable digital health interventions to map a much larger portion of the social network than has been possible using traditional methods (e.g., via self-report surveys). Passively collected data from digital health interventions also make it easier for researchers to track engagement with communication tools and interactions among participants, potentially facilitating more accurate estimation of intervention effects (Hunter et al., 2015).

Network analyses using data from digital health interventions suggest that many network effects are consistent across online and offline social environments. For instance, recent evidence about the prevention of HIV and reduction of risky sexual behavior suggests that network effects observed in face-to-face trials extend to online settings such as Facebook (Young et al., 2014). Observational studies that have employed true network analyses have also demonstrated that social embeddedness in an online weight loss community affects weight loss (Poncela-Casasnovas et al., 2015), and that friends' online behaviors (e.g., Facebook posting) affect adolescents' drinking and smoking behavior (Huang et al., 2014). Digital health interventions that have taken a social network approach but not conducted true network analysis have demonstrated that social support, accountability, and a positive team environment are associated with improved health outcomes, including greater weight loss and increased physical activity over time (Carson et al., 2013; Leahey, Kumar, Weinberg, & Wing, 2012; Maher et al., 2015).

Although there is good evidence that online social networks can influence behavioral health, there is currently a dearth of research testing which behavior change techniques (BCTs) related to social interaction can be most effectively employed in digital interventions. In a recent review of how social network technologies were used in online health promotion, just under half of the studies evaluated were grounded in theory, and fewer still described how theories were specifically applied in delivering the intervention (Balatsoukas, Kennedy, Buchan, Powell, &

Ainsworth, 2015). Of the 93 BCTs in BCT Taxonomy v1, four relate to social interaction: those focused on social support, social comparison, social incentives, and restructuring of the social environment (Michie et al., 2015; Michie et al., 2014). Interventions could also focus on changing social norms within the network, or encouraging individuals to actively promote behavior change within their network as a strategy for changing their self-identity (Latkin & Knowlton, 2015).

Future research should investigate how to maximize the potential for positive social network effects on health, specifically in the context of digital health interventions. Examples of research questions to tackle are: (i) how users may interact or socialize using technology differently than in-person, for example, the Uses and Gratification framework considers how different features of social media are utilized based on users' motivation for use and expectations about outcomes of use (Smock, Ellison, Lampe, & Wohn, 2011); (ii) how human-computer interaction influences social network effects, and (iii) to what extent computer-mediated communication is different from face-to-face communication in producing social network effects. Future work would also benefit from social network data collection that goes beyond individual approaches (i.e., collecting data just on the individual targeted by the intervention), and collects data from others in the participants' networks (e.g., Facebook friends). This enables the evaluation of how the health and behavior of others (e.g., friends) affects people. Collecting data on others also provides insight as to whether the intervention has spread beyond the participants targeted in the intervention, broadening the public health impact (i.e., social diffusion). However, in research trials, when social diffusion spreads to the control/non-intervention group(s), trials are said to suffer from "contamination." Contamination may be especially prevalent in digital health interventions that provide opportunities for communication with other participants. A further research question to consider is how structural properties of individuals' social networks influence behavioral health outcomes. For example, multiple sources of social reinforcement, available within clustered networks, may be necessary for optimizing healthy behavior change (Centola, 2013). These are just a few of the promising research directions for those using social network research methods for the purpose of intervention development and theory testing on digital platforms.

4. Conclusions

We believe we are facing a paradigm shift in opportunities for delivering behavior change interventions through digital technologies and use of these to study theories and techniques of behavior change. To make the most of this, it could be valuable to explicitly identify and systematically apply the evidence-based behavior change techniques (BCTs) in these interventions. It could also be important to look for creative ways to more effectively leverage the richness of data generated by digital health platforms, such as by using digital trace data that can often be passively captured for little cost or effort. In addition, there are promising new research designs and statistical methods capable of extracting more from the rich sets. Embracing these emerging technologies and methods should generate more successful interventions and advance behavior change theory in ways not possible before, driving faster progress.

