REVISTA MEXICANA DE ANÁLISIS DE LA CONDUCTA 2014 NÚMERO 2 (SEPTIEMBRE)
MEXICAN JOURNAL OF BEHAVIOR ANALYSIS VOL. 40, 106-126 NUMBER 2 (SEPTEMBER)

INTEGRATING TECHNOLOGICAL ADVANCEMENTS IN BEHAVIORAL INTERVENTIONS TO PROMOTE HEALTH: UNPRECEDENTED OPPORTUNITIES FOR BEHAVIOR ANALYSTS

LA INTEGRACIÓN DE LOS AVANCES TECNOLÓGICOS EN INTERVENCIONES CONDUCTUALES PARA PROMOVER LA SALUD: OPORTUNIDADES SIN PRECEDENTES PARA LOS ANALISTAS DE LA CONDUCTA

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Abstract

The use of mobile devices is growing worldwide in both industrialized and developing nations. Alongside the worldwide penetration of web-enabled devices, the leading causes of morbidity and mortality are increasingly modifiable lifestyle factors (e.g., improving one's diet and exercising more). Behavior analysts have the opportunity to promote health by combining effective behavioral methods with technological advancements. The objectives of this paper are (1) to highlight the public health gains that may be achieved by integrating technology with a behavior analytic approach to developing interventions, and (2) to review some of the currently, under-examined issues related to merging technology and behavior analysis (enhancing sustainability,

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I would like to acknowledge all of the members of Dr. Jesse's Dallery's behavioral pharmacology laboratory (Brantley Jarvis, Sarah Martner, Vanessa Minervini, Philip Erb, Triton Ong, and David Cox) for the various insightful discussions that we had during lab meetings about the topics addressed in this paper. Address correspondence to Allison Kurti, Vermont Center on Behavior and Health, University of Vermont College of Medicine, 1 S. Prospect St., Burlington, VT 05401, USA. E-mail: akurti@uvm.edu

obtaining frequent measures of behavior, conducting component analyses, evaluating cost-effectiveness, incorporating behavior analysis in the creation of consumer-based applications, and reducing health disparities). Thorough consideration of these issues may inspire the development, implementation, and dissemination of innovative, efficacious interventions that substantially improve global public health.

Keywords: behavior analysis, contingency management, health behavior, mHealth, technology

Resumen

El uso de dispositivos móviles está en aumento en todo el mundo tanto en naciones industrializadas como en desarrollo. Junto con la penetración en todo el mundo de dispositivos habilitados para internet, las principales causas de morbilidad y mortalidad son factores relacionados con el estilo de vida cada vez más modificables (e.g., mejorar la dieta propia y ejercitarse más). Los analistas de la conducta tienen la oportunidad de promover la salud mediante la combinación de métodos conductuales efectivos con los avances tecnológicos. Los objetivos de este artículo son (1) resaltar las mejoras a la salud pública que pueden lograrse integrando tecnología con aproximaciones conductuales para desarrollar intervenciones, y (2) revisar algunos de los actuales, y poco examinados, problemas relacionados con fusionar la tecnología y el análisis de la conducta (aumentar la sustentabilidad, obtener mediciones frecuentes de la conducta, realizar análisis de componentes, evaluar la relación costo-efecto, incorporar el análisis de la conducta en la creación de aplicaciones basadas en el consumidor, y reducir la inequidad en términos de salud). Considerar estos aspectos puede inspirar el desarrollo, implementación y diseminación de intervenciones innovadoras y eficaces que mejoren sustancialmente la salud pública global.

Palabras clave: análisis de la conducta, arreglo de contingencias, conducta saludable, mHealth, tecnología

The leading causes of morbidity and mortality in both industrialized and developing countries are increasingly modifiable lifestyle factors (e.g., eating healthier, meeting physical activity requirements; Anderson & Frogner, 2008). In their estimation of deaths and loss of healthy life years in Mexico, for example, Stevens et al. (2008) reported that high body mass index (BMI), high blood glucose, and alcohol use were the leading risk factors for disease burden. These risk factors, in turn, contribute to the leading causes of death in Mexico, which include heart disease, diabetes, and liver cirrhosis. Paradoxically, the situation is not necessarily better in wealthier countries. Some suggest, for example, that "the United States [has] the most lives to gain compared to…other industrialized countries by treating preventable diseases with timely and efficient health care" (Nolte & Mckee, 2008). Although seemingly disheartening, this reality also represents an opportunity for behavior analysts to make a large impact on public health.

