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TECHNOLOGY-BASED MONITORING AND INTERVENTION DELIVERY: EXPANDING BEHAVIOR-ANALYTIC TREATMENT TO HEALTH BEHAVIOR

MONITOREO Y REALIZACIÓN DE INTERVENCIONES BASADAS EN LA TECNOLOGÍA: EXPANDIENDO LOS TRATAMIENTOS ANALÍTICO CONDUCTUALES PARA LA CONDUCTA SALUDABLE

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Abstract

Technology-based health interventions are providing unprecedented ways to improve a range of socially significant behavior. In this article, we provide behavior analysts with an overview of technology-based platforms and applications to help broaden research and practice. First, we discuss "high-tech" platforms, such as smartphones, wearable sensors, and other wireless devices. Second, we provide information about "low-tech" platforms, such as text messaging, which may be more feasible to implement than high-tech platforms. Finally, we discuss challenges and opportunities, and we provide specific guidance regarding the prescription of these assessment and intervention tools as a part of behavior analytic services.

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Keywords: clinical behavior analysis, eHealth, health behavior, mHealth, technology

Resumen

Las intervenciones para la salud basadas en la tecnología están produciendo formas de mejorar un rango de conductas socialmente significativas sin precedentes. En este artículo proporcionamos a los analistas de la conducta una visión general de las plataformas y aplicaciones basadas en la tecnología para ayudar a expandir la investigación y la práctica. Primero discutimos las plataformas de "alta tecnología" como los teléfonos inteligentes, sensores para vestir y otros dispositivos inalámbricos. En segundo lugar, proporcionamos información sobre plataformas de "baja tecnología", como los mensajes de texto, que pueden ser implementadas de manera más accesible que las plataformas de alta tecnología. Finalmente, discutimos los retos y las oportunidades y proporcionamos guías específicas respecto a la prescripción de estas herramientas para la evaluación y la intervención como parte de los servicios analítico-conductuales.

Palabras clave: análisis conductual aplicado clínico, eHealth, conducta saludable, mHealth, tecnología

Behavior-analytic practitioners work primarily with individuals with autism spectrum disorder (Association of Professional Behavior Analysts, 2015). Several authors have discussed the need to expand clinical services to new populations and settings (Augustson, 2002; Friman, 2010; Leblanc, Heinicke, & Baker, 2012; Normand & Kohn, 2013; Poling, 2010). One area of propitious opportunity is in the assessment and treatment of health behavior through technology-based platforms. For the purposes of the present article, health behavior refers to choices about diet, physical activity, tobacco use, medication adherence, and adherence to medical regimens (e.g., monitoring blood glucose). Commercially available e-health devices and programs have become increasingly popular (Rainie, 2012; Srivastava, Pant, Abraham, & Agrawal, 2015) and demonstrate a strong potential for revolutionizing health-behavior monitoring and intervention delivery (Asch, Muller, & Volpp, 2012). As such, technology-based behavioral healthcare is an area with high demand for qualified clinicians, and it represents one avenue to expand the breadth of behavior-analytic practice.

Arguably, the greatest extension of clinical behavior analysis outside of autism, thus far, has been to illicit and licit substance use (Donlin, Knealing, Needham, Wong, & Silverman, 2008; Higgins & Petry, 1999; Holtyn et al., 2014; Silverman et al., 2007). By integrating biomedical procedures with operant conditioning procedures, behavior analysts have been able to monitor metabolites produced through substance use and deliver consequences contingent on their reduction (i.e., contingency management). Contingency management (CM) is now regarded as one of the most effective treatments for promoting abstinence from alcohol, stimulants, opioids, marijuana, and nicotine (National Institute on Drug Abuse, NIDA, 2012; Prendergast, Podus, Finney, Greenwell, & Roll, 2006) and is used in communities and healthcare centers throughout the United States (NIDA, 2012; Substance Abuse and Mental Health Services Administration, n.d.).

In addition to developing CM, behavior analysts are expanding CM by capitalizing on advancements in technology. For example, Dallery and Glenn (2005) pioneered the use of Internet-based CM for smoking cessation by having participants record and send videos of their breath carbon monoxide tests using webcams and email. These technology-based procedures have since been replicated successfully across multiple studies (Dallery & Raiff, 2011; Dallery, Raiff, & Grabinski, 2013; Glenn & Dallery, 2007; Meredith, Grabinski, & Dallery, 2011; Reynolds, Dallery, Shroff, Patak, & Leraas, 2008) including extensions to website and mobile phone platforms, as well as different substance targets (Alessi & Petry, 2013; Dan, Grabinski, & Raiff, 2016; Hertzberg et al., 2013; Meredith et al., 2014; see Kurti et al. 2016 for a review).

