

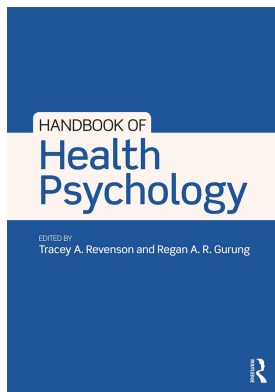
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DIGITAL HEALTH PSYCHOLOGY

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and Cheryl Hunter*

Introduction: Implications of Digital Technology for Health Psychology

Digital technology is transforming all aspects of our lives. Computer-controlled data-processing devices and systems, empowered by internet connectivity, are changing how we learn about our world, communicate with each other and pursue our goals. It is therefore inevitable that digital technology will have far-reaching implications for health psychology (Borrelli & Ritterband, 2015; Patrick et al., 2016).

Digital technology changes how people experience health and illness, vastly increasing access to information about health risks and health management. The proliferation of self-test and self-monitoring devices (such as glucose meters and physical activity trackers) together with web-based information resources allows us all to engage in assessment, diagnosis and management of our own health. This capability is leading to fundamental changes in the relationship between patients and health care providers, as patients have ever more involvement and responsibility for their own health maintenance. Growing expectations for digitally supported self-management can have both positive and negative consequences (Lupton, 2015), empowering patients to take control but also potentially disrupting valuable patient-provider relationships. These changes in the subjective experience and social interactions associated with health and illness open up important fields of investigation for health psychology.

Digital technology also provides unprecedented opportunities for measuring and changing health-related behavior. Mobile, physiological and environmental sensors provide an efficient and relatively unobtrusive means of collecting objective longitudinal data regarding health indices, health behavior, and their context. Detailed automatically sensed data about individuals can be used to trigger interventions utilizing 'just-in-time' behavioral prompts (Spruijt-Metz et al., 2015). There is potential to aggregate individual-level data into 'big data' sets, generated by potentially millions of digital technology users. This revolution in assessment and intervention has the capacity to drive and support novel ways of analyzing the antecedents and consequences of behavior. Previously, health psychologists have been obliged to rely on examining associations with behavior or comparisons between group trends and averages in small samples at limited points in time. With digital technology, it should be possible to map a huge variety of individual trajectories and aggregate the findings to identify distal and proximal personal and contextual influences on these trajectories. To make the most of these new opportunities will require complex new methods of analysis, exploiting machine learning and real-world experiments to test the effects on behavior of changes to the digital

information presented to users (Hekler et al., 2016). These new methods of assessment, intervention and analysis will, in turn, inform new ways of theorizing health-related behavior.

Digital technology also presents exciting opportunities and challenges for global health psychology. The cost of allowing additional users to access an existing digital resource is negligible. Consequently, digital technology should make it cheaper and easier to share health psychology resources internationally, including with lower and middle income countries (Muñoz, 2010). Access to digital technology is a diminishing barrier to global use of digital tools and interventions, because of the rapid uptake of mobile phone technology worldwide, even among people with limited incomes and literacy. However, an important topic for future research concerns how much and in what ways digital interventions may need to be adapted for people from different socioeconomic and ethnic backgrounds (Latulippe, Hamel, & Giroux, 2017).

The first section of this chapter considers the psychology of user-initiated use of digital technology. We discuss typical patterns, benefits and possible harms of activities such as accessing health-related information and joining peer support groups online. We then provide an overview of the exploding field of digitally supported behavior change, reviewing theories and methods guiding intervention development, and noting key issues relating to how best to evaluate these interventions and integrate them with other forms of psychological and behavioral support. Finally, we briefly outline potential future directions for the emerging field of digital health psychology.

Internet Use and Social Networking for Health

Seeking information about medical treatment, sensitive health issues, and illness recovery are now common online behaviors. The internet offers instant access to rich health information, anonymity and scope for interaction and social support. Using the internet for health is associated with psychological attributes such as self-efficacy, neuroticism and health anxiety, and influenced by factors such as racial identity, income, severity of one's health condition, caregiver status, and perceived reliability, relevance and trust in information source (Marton & Choo, 2012). While internet-assisted self-diagnoses are often incorrect, seeking information online can have a positive influence on the patient-physician relationship, by increasing patient comprehension of medical advice and promoting patient self-management and self-care (Tan & Goonawardene, 2017).

A number of theories have been employed to understand online health information seeking (Marton & Choo, 2012). These models propose that online health information seeking is driven by user needs, personal circumstances and the characteristics of information systems. For example, Uses and Gratification Theory (Palmgreen, 1984) postulates that people seek information on the internet to gratify needs such as knowledge acquisition, tension release, identification with others and social interaction. The Technology Acceptance Model (Davis, 1989) proposes that perceived ease of use and perceived usefulness of the internet should predict intentions to use online information resources.