Behavior analysts can impact health behavior through the development and implementation of technology-based interventions. Technological innovations that enable the assessment and promotion of health include mobile devices, wearable sensors, biomarker detectors, and real-time access to therapeutic interventions via information technology (see Dallery, Kurti, & Erb, 2014 for a review). The potential of such technology lies in its ability to permit "hovering" (i.e., real-time monitoring) of patients' behavior during the everyday activities during which choices about health are typically made (Asch, Muller, & Volpp, 2012). Using technology to monitor these choices and deliver positive consequences contingent on healthy choices provides an important opportunity to reduce premature deaths whose causes are widely understood to be preventable (Shroeder 2007, p. 1222).

A behavior analytic approach to health holds that health behaviors are operant (i.e., voluntary behaviors that are determined primarily by their consequences). For example, smoking a cigarette or skipping a workout offer positive consequences in the short term (e.g., a euphoric buzz, avoiding exercise-induced discomfort), but can be harmful if such patterns persist long-term. In contrast, abstaining from smoking and exercising regularly may have punishing consequences in the short term (e.g., withdrawal symptoms, muscle soreness), but offer benefits (e.g., better health) in the future. Because unhealthy behaviors offer positive consequences that are available immediately, whereas healthy behaviors entail a delay before positive consequences are experienced, individuals are more likely to smoke and watch television in favor of abstaining and going for a run.

An operant view of health behavior has inspired the development of contingency management (CM) interventions to promote healthier behavior. Petry's (2000) guide to implementing CM in clinical settings identifies the necessary components of CM interventions, which include (1) arranging the environment such that objective verification of some target behavior is possible (e.g., drug abstinence, clinic attendance, medication compliance), (2) providing tangible reinforcers (e.g., vouchers exchangeable for goods or services) contingent on participant's emitting the target behavior, and (3) withholding reinforcers in the absence of the target behavior. Because any intervention in which reinforcers are delivered contingent on objective verification of some target could be characterized as CM, CM interventions are used in domains other than health (e.g., management practices that emphasize positive reinforcement in order to change organizational behavior; Daniels & Daniels, 2004). Aside from acknowledging this, however, we will restrict our focus in this paper to health-based CM interventions. CM has shown great versatility and efficacy in promoting many health behaviors, including smoking cessation (Dallery et al., 2007; Dallery et al., 2008; Dallery, Raiff, & Grabinski, 2013; Hertzverg et al., 2013), medication adherence (Rigsby et al., 2000; Sorensen et al., 2007), alcohol abstinence (Barnett et al., 2011), and physical activity (Donlin Washington et al., 2014; Kurti & Dallery, 2013; Van Camp & Hayes, 2012).

It may be useful to briefly describe the procedures used in one of the above interventions in which technology was used as the medium for delivering the intervention.

The target behavior in Dallery et al.'s (2013) randomized controlled trial was smoking abstinence. Objective verification of abstinence was defined as expired breath carbon monoxide ≤ 4 parts per million (ppm). To demonstrate their smoking status, participants used a web camera to record themselves blowing into a breath CO meter two times each day. These videos were submitted to researchers over a secure server and participants in the treatment condition received vouchers for samples that met the abstinence criterion. Participants in the control condition earned vouchers of equal value to treatment participants but vouchers were delivered contingent on submitting breath CO samples rather than smoking status. Results indicated that participants in the treatment condition submitted significantly more negative samples during the duration of the intervention (66.7%) than participants in the control condition (25%).

Kurti and Dallery (2013) used similar methods in their internet-based CM intervention to increase physical activity. In this study, participants used a web camera to display the total number of steps displayed on an accelerometer (Fitbit®) at the end of each day, and vouchers were provided for meeting specific step goals on at least three days during consecutive five-day blocks. All six participants increased steps in a way that tracked the experimenter-arranged changes in step goals, and five of six participants reached the terminal goal of 10,000 steps per day across two consecutive five-day blocks. Participant's average increase in steps over the course of the intervention was 182%. In addition, a treatment acceptability questionnaire indicated that participants found the internet-based program easy to use, convenient, and effective at helping them increase their physical activity levels.