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References

Abroms, L. C., Lee Westmaas, J., Bontemps-Jones, J., Ramani, R., & Mellerson, J. (2013). A Content Analysis of Popular Smartphone Apps for Smoking Cessation. *American Journal of Preventive Medicine*, *45*(6), 732–736. http://doi.org/10.1016/j.amepre.2013.07.008

Almirall, D., Nahum-Shani, I., Sherwood, N. E., & Murphy, S. A. (2014). Introduction to SMART designs for the development of adaptive interventions: with application to weight loss research. *Translational Behavioral Medicine*, *4*(3), 260–274. http://doi.org/10.1007/s13142-014-0265-0

Balatsoukas, P., Kennedy, C. M., Buchan, I., Powell, J., & Ainsworth, J. (2015). The Role of Social Network Technologies in Online Health Promotion: A Narrative Review of Theoretical and Empirical Factors Influencing Intervention Effectiveness. *Journal of Medical Internet Research*, *17*(6), e141. http://doi.org/10.2196/jmir.3662

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From Social Integration to Health: Durkheim in the New Millennium. *Social Science & Medicine (1982)*, *51*(6), 843–857. http://doi.org/10.1016/S0277-9536(00)00065-4

Berkman, L. F., & Syme, S. L. (1979). Social Networks, Host Resistance, and Mortality: A Nine-Year Follow-Up Study of Alameda County Residents. *American Journal of Epidemiology*, *109*(2), 186–204.

Borrelli, B., Sepinwall, D., Ernst, D., Bellg, A. J., Czajkowski, S., Breger, R., … Orwig, D. (2005). A new tool to assess treatment fidelity and evaluation of treatment fidelity across 10 years of health behavior research. *Journal of Consulting and Clinical Psychology*, *73*(5), 852–860. http://doi.org/10.1037/0022-006X.73.5.852

Breton, E. R., Fuemmeler, B. F., & Abroms, L. C. (2011). Weight Loss—There Is an App for That! But Does It Adhere to Evidence-Informed Practices? *Translational Behavioral Medicine*, *1*(4), 523–529. http://doi.org/10.1007/s13142-011-0076-5

Carson, T. L., Eddings, K. E., Krukowski, R. A., Love, S. J., Harvey-Berino, J. R., & West, D. S. (2013). Examining Social Influence on Participation and Outcomes Among a Network of Behavioral Weight-Loss Intervention Enrollees. *Journal of Obesity*, *2013*, 1–8. http://doi.org/10.1155/2013/480630

Centola, D. (2013). Social Media and the Science of Health Behavior. *Circulation*, *127*(21), 2135–2144. http://doi.org/10.1161/CIRCULATIONAHA.112.101816

Christakis, N. A., & Fowler, J. H. (2007). The Spread of Obesity in a Large Social Network Over 32 Years. *New England Journal of Medicine*, *357*(4), 370–379. http://doi.org/10.1056/NEJMsa066082

Collins, L. M., Baker, T. B., Mermelstein, R. J., Piper, M. E., Jorenby, D. E., Smith, S. S., … Fiore, M. C. (2011). The Multiphase Optimization Strategy for Engineering Effective Tobacco Use Interventions. *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine*, *41*(2), 208–226. http://doi.org/10.1007/s12160-010-9253-x

Collins, L. M., Trail, J. B., Kugler, K. C., Baker, T. B., Piper, M. E., & Mermelstein, R. J. (2014). Evaluating individual intervention components: making decisions based on the results of a factorial screening experiment. *Translational Behavioral Medicine*, *4*(3), 238–251. http://doi.org/10.1007/s13142-013-0239-7

Conroy, D. E., Yang, C.-H., & Maher, J. P. (2014a). Behavior Change Techniques in Top-Ranked Mobile Apps for Physical Activity. *American Journal of Preventive Medicine*, *46*(6), 649–652. http://doi.org/10.1016/j.amepre.2014.01.010

Conroy, D. E., Yang, C.-H., & Maher, J. P. (2014b). Behavior change techniques in top-ranked physical activity apps. *American Journal of Preventive Medicine*, *46*(6), 649–652. http://doi.org/doi: 10.1016/j.amepre.2014.01.010

Crane, D., Garnett, C., Brown, J., West, R., & Michie, S. (2015). Behavior Change Techniques in Popular Alcohol Reduction Apps: Content Analysis. *Journal of Medical Internet Research*, *17*(5), e118. http://doi.org/10.2196/jmir.4060

Davies, E. B., Morriss, R., & Glazebrook, C. (2014). Computer-Delivered and Web-Based Interventions to Improve Depression, Anxiety, and Psychological Well-Being of University Students: A Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, *16*(5), e130. http://doi.org/10.2196/jmir.3142

Direito, A., Dale, L. P., Shields, E., Dobson, R., Whittaker, R., & Maddison, R. (2014). Do physical activity and dietary smartphone applications incorporate evidence-based behaviour change techniques? *BMC Public Health*, *14*(1), 646. http://doi.org/10.1186/1471-2458-14-646