Social media and social networking sites, in which content is generated by users, can aid health education through direct information sharing between the public, patients and health professionals. Sites, such as Facebook and Twitter, can offer resources for hard-to-reach individuals and provide opportunities for peer, social and emotional support, making them an appealing medium for behavior change interventions (Moorhead et al., 2013). So far, evidence for the effectiveness of social networking interventions from randomized control trials is mixed, with some indications that they can improve health behavior-related outcomes but often have high attrition and poor intervention fidelity (Laranjo et al., 2014; Maher et al., 2014). One drawback is that the information, which is provided by users, can be of variable quality and even inaccurate. In a study of four digital health social networks, van Mierlo (2014) found that only 1% of users actively generate the content, while

24% contribute occasionally and 75% are completely unengaged. Due to the increasing popularity of social media, it is essential for health psychologists to identify ways of disseminating reliable health information effectively through social networks.

Designing and Developing Effective Digital Interventions

Recently, models and theories for developing digital interventions have proliferated. Theoretical models offer structured guides for developing and evaluating interventions, often drawing on theories across psychology, marketing, information technology and design. Designing digital interventions requires consideration of user characteristics, behavioral targets, the specific and general context of intervention, and the technological characteristics and capabilities of the digital intervention (Oinas-Kukkonen & Harjumaa, 2009). The models proposed vary in terms of their specificity and applicability to different digital technologies, and none have yet been validated, but they can nevertheless provide a helpful guide to likely influences on outcomes that should be considered when developing an intervention.

The Internet Intervention Model outlines how user characteristics, environmental factors, website features and external support may all drive website use and behavior change (Ritterband, Thorndike, Cox, Kovatchev, & Gonder-Frederick, 2009). The Behavioral Intervention Technology (BIT) Model proposes a series of questions to guide intervention development (Mohr, Schueller, Montague, Burns, & Rashidi, 2014). The first questions are theoretical, focusing on clinical and usage aims of the intervention and the ways in which behavior change will be achieved. The final questions focus on implementation, namely what will be delivered to users (intervention ‘elements’), and when (‘workflow’) and how (technical characteristics of the elements) it will be delivered.

Increasingly, digital interventions are being developed to provide behavior change prompts precisely when and where they are needed; for example, sending prompts to be active only after the digital device has detected a period of extended immobility in the home. Consequently, models of behavior change support for these ‘Just-in-Time Adaptive Interventions’ (JITAI) also take into account that user characteristics, environments and needs are dynamic (Spruijt-Metz et al., 2015).

There is widespread consensus that user-centered approaches to developing digital interventions are required to overcome potential barriers to engagement (Yardley et al., 2016). User-centered design is a widely used participatory approach, where users are treated as partners in the design process, in order to improve usability, engagement, trust and satisfaction with an intervention (Abrás, Maloney-Krichmar, & Preece, 2004). User-centered approaches originated in the field of human-computer interactions, where the initial focus was on usability testing to improve basic functions, such as ease of navigation through the digital intervention. The Person-Based Approach (PBA) is rooted in health psychology and aims to ensure that interventions are persuasive, motivating, engaging and support behavior change (Yardley, Morrison, Bradbury, & Muller, 2015). The PBA uses in-depth qualitative research to explore users’ needs, preferences, beliefs and situations, enabling developers to take these into account when designing interventions, to maximize user engagement and intervention effectiveness.

High rates of drop-out and non-usage are common in digital interventions (Eysenbach, 2005). As digital interventions are often delivered remotely and outside of formal health care, being able to engage users is crucial. To address this problem directly, O’Connor and colleagues (2016) proposed the DIgital Health EnGagement MOdel (DIEGO). DIEGO outlines four processes affecting engagement with an intervention: 1) making sense of the intervention (in terms of awareness, comprehension, motivation and personal agency); 2) considering intervention quality (in terms of information, interaction and usability); 3) gaining support for enrollment (from social sources such as clinicians and researchers); and 4) registering for the intervention (in terms of fit with lifestyle,

security and privacy concerns, skills and equipment). The relationship between engagement with the digital intervention and with desired behavior change is complex, involving a dynamic process of engaging with the digital intervention as and when required. 'Effective engagement'—the engagement required for positive outcomes—will therefore vary for each intervention, and multiple measures of online usage and offline adherence to the behavior change are needed to establish whether and how this has been achieved (Yardley et al., 2016).

Tailoring is a commonly used approach to promoting user engagement with interventions. Tailoring involves delivering personalized messages to an individual, based on data such as their characteristics, behavior, context and relevant theoretical constructs (Noar, Benac, & Harris, 2007). For example, in a digital intervention to help users quit smoking, tailoring resulted in greater perceived personal relevance of messages, increased engagement and higher quit rates (Strecher et al., 2008). Interventions using tailored messages tend to be more effective than non-tailored interventions, but there is still much to learn about when tailoring is beneficial and how to optimize tailoring to greatest effect (Muench & Baumel, 2017).