The above examples illustrate a key component of CM interventions. Specifically, because consequences in CM are delivered contingent on behavior, the procedure requires a system to facilitate frequent monitoring of behavior. For example, providing financial incentives contingent on urine-negative toxicology test results requires that there are personnel and transportation options in place for collecting participants' urine samples frequently (e.g., twice weekly to evaluate nicotine metabolites; Higgins et al., 2004). Consequently, in-person CM interventions may be limited to participants who have transportation to treatment centers and/or researchers with adequate time and resources to visit participants at their homes. This limitation makes it difficult to reach the most high-risk, under-served people among whom rates of unhealthy behaviors (e.g., cigarette smoking, sedentary lifestyles) are highest (e.g., Everson, Maty, Lynch, & Kaplan, 2002; Gordon-Larsen, Nelson, Page, & Popkin, 2006). Encouragingly, these high-risk groups increasingly have access to access to technology, and technology-based CM is emerging as a way to surmount geographic and socioeconomic barriers to treatment delivery (e.g., smoking cessation among rural Americans; Stoops et al., 2009; smoking cessation among individuals with post-traumatic stress disorder, [PTSD]; Hertzberg et al., 2013).

Aside from reaching high-risk, under-served populations, merging a behavior analytic approach to health with technology offers numerous other advantages. These possibilities are reviewed extensively in Dallery et al. (2014), in which technology is

discussed as a tool for detecting endogenous (e.g., stress) and exogenous (e.g., presence of other people) antecedents to health behavior, detecting discrete instances of health behavior (e.g., medication taking), delivering a diverse array of reinforcing consequences (e.g., financial incentives, social praise, video-game access), and facilitating the use of research designs that focus on changing an individual's behavior over time (e.g., single-case designs; Dallery, Cassidy, & Raiff, 2013; Dallery & Raiff, 2014). Because the potential of merging behavior analysis and technological advancements is reviewed at length in Dallery et al. (2014), the present paper is intended primarily to discuss seven currently under-examined issues related to integrating technology and a behavior analytic approach to health.

The issues that will be explored in the present article include: (1) using technology to enhance the sustainability of health-based behavioral interventions, (2) advantages offered by technology in terms of obtaining frequent, objective measures of behavior, (3) using technology to identify the influence of individual treatment components that comprise a treatment package, (4) the cost-effectiveness of technology-based interventions, (5) incorporating behavior analysis in the creation of consumer-based applications (i.e., "apps"), (6) the capacity for technology to reduce health disparities and the related decline in the degree to which socioeconomic barriers limit some peoples' access to technology (i.e., the closing of the "digital divide"), and (7) the reasons that technology may be integral to the success of behavior analysts interested in improving human health. We envision that adequate consideration of these issues will inspire the development of innovative, efficacious, technology-based health interventions that are grounded in a theoretical framework from which some of the most effective approaches to behavior modification have already been derived.

Enhancing Sustainability and Maintaining Treatment Gains

Although CM has been established as an effective approach to promoting behavior change, the extent to which new behavior endures over extended durations remains a challenge. That is, participants who successfully quit smoking, increase exercise, or adhere to a medication regimen when the CM treatment is in place often revert to pre-intervention rates of behavior when the treatment is withdrawn (Petry, 2010). The difficulties inherent in maintaining behavior change suggest that perhaps enduring change will require enduring interventions. Sustainability refers to delivering CM interventions for extended durations.

Recognizing that treatment must be sustained for long durations, researchers have developed various strategies to sustain CM in cost-effective ways (e.g., gradually fading out or "thinning" abstinent-contingent voucher delivery; Dallery et al., 2007, using variable or prize-based reinforcement schedules; Petry et al., 2005; Washingon, Banna, & Gibson, 2014). Similarly, Silverman and colleagues devised a sustainable model in which drug users earned access to a workplace contingent on providing drug-negative urine samples (DeFulio et al., 2009; Donlin Washington et al., 2008;

Silverman et al., 2005). Perhaps technology-based CM could be embedded in more sustainable platforms such as employment- or insurance-based reimbursement models (Madison, Volpp, & Halpern, 2013). For example, employers interested in increasing physical activity among their employees could use technology (e.g., an accelerometer) to perform automated hovering (e.g., passive, ongoing data collection that would occur while the employee engages in typical day-to-day activities), in addition to performing "automated nudging" in the form of reimbursements or other consequences contingent on objective verification of health behavior (e.g., health insurance premium adjustments for meeting some predetermined activity goal on several consecutive weeks).

As discussed in Dallery et al. (2014), maintenance of treatment gains may also be accomplished by shifting from the delivery of the contrived consequences typically associated with CM (e.g., vouchers) to more natural consequences (e.g., social reinforcers). For example, during and following CM, perhaps family, friends, or significant others could be enlisted to detect and reinforce health behaviors using technology-based systems (e.g., online social support forums; Meredith et al., 2011). Systems capable of performing these functions are already available in some cases. For example, the Fitbit® is a triaxial accelerometer that uploads automatically-generated data to an individual's computer or smartphone. The individual can then join various online communities, with which he or she can share and receive social praise for his or her physical activity data and earn "badges" or other consequences.