Dombrowski, S. U., Sniehotta, F. F., Avenell, A., Johnston, M., MacLennan, G., & Araújo-Soares, V. (2012). Identifying active ingredients in complex behavioural interventions for obese adults with obesity-related co-morbidities or additional risk factors for co-morbidities: a systematic review. *Health Psychology Review*, *6*(1), 7–32. http://doi.org/10.1080/17437199.2010.513298

Goldbeck, J., Robles, C., & Turner, K. (2011). Predicting personality with social media. Retrieved January 20, 2016, from http://dl.acm.org/citation.cfm?id=1979614

Heckler, E. ., Klasnja, P., Traver, V., & Hendriks, M. (2013). IEEE Xplore Abstract - Realizing Effective Behavioral Management of Health: The Metamorphosis of Behavioral Science

Methods. Retrieved January 20, 2016, from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6603401

Hirschberg, D. L., Betts, K., Emanuel, P., & Caples, M. (2014). *Assessment of Wearable Sensor Technologies for Biosurveillance* (Department of Defense No. ECBC-TR-1275).

Huang, G. C., Unger, J. B., Soto, D., Fujimoto, K., Pentz, M. A., Jordan-Marsh, M., & Valente, T. W. (2014). Peer Influences: The Impact of Online and Offline Friendship Networks on Adolescent Smoking and Alcohol Use. *The Journal of Adolescent Health: Official Publication of the Society for Adolescent Medicine*, *54*(5), 508–514. http://doi.org/10.1016/j.jadohealth.2013.07.001

Hunter, R. F., McAneney, H., Davis, M., Tully, M. A., Valente, T. W., & Kee, F. (2015). “Hidden” Social Networks in Behavior Change Interventions. *American Journal of Public Health*, *105*(3), 513–516. http://doi.org/10.2105/AJPH.2014.302399

Kan-Leung, C., Inon, Z., Dana, N., & Jennifer, G. (2014). Predicting Agents’ Behavior by Measuring their Social Preferences. *Frontiers in Artificial Intelligence and Applications*, 985–986. http://doi.org/10.3233/978-1-61499-419-0-985

Kumar, S., Nilsen, W. J., Abernethy, A., Atienza, A., Patrick, K., Pavel, M., … Swendeman, D. (2013). Mobile health technology evaluation: the mHealth evidence workshop. *American Journal of Preventive Medicine*, *45*(2), 228–236. http://doi.org/10.1016/j.amepre.2013.03.017

Lagoa, C. M., Bekiroglu, K., Lanza, S. T., & Murphy, S. A. (2014). Designing adaptive intensive interventions using methods from engineering. *Journal of Consulting and Clinical Psychology*, *82*(5), 868–878. http://doi.org/10.1037/a0037736

Latkin, C. A., & Knowlton, A. R. (2015). Social Network Assessments and Interventions for Health Behavior Change: A Critical Review. *Behavioral Medicine*, *41*(3), 90–97. http://doi.org/10.1080/08964289.2015.1034645

Leahey, T. M., Kumar, R., Weinberg, B. M., & Wing, R. R. (2012). Teammates and Social Influence Affect Weight Loss Outcomes in a Team-Based Weight Loss Competition. *Obesity*, *20*(7), 1413–1418. http://doi.org/10.1038/oby.2012.18

Leroux, J. S., Moore, S., & Dubé, L. (2013). Beyond the I'' in the Obesity Epidemic: A Review of Social Relational and Network Interventions on Obesity. *Journal of Obesity*, *2013*, 1–10. http://doi.org/10.1155/2013/348249

Ljung, L. (1999). *System identification: theory for the user* (2nd ed). Upper Saddle River, NJ: Prentice Hall PTR.

Lorencatto, F., West, R., & Michie, S. (2012). Specifying Evidence-Based Behavior Change Techniques to Aid Smoking Cessation in Pregnancy. *Nicotine & Tobacco Research*, *14*(9), 1019–1026. http://doi.org/10.1093/ntr/ntr324

Lyzwinski, L. N. (2014). A systematic review and meta-analysis of mobile devices and weight loss with an intervention content analysis. *Journal of Personalized Medicine*, *4*(3), 311–385. http://doi.org/10.3390/jpm4030311

Maher, C., Ferguson, M., Vandelanotte, C., Plotnikoff, R., De Bourdeaudhuij, I., Thomas, S., … Olds, T. (2015). A Web-Based, Social Networking Physical Activity Intervention for Insufficiently Active Adults Delivered via Facebook App: Randomized Controlled Trial. *Journal of Medical Internet Research*, *17*(7), e174. http://doi.org/10.2196/jmir.4086