Several other technologies have been developed to monitor an increasingly broad array of health behavior and deliver interventions in real-time. Previous articles have addressed the conceptual and empirical foundations of these interventions from a behavior-analytic perspective (Dallery, Kurti, & Erb, 2015; Kurti & Dallery, 2014). The purpose of this paper is to provide behavior analysts with an overview of technology-based platforms and applications to help broaden research and practice across a range of health-related behavior. First, we cover "high-tech" platforms, such as smartphones, wearable sensors, and other wireless devices. Second, we provide information about "low-tech" platforms, such as text messaging, which may be more feasible to implement than high-tech platforms. Third, we discuss options and considerations regarding the prescription of these assessment and intervention tools as a part of behavior- analytic services.

High-Tech Platforms

High-tech electronics, such as smartphones, wearable devices, and videogame consoles are now commercially available in markets throughout the world. Some of these technologies were designed for entertainment purposes, but researchers (e.g., Kratzke & Cox, 2012), software developers (e.g., Macadamian Technologies, Inc., n.d.), and even government organizations (e.g., Office of Disease Prevention and Health Promotion, 2017) are realizing their potential for disseminating health information, monitoring health behavior, and improving health outcomes. Interestingly, the area of "behavioral intervention technologies" (BITs) has exploded over the past few years, primarily through contributions from researchers in other fields of psychology (see Mohr, Burns, Schueller, Clarke, & Klinkman, 2013 for a review). Some behavior analysts may be surprised to find, however, that much of the research on BITs is either grounded in or closely aligned with principles of operant conditioning (Wells & Gallelli, 2011).

Aside from the conceptual similarities, there are also professional opportunities in the realm of technology-based healthcare, which may appeal to clinical behavior analysts. At present, we know of few clinicians or agencies providing technology-based interventions targeting health behavior as part of their service delivery models; however, the potential for doing so is apparent. Thus, in the following sections, we outline some popular modern technologies that can be used for health behavior monitoring and intervention delivery, with the implication that behavior analysts may utilize these tools to conduct research and provide services.

High-Tech Monitoring

Since the invention of the Internet a little over two decades ago, commercially available technologies have evolved rapidly (Pew Research Center, 2014). One of the most influential new advancements has been the introduction of smartphones, which are equipped with operating systems that can be used to access the Internet and download third-party software applications ("apps"). As app development is open to the public (Haselmayr, 2013), there are now more than one million free and for-pay apps accessible worldwide through the Google Play marketplace alone (Google, 2017a; Olmstead & Atkinson, 2015). Of these, over 40,000 are specifically categorized as medical- or health and fitness-related (Olmstead & Atkinson, 2015). One common use for health-related apps is direct monitoring of physical activity, as most smartphones come equipped with global positioning receivers (GPS), inertial measurement units (IMUs), and magnetometers which allow a person's phone to track geographic location, speed of movement, and distance travelled in real-time (del Rosario, Redmond, & Lovell, 2015). When an app is also used, it serves as an interface between the user and the phone's hardware, displaying different types of information. Many phones come standard with built-in health apps that display the number of steps the person has taken through calculations based on distance, duration, and the individual's reported height and weight (e.g., see Figure 1 for an image of the iOS Health app, Apple, Inc., 2017).

For users looking for more options to measure activity, numerous third-party apps are available. A popular example is the JogTracker app, which is free to download, measures distance and duration of movement, and also calculates calorie expenditure during various activities (e.g., walking, cycling, skiing; Highway North Interactive, Inc., 2011). Other examples include the Fitbit app (Fitbit, Inc., 2017a), the Moves app (Moves, n.d.), and the Google Fit app (Google, n.d.). Some of the major benefits of tracking physical activity through smartphones include cost effectiveness (numerous free apps available), flexibility (various types of interfaces to choose from), ease of access (apps can be used at anytime, from almost anywhere), and direct observation (activity measures are recorded in real-time). Some apps also continually track activity without the need for manual initiation, which can reduce the amount of response effort required from the user. Moreover, smartphone apps are available to anyone in the world with access to a compatible device, a data plan, and the Internet. Many app websites are also viewable in different languages, such as Fitbit's Spanish language website (https://www.fitbit.com/mx).