In addition to capitalizing on systems that are already in place to receive social reinforcers contingent on health behavior, another possibility would be to explicitly construct group-based incentive treatments. For example, Meredith et al. (2011) developed an internet-based CM intervention to reduce smoking in which vouchers could be earned contingent on the performance of four group members. Participants had access to graphical displays of their own progress and those of their teammates, as well as a social support forum where they could communicate with one another. This arrangement reduced smoking and participants reported that they liked having access to an online forum where they could correspond with and encourage their team members. Permitting ongoing access to online social support forums after contrived consequences (e.g., vouchers) are withdrawn may represent an opportunity to sustain treatment gains via continued access to more natural, social reinforcers.

Another method for enhancing sustainability may involve capitalizing on gamification platforms (Morford et al, 2014). For example, Raiff, Jarvis, & Rapoza (2012) proposed an internet-based CM intervention in which participants could earn access to videogames contingent on providing objective verification of smoking abstinence. Interventions involving contingent video-game access may be sustainable because they do not require additional financial commitments once the game-based platform is developed. Baranowski, Buday, Thompson, and Baranowski (2008) reviewed video game-based interventions targeting a range of health outcomes including diet, physical activity, and self-management skills for individuals with asthma and diabetes.

Overall, the interventions improved outcomes and the authors discussed factors that might enhance engagement such as the inclusion of a compelling story in the game. Thus, gamification may represent another means through which technology can enhance the sustainability of CM interventions.

Collecting Objective Measures of Behavior

A hallmark of behavior analytic treatments in general, and an integral component of CM interventions specifically, is obtaining objective measures of target behaviors (Crowley-Koch & Van Houten, 2013). With respect to CM, these measures may be discrete instances of behavior (e.g., taking a medication) or byproducts of behavior (e.g., expired breath carbon monoxide or nicotine metabolites in urine) on which reinforcement is contingent. Consequently, tools that permit the frequent collection of these measures and protect their integrity are critical, and technology offers major advantages in this area.

There are several currently available technologies that can detect the occurrence of specific health behaviors. For example, medication event monitoring systems (MEMS) are pill bottles or containers fitted with microcircuitry that provide time stamps every time the container is opened or closed. These data are then transmitted to research or medical personnel, who can track and provide consequences (e.g., monetary incentives, social praise) for medication adherence. MEMS have been used to assess adherence to numerous medication regimens, including highly active antiretroviral therapy (HAART; Krummenacher et al., 2011), analgesics (Oldenmenger et al., 2007), and antipsychotics (Acosta et al., 2009). Although one limitation of MEMS is that pill ingestion per se cannot be verified, technologies are emerging that can accomplish this function (e.g., digital pills that produce a voltage during digestion and communicate this information to external sensors; Bosworth, 2012; Zullig et al., in press). In addition to medication taking, physical activity can also be monitored remotely with sensors by measuring changes in velocity over time (i.e., acceleration; Intille et al., 2010; King et al., 2013). For example, King et al. (2013) capitalized on the smartphone's built-in accelerometer to monitor and provide incentives for physical activity, therein increasing physical activity among a sample of sedentary adults.

In addition to permitting objective measures of discrete instances of behavior, technology also offers advantages in terms of detecting the byproducts of behavior (i.e., biomarkers). For example, Meredith et al. (2013) developed a prototype of a mobile phone-based breath CO meter to detect smoking status. Similarly, emerging alcohol sensors (e.g., the Secure Continuous Remote Alcohol Monitoring [SCRAM, Alcohol Monitoring Systems 2013] bracelet) detects alcohol ingestion via sensors that measure alcohol excreted in sweat (Swift, 2003).

Although technology offers many advantages with respect to collecting objective measures of health behaviors, using technology for this purpose raises some privacy and confidentiality concerns. For example, common threats to data security and par-

ticipants' privacy involve unauthorized access or loss of the mobile device (Luxton et al., 2011). One first line of defense in this case is simply to use the smartphone's built-in password protection feature. In addition, third party encryption apps such as *Lookout Mobile Security* (Lookout, 2011) can help secure data that is stored and transmitted via smartphone.