Michie, S., Ashford, S., Sniehotta, F. F., Dombrowski, S. U., Bishop, A., & French, D. P. (2011). A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: The CALO-RE taxonomy. *Psychology & Health*, *26*(11), 1479–1498. http://doi.org/10.1080/08870446.2010.540664

Michie, S. F., Atkins, L., & West, R. (2014). *The Behaviour Change Wheel: A Guide to Designing Interventions*. (S. F. Michie, Ed.) (1st ed.). London: Silverback Publishing. Retrieved from http://discovery.ucl.ac.uk/1450989/

Michie, S., Hardeman, W., Fanshawe, T., Prevost, A. T., Taylor, L., & Kinmonth, A. L. (2008). Investigating theoretical explanations for behaviour change: The case study of ProActive. *Psychology & Health*, *23*(1), 25–39. http://doi.org/10.1080/08870440701670588

Michie, S., Johnston, M., Francis, J., Hardeman, W., & Eccles, M. (2008). From Theory to Intervention: Mapping Theoretically Derived Behavioural Determinants to Behaviour Change Techniques. *Applied Psychology*, *57*(4), 660–680. http://doi.org/10.1111/j.1464-0597.2008.00341.x

Michie, S., & Prestwich, A. (2010). Are interventions theory-based? Development of a theory coding scheme. *Health Psychology*, *29*(1), 1–8. http://doi.org/10.1037/a0016939

Michie, S., Whittington, C., Hamoudi, Z., Zarnani, F., Tober, G., & West, R. (2012). Identification of behaviour change techniques to reduce excessive alcohol consumption: Behaviour change and excessive alcohol use. *Addiction*, *107*(8), 1431–1440. http://doi.org/10.1111/j.1360-0443.2012.03845.x

Michie, S., Wood, C. E., Johnston, M., Abraham, C., Francis, J. J., & Hardeman, W. (2015). Behaviour change techniques: the development and evaluation of a taxonomic method for reporting and describing behaviour change interventions (a suite of five studies involving consensus methods, randomised controlled trials and analysis of qualitative data). *Health Technology Assessment*, *19*(99), 1–188. http://doi.org/10.3310/hta19990

Moller, A. C., Deci, E. L., & Ryan, R. M. (2006). Choice and Ego-Depletion: The Moderating Role of Autonomy. *Personality and Social Psychology Bulletin*, *32*(8), 1024–1036. http://doi.org/10.1177/0146167206288008

Nahum-Shani, I., Hekler, E. B., & Spruijt-Metz, D. (2015). Building health behavior models to guide the development of just-in-time adaptive interventions: A pragmatic framework. *Health Psychology*, *34*(Suppl), 1209–1219. http://doi.org/10.1037/hea0000306

Nandola, N. ., & Rivera, D. . (2013). IEEE Xplore Abstract - An Improved Formulation of Hybrid Model Predictive Control With Application to Production-Inventory ... Retrieved January 20, 2016, from http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6112190

Ng, J. Y. Y., Ntoumanis, N., Thogersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Duda, J. L., & Williams, G. C. (2012). Self-Determination Theory Applied to Health Contexts: A Meta-Analysis. *Perspectives on Psychological Science*, *7*(4), 325–340. http://doi.org/10.1177/1745691612447309

Pagoto, S., Schneider, K., Jojic, M., Debiasse, M., & Mann, D. (2013). Evidence-based strategies in weight-loss mobile apps. *American Journal of Preventive Medicine*, *45*(5), 576–582. http://doi.org/10.1016/j.amepre.2013.04.025

Pellegrini, C. A., Hoffman, S. A., Collins, L. M., & Spring, B. (2014). Optimization of Remotely Delivered Intensive Lifestyle Treatment for Obesity Using the Multiphase Optimization Strategy: Opt-In Study Protocol. *Contemporary Clinical Trials*, *38*(2), 251–259. http://doi.org/10.1016/j.cct.2014.05.007

Poncela-Casasnovas, J., Spring, B., McClary, D., Moller, A. C., Mukogo, R., Pellegrini, C. A., … Amaral, L. A. N. (2015). Social Embeddedness in an Online Weight Management

Programme Is Linked to Greater Weight Loss. *Journal of The Royal Society Interface*, *12*(104), 20140686. http://doi.org/10.1098/rsif.2014.0686

Prestwich, A., Sniehotta, F. F., Whittington, C., Dombrowski, S. U., Rogers, L., & Michie, S. (2014). Does Theory Influence the Effectiveness of Health Behavior Interventions? Meta-Analysis. *Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association*, *33*(5), 465–474. http://doi.org/10.1037/a0032853