There are, however, a few limitations to direct tracking through smartphones that may lower its acceptability and/or utility. First, continuous physical activity monitoring can quickly drain a phone's battery (Min et al., 2015), especially when multiple apps or programs are processing data concurrently. Second, a user must carry the phone on their person when they wish to use it for tracking, which some have reported as challenging or uncomfortable (Casey et al., 2014). Third, at present, smartphones are only capable of directly monitoring the physiological characteristics of behavior previously mentioned. Although measures of an individual's physical movement can be highly informative, there may be other clinically significant dimensions of activity (e.g., movement types) or other categories of health behavior (e.g., dietary intake) that are also important to assess.

For situations in which continuous, automated tracking through a smartphone may be impractical or insufficient, an alternative (or complementary) option is to

Figure 1. The iOS Health app interface showing a user's step count and other measures.

use diary-based smartphone apps. With the free MyFitnessPal app, for example, participants can manually enter information about the food and fluids they consume, as well as any exercise they engaged in, at their own convenience throughout the day (MyFitnessPal, Inc., 2017). A unique aspect of MyFitnessPal is that it also has a barcode scanner, which can be used to upload nutritional facts about packaged food products. Based on the types and quantities of foods and drinks entered, the app calculates the amount of calories, carbohydrates, fat, protein, sodium, and sugar that a person has reported consuming. These data are automatically summarized across meals and days and stored on the app's server. An example of another type of diary-based app is, "See How You Eat" (Google, 2017b), which integrates with a phone's camera so that users can take and store pictures of the food they consume each meal. Although the See How You Eat app interface does not provide, or allow input of, detailed information (such as the types or nutritional contents of food), it does provide a timestamp for each picture, which can be used to track the timing of daily intake. Timing may be an important behavioral dimension for individuals who often miss meals (such as breakfast), overeat at certain times of the day, or eat at times which may be maladaptive (such as prior to sleeping or during the night). Moreover, the timing of a person's fluid intake may be clinically-significant, as some research has suggested that drinking water prior to meals can lead to reductions in caloric intake (Davy, Dennis, Dengo, Wilson, & Davy, 2008; Dennis et al., 2010).

A myriad of diary-based apps are now available, each geared towards different types of health behavior and dimensions of behavior. One of the primary benefits of these apps is that users can input detailed information at their own convenience without having to carry their phone or risk draining its battery through

Figure 2. The Fitbit Surge displaying heart rate, distance travelled, and time travelled.

continuous monitoring. One of the tradeoffs, however, is that health behavior data must be self-reported by the user, which raises issues with respect to diary entry compliance and the validity of entries. Although some evidence suggests that individuals may at least monitor their physical activity using mobile diary-based apps more often than other traditional self-report methods (e.g., paper journals; Turner-McGrievy et al., 2013), researchers may combine diary-based self-monitoring with devices that provide more objective measures.

Wearable accelerometers allow for continuous direct observation, while still mitigating the practical challenges associated with smartphone tracking. Depending on the model, wearable accelerometers can track and/or calculate an individual's step count, pace, floors climbed, distance travelled, calorie expenditure, duration of sleep, and even heart rate (e.g., Figure 2 shows the Fitbit Surge, Fitbit, Inc., 2017b). Many models are also waterproof, which means they can track activity while swimming or be taken into the shower, and they can be synced with other interfaces, such as the diary-based MyFitnessPal app (Fitbit, Inc., 2017c). In addition to activity, technology developers are producing devices to collect a range of biometric data such as blood pressure, heart activity, and even mood (Burns et al., 2011; H2 Care, 2016). With the emerging capabilities of commercial technologies to obtain biometric data across time, many have predicted a revolution in the way medical and behavioral diagnostics are conducted (Asch et al., 2012; Kumar, Nilsen, Pavel, & Srivastava, 2013).

The potential of emerging technologies, however, is predicated upon the assumption that modern sensors measure what they claim to measure. Evidence suggests that some may be more accurate than others (e.g., Case, Burwick, Volpp, & Patel, 2015). In a recent systematic review of wearable activity monitors, authors summarized the results of 22 studies on the accuracy and reliability of different

Figure 3. The Wii Fit balance board.

models of Fitbit and Jawbone devices (Evenson, Goto, & Furberg, 2015). The authors found that most studies reported strong correlations between step count measures obtained through the trackers and measures obtained through comparative methods (i.e., manual counts, video recordings, pedometers, accelerometers, treadmills, and ellipticals), as well as high intra-device reliability. However, the authors also noted variability in the accuracy of step counts. For example, across evaluations, tracking devices worn on the hips typically provided more accurate results than those worn on the wrist. A few studies also found that certain trackers (e.g., Fitbit Flex, Jawbone UP24) underestimated step counts at various speeds of activity (i.e., slow walking and running), and others reported overestimations in step counts (e.g., Fitbit One). In addition, differences in characteristics of physical activity demonstrated by children, adults, and elderly populations, as well as individuals with different body mass indexes (BMIs), have been shown to influence some devices' accuracy (Sylvia, 2014).