Risks to participant confidentiality are also posed by the app software used on smartphones, as many of these apps gather and send information about an individual's age, gender, location and other personal information to software developers (Thurm & Kane, 2010). Researchers should explain to their participants specifically what information is collected by a particular app, how the information is used, and the benefits and risks associated with using their smartphone in a health-based behavioral intervention.

For specific information regarding the Health Insurance Portability and Accountability Act (HIPAA) requirements for psychologists, we recommend that readers consult the American Psychological Association (APA) Practice Central cite (http://www.apapracticecentral.org/). The Ethical Principles of Psychologists and Code of Conduct also provide relevant information with respect to client privacy and confidentiality. As technology-based monitoring of health behavior continues to grow, it will be vital to establish proven safeguards against breaches of privacy and confidentiality of participant's health behavior data.

Identifying the Effectiveness of Individual Treatment Components

Although the effectiveness of CM interventions is often attributed to the financial incentives that participants earn, most CM interventions are actually treatment packages, and the extent to which other components contribute to their efficacy are unclear. For example, Meredith et al.'s (2011) group-based smoking cessation intervention involved incentives as well as feedback from several different sources (e.g., experimenter, other group members, graphical progress displays, expired CO levels). The extent to which these sources of feedback contributed to treatment efficacy is unclear. However, evidence from other research hints that components other than financial incentives may contribute to treatment efficacy. For example, Kurti and Dallery (2013) reported little difference in treatment efficacy in an internet-based exercise intervention between treatments that involved (a) experimenter feedback, graphical progress displays, activity goals and financial incentives versus (b) all of the former treatment components minus financial incentives. Specifically, six of six participants who received the former treatment (and five of six participants who received the latter treatment) demonstrated increases in steps that tracked experimenter-arranged changes in step goals, thus the intervention was efficacious even without financial incentives for meeting step goals.

Component analyses can be conducted to reveal the extent to which individual treatment components contribute to treatment efficacy (Dallery, Riley, Nahum-Shani,

in press; Ward-Horner & Sturmey, 2010). Although these remain under-utilized in both in-person and technology-delivered CM interventions, technology may enhance the feasibility of conducting component analyses. That technology permits ongoing access to data on participants' health behavior lends itself to making sequential changes to consequences based on an individual participant's characteristics or response to treatment. For example, Kurti and Dallery could be replicated using a component analysis methodology, in which the various treatment components were introduced sequentially (e.g., self-monitoring activity, self-monitoring + physical activity goals, self-monitoring + goals + incentives) as opposed to simultaneously. Technology-based monitoring of behavior change would then permit researchers to evaluate whether behavior change coincided with the introduction of a new component.

In addition to using technology to conduct component analyses, data that emerges from these analyses (i.e. data indicating which treatment ingredients are therapeutic) could be used to tailor health-based behavior interventions. These tailored interventions could then be delivered using novel research methods that embrace individual differences in ways that the standard, randomized controlled trial (RCT) design does not. For example, sequential multiple assignment randomized trial (SMART) designs allow for adaptive interventions, in which treatment is altered based on ongoing evaluation of the individual's response (Collins et al., 2005, 2007). Derived from engineering, SMART designs entail a series of decision rules about when and how to modify the intervention. By lending themselves to treatment modifications based on an individual participant's behavior, it is feasible that SMART designs may produce more treatment responders than the "one size fits all" approach inherent in RCT's.

Evaluating Cost-effectiveness

Whether technology-based heath behavior interventions are cost-effective remains understudied, and no study to date has assessed the cost-effectiveness of technology-based CM interventions specifically. Although the cost of financial incentives has historically been identified as a barrier to dissemination (Petry & Simcic, 2002), research in the substance use domain suggests that in-person is cost-effective (Olmstead et al., 2007a, b; Sindlelar et al., 2007). For example, Olmstead et al. (2007b) estimated incremental cost-effectiveness ratios (i.e., cost per longest duration of stimulant abstinence) among individuals enrolled in an outpatient financial incentives treatment, as opposed to the cost of treatment as usual. Although the incentives group had both longer abstinence durations and higher costs (i.e., the incremental cost to lengthen the longest duration of abstinence by one week was $258), this number should be interpreted in light of the societal costs of drug use that may be offset by an effective treatment. For example, Olmstead et al. (2007b) suggested that extending the longest abstinence duration by one week would reduce the probability of a single robbery by .7% and reduce the probability of a single theft by 21%. In this case, CM would achieve savings in avoided crime costs that would be 90%

likely to outweigh its incremental costs, thus CM would be cost-effective in terms of minimizing future costs to society.