Riley, W. T., & Rivera, D. E. (2014). Methodologies for Optimizing Behavioral Interventions: Introduction to Special Section. *Translational Behavioral Medicine*, *4*(3), 234–237. http://doi.org/10.1007/s13142-014-0281-0

Riley, W. T., Rivera, D. E., Atienza, A. A., Nilsen, W., Allison, S. M., & Mermelstein, R. (2011). Health Behavior Models in the Age of Mobile Interventions: Are Our Theories up to the Task? *Translational Behavioral Medicine*, *1*(1), 53–71. http://doi.org/10.1007/s13142-011-0021-7

Schoffman, D. E., Turner-McGrievy, G., Jones, S. J., & Wilcox, S. (2013). Mobile Apps for Pediatric Obesity Prevention and Treatment, Healthy Eating, and Physical Activity Promotion: Just Fun and Games? *Translational Behavioral Medicine*, *3*(3), 320–325. http://doi.org/10.1007/s13142-013-0206-3

Smith, K. P., & Christakis, N. A. (2008). Social Networks and Health. *Annual Review of Sociology*, *34*(1), 405–429. http://doi.org/10.1146/annurev.soc.34.040507.134601

Smock, A. D., Ellison, N. B., Lampe, C., & Wohn, D. Y. (2011). Facebook as a Toolkit: A Uses and Gratification Approach to Unbundling Feature Use. *Computers in Human Behavior*, *27*(6), 2322–2329. http://doi.org/10.1016/j.chb.2011.07.011

Spruijt-Metz, D., Hekler, E., Saranummi, N., Intille, S., Korhonen, I., Nilsen, W., … Pavel, M. (2015). Building New Computational Models to Support Health Behavior Change and Maintenance: New Opportunities in Behavioral Research. *Translational Behavioral Medicine*, *5*(3), 335–346. http://doi.org/10.1007/s13142-015-0324-1

Strecher, V. J., McClure, J. B., Alexander, G. L., Chakraborty, B., Nair, V. N., Konkel, J. M., … Pomerleau, O. F. (2008). Web-Based Smoking-Cessation Programs: Results of a Randomized Trial. *American Journal of Preventive Medicine*, *34*(5), 373–381. http://doi.org/10.1016/j.amepre.2007.12.024

Tausczik, Y. R., & Pennebaker, J. W. (2010). The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. http://doi.org/10.1177/0261927X09351676

Timms, K. P., Martin, C. A., Rivera, D. E., Hekler, E. B., & Riley, W. (2014). Leveraging Intensive Longitudinal Data to Better Understand Health Behaviors. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 6888–6891). http://doi.org/10.1109/EMBC.2014.6945211

Topol, E. J. (2013). *The creative destruction of medicine: how the digital revolution will create better health care* (1st pbk. ed). New York: Basic Books.

Ubhi, H. K., Michie, S., Kotz, D., Wong, W. C., & West, R. (2015). A Mobile App to Aid Smoking Cessation: Preliminary Evaluation of SmokeFree28. *Journal of Medical Internet Research*, *17*(1), e17. http://doi.org/10.2196/jmir.3479

Webb, T. L., 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. *Journal of Medical Internet Research*, *12*(1), e4. http://doi.org/10.2196/jmir.1376

West, R., Evans, A., & Michie, S. (2011). Behavior Change Techniques Used in Group-Based Behavioral Support by the English Stop-Smoking Services and Preliminary Assessment of Association with Short-term Quit Outcomes. *Nicotine & Tobacco Research*, *13*(12), 1316–1320. http://doi.org/10.1093/ntr/ntr120

Wyrick, D. L., Rulison, K. L., Fearnow-Kenney, M., Milroy, J. J., & Collins, L. M. (2014). Moving Beyond the Treatment Package Approach to Developing Behavioral Interventions: Addressing Questions That Arose During an Application of the Multiphase Optimization Strategy (MOST). *Translational Behavioral Medicine*, *4*(3), 252–259. http://doi.org/10.1007/s13142-013-0247-7

Yang, C.-H., Maher, J. P., & Conroy, D. E. (2015). Implementation of behavior change techniques in mobile applications for physical activity. *American Journal of Preventive Medicine*, *48*(4), 452–455. http://doi.org/10.1016/j.amepre.2014.10.010

Young, S. D., Holloway, I., Jaganath, D., Rice, E., Westmoreland, D., & Coates, T. (2014). Project HOPE: Online Social Network Changes in an HIV Prevention Randomized Controlled Trial for African American and Latino Men Who Have Sex With Men. *American Journal of Public Health*, *104*(9), 1707–1712. http://doi.org/10.2105/AJPH.2014.301992