Additional high-tech devices can measure other types of health behavior or products of behavior. For example, the company Nintendo manufacturers the Wii Balance Board, which can connect to a Wii videogame console and wirelessly measure a user's weight as they stand on the board (see Figure 3, Nintendo, 2017). The device also monitors balance, physical movement, and body posture as the individual interacts with various Wii Fit videogame programs, such as virtual yoga or skiing. Ownership of a Wii console is not required to use the Wii Balance Board, however, as it can also be used to record weight when connected through Bluetooth

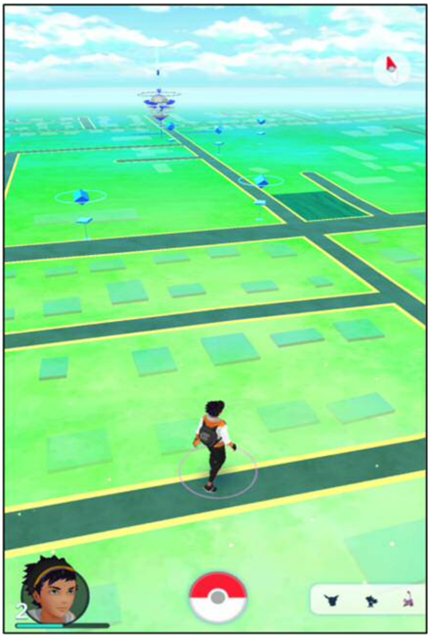

Figure 4. The Pokémon Go app interface.

to the FitScales smartphone app (Google, 2017c). Additionally, the FitScales app can be synced with the Fitbit and Runkeeper smartphone apps to allow for the integration of physical activity and weight measures. Withings, a company associated with the Nokia phone company, also produces Wi-Fi scales that can be connected through Bluetooth to their Health Mate app, or to over 100 other health apps (Withings SA, 2017). In addition to scales, commercial smart water bottles for tracking fluid intake (MyHydrate, 2017), wearable devices for measuring body temperature (Cosinuss GmbH, 2017), and sensors for monitoring an individual's posture (Lumo Bodytech, Inc., 2016) have been created.

High-Tech Intervention Delivery

A variety of free web- and mobile phone-based programs exist to promote physical activity. For example, the smartphone app Sworkit offers video guided workouts focused on strength, yoga, and pilates, and requires no equipment (Nexercise Apps, Inc., n.d.). Some programs also provide consequences contingent on changes in physical activity. For example, the augmented virtual reality game Pokémon Go (shown in Figure 4) provides game-based rewards for being active as measured by location (i.e., GPS; Niantic, Inc., 2016). Although initial reports suggest increases in activity, long-term studies on risks and benefits are lacking (LeBlanc & Chaput, 2016). In terms of benefit, however, one study suggested that Pokémon Go added 144 billion steps within the first 30 days among the 25 million Pokémon Go users in the United States (Althoff, White, & Horvitz, 2016). This study also indicated that, for engaged users, step counts increased by an average of 1,473 daily steps, which, if sustained, could have measurable impact on public health. It should be noted that these types of programs may be especially beneficial for children, as childhood is a particularly risky period for sedentary behavior and associated health issues (Pakarinen, Parisod, Smed, & Salanterä, 2016). Pokémon Go is also available in Mexico and other areas of Latin America (http://www.pokemongo.com/es-la/).

In addition to gamified consequences, several programs arrange monetary consequences based on behavior change. For example, Pact is a smartphone app that uses GPS, photos, and other methods to verify completion of various activity goals (e.g., attending a gym, running, biking; Pact, 2015). Users begin by creating a monetary "pact" to complete self-selected activities and incur a penalty if they do not complete the activities. If the user completes the activity, she receives monetary rewards that are forfeited from users who have not completed their activity. If the user does not complete the activity, her monetary donation is forfeited and used for other pact participants. To our knowledge, there are no published reports that speak to Pact's efficacy in initiating and/or maintaining behavior change.