Implementation and Evaluation

There is considerable evidence that providing human support alongside digital interventions can enhance engagement and health outcomes (Baumeister, Reichler, Munzinger, & Lin, 2014). However, self-guided interventions can be effective and are easy to roll out at scale, at a low per person cost. Moreover, not all studies show differences in effectiveness between supported and self-guided interventions (Riper et al., 2014). Delivering human support remotely (via email, web chat or telephone) may be a compromise solution, as it is cheaper and easier to implement than face-to-face support, and can be equally effective (Little et al., 2016). It remains unclear what the optimal support 'dose' should be, which is likely to vary depending on the targeted behavior and user group.

Although digital interventions have the potential to reduce health disparities through wide, low cost dissemination, there is little evidence of interventions yet achieving this potential. As digital inequalities in access, participation, literacy and skills overlap with, and can exacerbate, existing social inequalities (Robinson et al., 2015), it is crucial that digital interventions address both types of inequalities in design and implementation. Involving intended users in design and addressing digital inequality and literacy is important (Latulippe et al., 2017), and culturally sensitive digital interventions may be required, for example, taking into account traditional or religious influences on diet in particular ethnographic groups.

It is often assumed that digital interventions are cheaper to provide than in person interventions, but the cost of digital interventions depends on the size of the population to which they are disseminated, as digital interventions incur significant development and maintenance costs (Murray et al., 2016). The more interactive and tailored an intervention is, the higher the costs of development and updating are likely to be. It is therefore important to investigate the extent of tailoring and interactivity that is really necessary to ensure interventions are engaging and effective for different user groups and contexts.

Formative evaluation throughout development and implementation is advocated to optimize intervention design (Mohr, Cheung, Schueller, Brown, & Duan, 2013). A number of methodological approaches have been proposed (Collins, Murphy, & Strecher, 2007). Qualitative and mixed methods studies aim to understand how users perceive and use digital interventions, enabling optimization in terms of accessibility, feasibility, acceptability and usability (Yardley et al., 2015). The Multiphase Optimization Strategy (MOST) and Sequential Multiple-Assignment Randomized Trial (SMART) approaches involve using randomized factorial designs to establish active components, optimum dosage, and costs, with the aim of identifying and optimizing the effective components. For example, the

MOST approach has been used to try to identify the most effective components of interventions to support smoking cessation (McClure et al., 2014; Piper et al., 2016).

There is a current debate about whether the traditional randomized controlled trial is an appropriate method of evaluating digital interventions, given that they need to evolve rapidly and continuously as the technology platform delivering them changes (Patrick et al., 2016). However, robust evaluation of effectiveness remains crucial to allow users to distinguish effective interventions from the huge proliferation of interventions that are attractive but ineffective for behavior change. Use of ineffective behavior change interventions can result in real harm to users, reducing their motivation and confidence to attempt future behavior change. There is also a need for cost-effectiveness evaluations to convince health care providers of the value of digital behavior change interventions.

One solution to the question of how to carry out robust evaluations of interventions that constantly evolve may be to use 'Trials of Intervention Principles' (TIPS; Mohr et al., 2015), specifying the intervention elements and characteristics of an intervention that should be regarded as essential and preserved when adapting the intervention for new contexts or forms of delivery. It should also be possible in the future to embed automated robust assessment of digital interventions in emerging 'learning health care systems' (Friedman et al., 2017) or 'implementation laboratories' (Ivers & Grimshaw, 2016), which could utilize automatically collected patient data to inform continuous quality improvement of health care (Mohr, Lyon, Lattie, Reddy, & Schueller, 2017). Systems of this kind would have the potential to boost behavior change research, as they collect data from very large samples, permitting experimental and non-experimental evaluation of outcomes, moderators and effective ingredients of digital interventions.

Future Directions

Despite the very rapid expansion of digital health interventions, theory and research in digital health psychology is still at a very early stage of development. Rapid strides have been made in our knowledge of online health-related behavior and how to create effective digital interventions, but many important issues and questions still need to be addressed (Fairburn & Patel, 2017). While a number of theories and models have been proposed as frameworks for guiding research in this field, to date there has been very little empirical research to test, validate or refine them. Digital technology offers exciting new possibilities to detect and predict behavior and intervene in real time to support positive behavior change, but there have not yet been many demonstrations that this results in better health outcomes. Although the reach of digital technology should make it available to a wide global population, there remain significant barriers to uptake, engagement and universal dissemination (Kohl, Crutzen, & de Vries, 2013). Nonetheless, there is great optimism that digital technology will soon transform our ability to support people in their management of health and health problems.

To realize this potential will require digital health psychologists to engage in exciting new interdisciplinary ways of working (Schueller, Muñoz, & Mohr, 2013). Naturally, health psychologists will need to work with experts in digital technology, data analysis, and machine learning to create cutting-edge systems able to sense, predict and respond to users' behaviors. We have already learned that it is essential to work closely with intended users and stakeholders to ensure that digital resources are accessible, usable and useful. In order to be able to implement interventions widely and reap the benefits of carrying out large scale real-world research we also need to work with commercial partners, global health care providers and experts in business, economics and policy (McNamee et al., 2016). Learning how to collaborate and communicate effectively with this broad community of experts itself presents a vital and novel undertaking for digital health psychologists.

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