Like Olmstead et al. (2007a; 2007b), Sindlelar et al. (2007) also estimated the incremental costs associated with one-week increases in the longest duration of stimulant abstinence. In addition to CM, participants in this work also underwent methadone maintenance therapy in the context of a multi-site clinical trial. Compared to a usual care condition, the incremental cost of using CM to extend participants' longest duration of abstinence by one week was $141, and the incremental cost to obtain an additional stimulant-negative urine sample was $70. As with Olmstead et al.'s (2007a; 2007b) work, however, these costs are expected to offset the long-term societal costs of continued drug use. Sindlelar et al. (2007) estimated that substantial savings might result over time given that promoting abstinence would presumably contribute to reductions in crime, spread of contagious disease, and reliance on welfare.

It will be important for developers of technology-based CM interventions to conduct analyses similar to those above to determine whether these interventions are cost-effective as well. It is feasible that technology-based CM will be even more cost-effective than in-person CM given its ability to reduce transportation costs and personnel associated with traditional CM interventions. Assuming that technology-based CM proves to be cost effective, it will be interesting to see whether those technology-based CM interventions that deliver non-monetary reinforcers (e.g., social praise, gamification platforms) are even more cost-effective than those involving financial incentives. If so, then perhaps the notion that implementation costs represent a substantial limitation of CM will vanish as a criticism of this treatment.

Integrating Behavior Analysis and Consumer-based Apps

Thus far, we have focused on merging a behavior analytic approach to health with technological advancements. However, a vast number of consumer-based apps already exist that also attempt to promote behavior change. Thus, it is worthwhile to distinguish these consumer-based apps (i.e., apps developed by third parties that are available to the general public but not necessarily grounded in empirically supported principles of behavior or reflective of public health recommendations) from science-based apps (i.e., those that rely on empirically supported techniques for promoting behavior change or adhere to public health recommendations with respect to the behavior in question). Although the two are not necessarily mutually exclusive (e.g., a behavioral scientist could design a science-based app), the ease with which third parties can develop and make their apps widely available, combined with a lack of oversight, have contributed to the development of many apps that are not science-based. Although this does not necessitate that they are ineffective, it is worthwhile to consider some benefits that may result from integrating behavior analysis in the development of consumer-based health apps.

There are now over one million mobile applications or "apps" for smartphones in both Google Play and the iTunes app store alike (Perez, 2014) and more than 8,000 of these are health-related (Dolan, 2010). Among the 8,000 health apps, more than 200 are specifically associated with behavioral health and cover topics such as anxiety, depression, smoking, alcohol use, diet, exercise and sleep. For example, *Cessation Nation* informs smokers about the immediate and delayed rewards associated with abstinence, and offers users a distracting game to play when they are experiencing cravings. Because consumer-based health apps can be easily accessed by any smartphone owner, they can reach more people than most science-based apps. On account of being widely available and easily accessible, these apps may have greater potential to improve public health.

One way to scale up science-based tools is to partner with industry, such that science-based apps can be disseminated more quickly and more widely. Another option is to make training in CM procedures more accessible to community-based clinicians (Carroll, 2014), as these individuals are capable of implementing CM given adequate support by clinical leadership and access to resources. Perhaps technology-delivered training programs could be developed to disseminate training materials to community providers. Encouragingly, some steps in this direction have already been initiated. For example, training materials intended to facilitate the implementation of CM in community-based and clinical settings have been developed by the National Institute of Drug Abuse (NIDA) Clinical Trials Network in partnership with the Substance Abuse and Mental Health Services Administration (SAMHSA). These materials can be downloaded at http://www.bettertxoutcomes.org/bettertxoutcomes/. By making efficacious, science-based tools increasingly available to the general public, behavior analysts stand poised to contribute substantially to improving health behavior.

The sheer number of consumer-based apps raises important concerns about quality control (Tomlinson, Rotheram-Borus, Swartz, & Tsai, 2013). With respect to smoking, Abroms et al. (2013) reported that many apps did not adhere to the U.S. Public Health Service's 2008 Clinical Practice Guidelines for Treating Tobacco Use and Dependence (Fiore, 2008). Given the lack of oversight, it is important for researchers or clinicians who use behavioral health apps to be aware of the evidence base for the particular apps in question. Additionally, Luxton et al. (2011) recommend seeking information about the app's developer, which may reveal information about the app's quality. For example, an app called *PTSD Coach* (Department of Veterans Affairs, 2011) was developed by the Veteran's Administration's National Center for Telehealth and Technology in the U.S., which should increase user confidence about the app's accuracy and adherence to established treatment guidelines.