Two additional programs work in a similar manner to Pact. Specifically, StepBet and DietBet involve personalized goal setting and monetary commitments for activity and weight loss, respectively (StepBet, 2016; DietBet, 2017). StepBet is available only as a smartphone app, but DietBet can be accessed through their website or phone app. Both programs involve procedures to verify behavior change (accelerometers, visible weight measures via scales). Both involve "games" that combine social gaming elements (competition, support, fun) with a deposit contract. "Players" deposit ("bet") a specified amount of their money into the game's "pot." All players who meet the game's step count or weight loss goal split the pot equally, such that they are refunded their deposit, plus they receive extra money funded by the forfeited deposits of the players who did not meet the goal. One longitudinal study suggests that DietBet can produce clinically meaningful weight loss (Leahey & Rosen, 2014), but more controlled and long-term studies are needed.

Several mobile phone-based apps also seek to promote cigarette smoking cessation using behavioral principles and procedures. Bricker, Wyzsynski, Comstock, and Heffner (2013) developed and tested the first web-based acceptance and commitment therapy (ACT) intervention for smoking cessation, and it is now available for smartphones (2Morrow Inc., 2015). ACT for smoking focuses on acknowledging and accepting emotions, thoughts, and other antecedents to smoking and weakening their control over subsequent behavior, and identifying values and behavior change procedures to commit to these values (e.g., smoking cessation). Core processes of ACT were embedded in the website by using personalized quit plans along with videos of former smokers sharing success stories and modeling acceptance. Phone-based interventions that incorporate behavioral principles are particularly noteworthy given that very few smokers receive behavioral treatment. A study of over 29,000 current and former smokers who had made a quit attempt within the past year revealed that only 8.8% received behavioral treatment (Shiffman, Brockwell, Pillitteri, & Gitchell, 2008), which suggests that in-person treatments have low appeal and reach. Accordingly, interest in mobile phone interventions, especially for underserved populations, is growing rapidly.

Many of these high-tech interventions entail a number of potentially active treatment components. Very little work has been done to isolate active components, however, which may be important to optimize treatment effects. Valle and Tate (2015) reviewed 21 technology-based studies targeting dietary intake, weight loss, and physical activity. The authors focused on studies that compared technological-delivery of treatment components to a technology-based control condition (e.g., a website with and without access to a component such as social support). They found that 19 studies used self-monitoring, 16 used feedback and tailoring (e.g., individualized goal setting based on changes in behavior relative to baseline levels), 14 used social support and social networking, and 19 used reminders or prompts to engage with intervention content. Relatively few interventions (< 6) used reinforcement, modeling, contingency contracting, or problem solving. Roughly half of the reviewed studies supported the effects of most of the treatment components compared to control conditions. Many studies involved treatment packages with several components, thus future component analyses will be valuable to isolate active components (Dallery, Riley, & Nahum-Shani, 2015).

Low-Tech Platforms

Although we have provided several examples of high-tech tools that could be used to measure and improve health behavior, many of these require patient access to a smartphone and/or the Internet. In Mexico, however, only 39.2% of individuals report having an Internet connection in their household (Instituto Nacional de Estadística y Geografía, 2016), and only 35% of adults report owning a smartphone (Poushter, 2016). Even in wealthier nations where smartphones are more common, they may be too expensive for low-income residents. In the United States for example, only 68% of all adults, and only 52% of adults with an annual household income below $30,000, report owning a smartphone (Anderson, 2015).

As Aulakh (2015) noted, "[T]here is a disconnect between the problems of those who need the most help and the tech solutions they are being offered." Unfortunately, individuals who could likely benefit most from health behavior treatments are often those with low-income and are least likely to own high-tech devices (Anderson, 2015; Centers for Disease Control and Prevention, 2013). Given the many potential advantages of technology-based health interventions, it is necessary to bridge this "digital divide" (Chinn & Fairlie, 2004; Poushter, 2016; Weiss, Yates, & Gulati, 2016) with additional low-cost and low-tech treatment options. As a step in that direction, we provide some current examples of low-tech platforms that could be used for health behavior monitoring and intervention delivery.

Low-Tech Monitoring

One capability of almost any mobile phone is multimedia messaging service (MMS), which enables recording and transmission of media content such as images, audio, and video (Ghaderi & Keshav, 2005). Some researchers, both within and outside the field of behavior analysis, have used video MMS as a method for directly observing health behavior. For example, Alessi & Petry (2013) monitored alcohol consumption during a contingency management intervention by having participants use MMS on mobile phones to self-record and submit videos of their alcohol breath tests. The researchers found that most videos were valid (i.e., test results could be seen clearly) and participant adherence to the submission procedures was high. In another application, Hoffman et al. (2010) used video MMS as a tool to conduct direct observation therapy (DOT) for medication adherence in residents of Nairobi, Kenya diagnosed with tuberculosis (TB). Treatment supporters (relatives or friends) were asked to record daily videos of the patient taking their medication, and the patient was asked to send the videos to a secure database. Results from acceptability surveys showed that patients, treatment supporters, and health professionals all strongly agreed that video-based monitoring was a better option than in-person monitoring.

Another feature shared by mobile phones is short message service (SMS), commonly referred to as text messaging. Given the availability and relative simplicity of SMS, it is another platform that can be used for monitoring with underserved populations. To our knowledge, no behavior-analytic researchers have utilized SMS as an assessment tool, but professionals in other fields have used it to measure individuals' self-reported behavior patterns, thoughts, and feelings. Of course, an inherent limitation to indirect measures is their questionable validity and reliability. Some believe, however, that recent advancements in sampling methods may improve data integrity (e.g., Smyth & Stone, 2003).

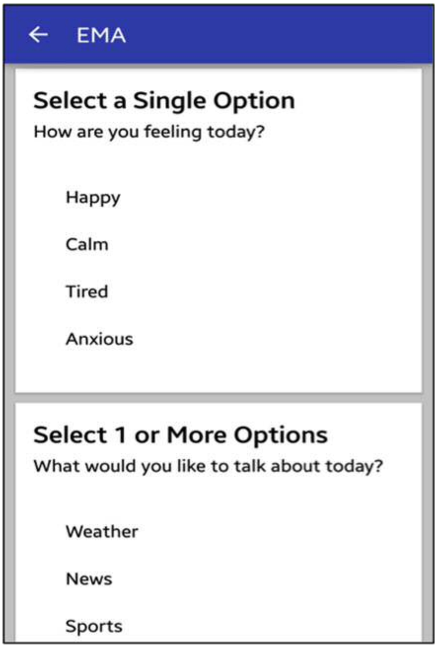

Figure 5. The PiLR EMA app used to conduct ecological momentary assessments.

Ecological momentary assessment (EMA; sometimes called, "ambulatory assessment") has gained popularity in many areas of psychology and health. EMA involves repeated sampling of participants' verbal reports in real-time, typically within the naturalistic contexts of their everyday lives, and can be used for monitoring across treatment conditions (Trull & Ebner-Priemer, 2009). Several smartphone EMA applications are currently available (see Figure 5 for the PiLR EMA app, MEI Research, Ltd, 2017; also see Dallery et al., 2015 for other examples), but EMA can also be employed through SMS. For example, one group of researchers asked children to send weekly text messages with information about the duration of their physical activity, frequency of healthy eating, and general emotional state as part of a self-monitoring intervention to maintain reductions in body-mass index (Bauer, de Niet, Timman, & Kordy, 2010). In another study, researchers employed daily text message self-monitoring to assess participants' reported consumption of sugar-sweetened beverages and time spent viewing electronic screens (Shapiro et al., 2008).

MMS and SMS are viable low-tech options for monitoring the health behavior of most populations; however, some individuals do not even have access to a mobile phone. In America, for example, 22% of adults ages 65 and older report not owning a cell phone (Anderson, 2015). For these populations, landline phone monitoring may be a solution. Commonly geared towards senior citizens, numerous phone calling services are available at low, or even no, cost (e.g., Caring.com, 2016). Calling services send automated phone calls to a recipient at regularly scheduled times as a method of checking-in on their current health status. If the primary recipient does not answer their phone, the service will first notify backup recipients, such as family members. If those members cannot be reached, local emergency services are usually alerted. Although these types of landline phone calling services are primarily used to detect severe health concerns, they can serve as a critical aid for monitoring individuals who are at home alone and for whom certain health behavior problems may result in emergency situations.

Low-Tech Intervention Delivery

Many of the low-tech tools that can be used for health behavior monitoring can also be used to deliver health behavior interventions. For example, in the Hoffman et al. (2010) study, researchers sent participants videos through MMS that included TB prevention strategies, testimonials from others who had recovered from TB, and general advice from physicians. In another study, aimed at young Maori (the indigenous population of New Zealand) who smoked cigarettes researchers sent participants video messages which included testimonials and coping strategies from ex-smokers (Whittaker et al., 2011). The control group in the study also received video messages with general health information and reminders. Although the researchers ultimately found no difference in smoking abstinence between intervention and control groups, most participants reported that they liked the video messages.