As reviewed in Dallery et al. (2014), behavior analytic principles and procedures should be incorporated into health applications. Behavior analysts interested in developing these applications could proceed much like those who have developed technology-based CM interventions (i.e., by relying on behavior analytic research regarding effects of variables such as reinforcer delay, magnitude, response effort, and

the schedule of reinforcement on operant behavior). The MILES (Mobile Interventions for Lifestyle Exercise at Stanford) project exemplifies how behavioral scientists may initiate the process of collaborating with other scientists and designers to develop health applications (Heckler et al., 2011). This project was initiated in response to the lack of theoretically driven smartphone applications to promote increased physical activity, and the group comprises behavioral and computer scientists, product designers, exercise physiologists and physicians.

Knowledge of the basic principles and procedures of operant behavior will increase the likelihood that the parameters chosen for heath applications generate good outcomes. Because selecting incorrect procedures may lead to an ineffective product, behavior analysts who are trained in operant procedures like CM can and should play a critical role in developing, implementing, and evaluating novel technology-based interventions.

Transcending Barriers to Treatment Delivery

Among the most exciting possibilities likely to result from behavior analysts capitalizing on technology to deliver health-based behavior interventions is the potential to reach populations that have historically been labeled as hard-to-reach or difficult-to-treat. For example, it has been difficult to circumvent geographic and personnel restrictions associated with reaching rural-dwelling individuals, minorities, and individuals of low socioeconomic status. However, because these individuals exhibit disproportionately high rates of risky health behaviors (e.g., Everson et al., 2002; Gordon-Larsen et al., 2006), methods for transcending barriers to treatment delivery are critical to improving the health of these high-risk, under-served populations.

Technology has potential as a treatment delivery platform that permits researchers to treat hard-to-reach populations. In the past decade, the mobile telephone industry has exhibited an impressive growth throughout the world, with developing countries expanding even faster than high-income countries (Bastawrous & Armstrong, 2013; Gamboa & Otero, 2008). The growing use of various mobile devices (e.g., smartphones, tablets) in Mexico, for example, has led some government agencies to create mobile platforms to increase the interaction, participation and transparency between citizens and government entities via open information and social networks (Fuentes-Enriquez & Rojas-Romero, 2013). We see no reason that similar developments could not occur in the domain of healthcare. Alongside the growth of mobile cell phone use in developing countries, African American, Hispanic, and low-income families comprise the fastest growing groups of smartphone users in the United States (Zickuhr & Smith, 2012). Rural populations have also experienced a recent uptick in smartphone penetration (Smith, 2012). Between May 2011 and February 2012, the number of rural households owning smartphones increased 13%. It is for these reasons that some suggest that the digital divide no longer exists in most geographical areas. Moreover, as cell phones and data plans become increasingly inexpensive, the rate at which

disadvantaged populations begin using them may continue to increase. If so, smartphone-based health behavior interventions may also continue to grow.

At present, few technology-based interventions have been developed specifically for hard-to-reach populations. However, among those that have, the results are promising. For example, Stoops et al. (2009) developed an internet-based smoking cessation intervention that was feasible, efficacious, and well-liked among rural Appalachian smokers. Internet-based CM has also been shown to decrease smoking among adolescents (Reynolds et al., 2008). Similarly, Hertzberg et al. (2013) evaluated whether mobile CM was an effective adjunct to a combined treatment (counseling plus nicotine replacement and bupropion) among smokers with PTSD. Four-week cessation rates were 82% among individuals receiving mobile CM and 45% among individuals receiving all other treatment components plus non-contingent incentives that were yoked to the earnings of those in the contingent group.

In addition to the promising results yielded by technology-based CM interventions among hard-to-reach and difficult-to-treat populations, there is also emerging evidence that these populations are enthusiastic about participating in these interventions. For example, Kurti and Dallery (2014) reported that 75.9% of a rural Floridian sample endorsed various features of a smartphone-based CM intervention to increase physical activity as being at least somewhat helpful. Because previously hard-to-reach populations exhibit higher rates of unhealthy behavior, implementing technology-based interventions among these populations represents a major opportunity to improve their health.

Why Behavior Analysis and Technology Are an Ideal Fit

Integrating technology with behavior analytic health interventions has the potential to profoundly impact public health. Behavior analysis embraces real-time, longitudinal assessment of behavior in naturalistic settings. Because this emphasis requires them to obtain frequent measures of behavior, such assessment has historically been limited to a narrow range of populations and behavioral problems. With technology, the range of populations and behavior problems can be broadened substantially.