SMS has also been used as part of antecedent-based interventions to promote a variety of health-related behavior, such as treatment adherence. In a recent behavior-analytic study, researchers sent customized text message reminders to adults with type 2 diabetes as part of a contingency management intervention to increase compliance with antidiabetic medication schedules (Raiff, Jarvis, & Dallery, 2016). Medication use was monitored through electronic pill bottle dispensers and the system automatically messaged participants' cell phones if they had not opened the dispenser during a pre-determined interval of time. On average, participants improved from taking 56.1% of their medication doses correctly during baseline to 93.5% of doses following treatment. In the Alessi & Petry (2013)study mentioned previously, researchers sent text messages reminding participants to submit the video recordings of their alcohol breath tests. These messages also included an amount of monetary compensation that could be earned if a valid video was submitted and, for the contingency management group, an amount that could be earned if alcohol test results were negative. Prompts also have been delivered through SMS to promote insulin injections in participants with type 1 diabetes (Louch, Dalkin, Bodansky, & Conner, 2013)to remind hospital clinic outpatients about upcoming appointments (Downer, Meara, & Da Costa, 2005), to increase retention rates in long-term maintenance programs for overweight individuals (de Niet et al., 2012), and more.

In addition to promoting treatment compliance, researchers have used SMS to deliver entire health interventions (see Lindhiem, Bennett, Rosen, & Silk, 2015 for a meta-analysis and Fjeldsoe, Marshall, & Miller, 2009 for a review). For example, as an intervention for participants that reported a readiness to quit smoking, researchers sent text messages with coping strategies and tips for mitigating side effects, such as weight gain, prior to scheduled quit dates (Free et al., 2011). In a similar intervention aimed at young adult smokers, researchers sent text messages with coping strategies and information about common difficulties associated with smoking cessation prior to quit dates (Ybarra, Holtrop, Prescott, Rahbar, & Strong, 2013). A unique aspect of this intervention was that it also included a "text buddy" component, where participants at similar stages of quitting could anonymously message each either for social support.

The diversity of populations targeted across these studies signals that low-tech interventions may be readily extended to patients worldwide, even to those who may be underserved. Some advocacy groups are now also implementing programs to help increase health literacy and provide critical resources to patients in need. One example is the "Text4baby" program, originally developed for Latino populations, which sends weekly health information to pregnant women and mothers of infants, at no charge (Voxiva Inc. and ZERO TO THREE, 2015; National Healthy Mothers, Healthy Babies Coalition, 2013). Although registration for these programs sometimes may require Internet access, they often can be initiated by a caretaker or a healthcare provider without the recipient present.

Moreover, antecedent-based interventions are not the only type that can be implemented via low-tech platforms. Thanks to the advancements in technology-based monitoring, contingent feedback can be easily, even automatically, delivered via SMS. For example, in the Raiff et al. (2016) study, confirmation was sent to participants' phones when they opened the electronic pill bottle dispensers. SMS monitoring programs also have been used to deliver feedback, contingent on the content of the text messages sent by participants. In the smoking cessation studies by Ybarra et al. (2013), Free et al. (2011), and Whittaker et al. (2011), feedback was automatically delivered anytime a participant sent a word such as, "CRAVE." In the study by de Niet et al. (2012), participants created their own messages, and the program analyzed them before suggesting feedback from a pool of pre-established statements. The program used by Shaprio et al. (2008) also delivered automated SMS feedback, generated through an algorithm that analyzed participants' current response regarding goal achievement in relation to their previous responses. Additionally, researchers have relayed content regarding treatment consequences as part of SMS interventions. In Alessi and Petry (2013), for example, after researchers reviewed the video submissions, information about the amount of participants' monetary earnings was sent to their phone via SMS. The review by Kurti et al. (2016) also includes other incentive-based reinforcement interventions delivered through SMS.

For the small minority of patients who do not own a cell phone, landline phone calls may also be a potential way to transmit health-related information and implement interventions. Numerous companies provide automated calling services with pre-determined messages, and many are available at low a cost (e.g., "Dial Them Up", http://dialthemup.com; "Reminder Calls", http://www.reminder-calls.com; "Reminder Guru", https://reminderguru.com). These services can be used to send prompts regarding patients' medical appointments, medications, or any other type of health-related activity. Theoretically, they might also be used to provide feedback; however, other aspects such as monitoring procedures would need to be considered.

Technology-Based Behavior-Analytic Treatment for Health Behavior

Researchers have used high-tech and low-tech technologies to monitor and promote health behavior. The next step is for behavior-analytic clinicians to begin integrating these tools into their service-delivery models and expanding their practices to the treatment of health behavior. A recent Treatment Improvement Protocol (TIP), published by The Substance Abuse and Mental Health Services Administration (SAMHSA), addressed guiding principles and procedures for technology-based intervention in behavioral healthcare (SAMHSA, 2015). The TIP emphasizes clinical judgment, and not the mere existence of a given technology, in deciding whether technology should be employed in any particular case. Practitioners and clients should carefully consider goals, risks, benefits, electronic literacy, confidentiality, and alternatives to technology-based interventions. Suler (2001) identified some key questions to ask when considering clients for technology-based care. We also recommend assessing each client's "technology proficiency" to determine whether assistance or modifications are needed (see Boot et al., 2015 for an example of a computer proficiency questionnaire). In addition to access considerations regarding high- and low-tech platforms, clinicians should also consider whether a program should be enlisted as a "clinician extender," (i.e., viewed as a way to enhance or monitor ongoing in-person therapeutic processes) or as standalone treatment packages (e.g., ACT for smoking cessation, Bricker et al. 2013).

In addition to assessing an end user's proficiencies and preferences with respect to technology, practitioners must comprehensively assess the necessary treatment components that should be implemented in a particular case. For example, various technological tools can provide education, goal setting, prompts, feedback, social support, and/or monitoring. Although some of these tools may be aligned with behavior-analytic science and method, some may require explicit restructuring via practitioner guidance. For example, for behavior that occurs infrequently or not at all, scheduling gradual shaping steps along with feedback may be necessary (Kurti & Dallery, 2013). In addition, the practitioner should consider motivating operations and reinforcement contingencies, not only for meeting treatment goals, but also for simply engaging with the technology. These could include monetary incentives, contingency contracts, peer-based social encouragement or feedback (Dallery et al., 2013; Mohr et al., 2014). Furthermore, a hallmark of behavior-analytic treatment is individualized assessment of the variables that maintain problem behavior, which in the present case means unhealthy behavior patterns. For example, a clinician could assess potential reinforcers for sedentary behavior (e.g., access to video games), and treatment may involve removal or attenuation of such access. Unfortunately, to our knowledge, we know of no reliable and valid structured assessment instruments to perform such assessment in the technology realm. It is possible that, for example, EMA-based protocols could be developed to provide valid information to guide treatment, but such work remains to be done (see Dallery et al., 2013 for more discussion).

In addition, practitioners should determine the general categories of health behavior for which they will provide technology-based services. Mohr et al. (2014) provided a useful system, the "Behavioral Intervention Technology Model," to facilitate decision making in the context of health interventions. Health related goals might be weight reduction, sleep hygiene, medication adherence, increasing physical activity, or promoting smoking cessation. The decision about goals likely will be based on several factors related to the clinician, including their professional training and experience, familiarity with the relevant research literature, and available resources. There also may be areas of need for which practicing behavior analysts do not possess the necessary skills, qualifications, and/or resources. In such cases, clinicians will need to gain the requisite competency by consulting or collaborating with professionals in related fields, such as nutritionists, exercise physiologists, medical doctors, or information technology specialists. Additionally, it could be advantageous for behavior analysts to become members of organizations or clinical teams that already provide health-related services, particularly if they are interested in receiving further training. Developing competence in technology-based intervention delivery is an ongoing process. SAMHSA (2015) provided guidance about requisite knowledge and skills to engage with clients via technology, such as being able to answer clients' questions about the technology, security risks, and troubleshoot technological problems.

Finally, clinicians must formulate policies and procedures about confidentiality, privacy, and security. There are a number of special considerations that arise, regarding protecting clients' privileged information (confidentiality), protecting clients' rights to control access to their electronic information (privacy), and protecting electronic data from being accessed without authorization (security). A number of resources can be found on the HealthIT.gov website (http://www.healthit.gov/providers-professionals/your-mobile-device-and-health-information-privacy-and-security), which is operated by the Office of the National Coordinator (ONC) for Health Information Technology. Although some of these resources will be specific to the United States, they also have applicability to services provided in other countries. We also recommend the TIP for additional recommendations regarding confidentiality, privacy, and security (SAMHSA, 2015).

Conclusion

Although behavior analysts will likely face challenges during the initial stages of implementing technology-based interventions, the promise of these tools is that they could be accessible to anyone, regardless of geographic or socioeconomic barriers. Technological tools provide unprecedented ways to improve a range of socially significant behavior. Uptake of these tools, however, will depend on whether behavior analysts change their behavior in response to advances in technology-based intervention. Using these new tools will depend on a number of variables, and especially the reinforcers. Reinforcers might include collaborating with experts in allied disciplines, solving new scientific problems, and, most fundamentally, reducing the behavioral causes of death, disease, and suffering.

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