In alleviating the difficulties associated with obtaining frequent measures of behavior, technology-enabled assessment of health behavior also lends itself to using research designs that are preferred by behavior analysts. For example, using technology to assess health behavior in an ongoing fashion permits the use of single-case research designs. These designs are consistent with the behavior analyst's interest in monitoring and changing behavior over time, which is substantially more feasible using technology. Importantly, we should also emphasize that there is growing interest in the use of single-case designs to evaluate technology-based interventions (Lillie et al., 2011). For example, in 2011, the National Institutes of Health held an mHealth (mobile health) Evidence Workshop and single-case approaches were well-represented as viable designs to evaluate mHealth interventions (Kumar et al., 2011). The workshop included researchers from domestic and international institutions, policymakers, health profes-

sionals, technologists, and representatives from regulatory and funding agencies. Additionally, interest in research methods that embrace individual differences (e.g., SMART designs; Collins et al., 2005; 2007) is also growing. These trends are promising in that they provide a means not merely for delivering and evaluating the effectiveness of technology-based interventions, but also for disseminating useful methodological foundations for developing these interventions.

Although work remains in terms of capitalizing on technological advancements to develop and implement effective behavior-based health interventions, there are signs that researchers are beginning to recognize the promise that this merger holds in terms of improving health behavior. In our own work, we have used internet-based CM to reduce smoking (Dallery et al., 2007), increase exercise (Kurti & Dallery, 2013), and promote glucose monitoring among individuals with diabetes (Raiff & Dallery, 2010). Other research groups have also capitalized on technological advances in activity monitoring devices to increase physical activity (Donlin Washington et al., 2014; Van Camp & Hayes, 2012).

The potential, far-reaching consequences of combining technology with a behavior analytic theoretical framework are discussed by Twyman (2011), in which technological advances are described as a "cusp" for behavior analysis. Specifically, a behavioral cusp is defined as behavior change that brings an organism into contact with new contingencies that have yet further, far-reaching consequences (Rosales-Ruiz & Baer, 1997, p. 533). With respect to technology and behavior analysis, Twyman suggests that technology can produce new environment-behavior relations by arranging virtual communities and social media and/or by capitalizing on powerful observation, recording and feedback technologies. In the domain of health, this may result in people living in a world in which morbidity and mortality from preventable causes in greatly reduced. Importantly, there is evidence from other domains to suggest that this optimism is not unfounded. For example, the behavioral technology Headsprout® has increased the reading abilities of thousands of learners across the US and the world (Layng, Stikeleather, & Twyman, 2006). Behavior analytic technology holds similar promise in the realm of behavioral health care.

Conclusions

The leading causes of morbidity and mortality among most developed countries are due to modifiable lifestyle factors. Thus, substantial efforts must be made to prevent or reduce unhealthy behaviors before they result in chronic health conditions or death. Specifically, health behaviors must be modified before an individual develops a chronic condition, and behavior modification is a task that behavior analysts are best-equipped to tackle. Although not a simple task, modifying health behaviors will be enabled if behavior analysts use technological advancements to their advantage. Technology is uniquely suited to transcend geographic and socioeconomic barriers to treatment delivery, to enable frequent, ongoing assessments of behavior, and to de-

liver treatments in which effective consequences are provided immediately contingent on behavior change. Thus, there are exciting prospects ahead in terms of developing innovative, efficacious interventions that can be disseminated widely to substantially impact human health.

Although training in behavior analysis is not a prerequisite to developing technology-based health interventions, an operant approach to health behavior may be particularly conducive to developing effective interventions. For example, Kaplan and Stone (2013) suggested that many mobile health interventions have been unsuccessful because they lacked an empirical and theoretical framework grounded in behavioral science. Similarly, Riley et al. (2011) noted that interventions derived from theories that rely on dispositional constructs as sources of behavior change (e.g., self-efficacy) may not lend themselves as readily to modifying behavior as theories that directly suggest the manipulable, environmental consequences that promote unhealthy behavior. Because behavior analysts have expertise in identifying and modifying environmental contingencies, we are uniquely suited to integrate technology with our demonstrably effective approach to producing behavior change. The combination of a behavior analytic conceptualization of health behavior, technological advancements, and the simple notion that any individual with access to a mobile phone has a platform for treatment delivery at their fingertips gives rise to important opportunities to improve public health. Behavior analysts have already capitalized on technological advancements to deliver efficacious treatments among hard-to-reach populations. Hopefully, these achievements represent the tip of the iceberg.

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