Behavior-Analytic Approaches to the Management of Diabetes Mellitus: Current Status and Future Directions

Bethany R. Raiff¹ • Connor Burrows¹ • Matthew Dwyer¹

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Abstract

Diabetes mellitus is the seventh leading cause of death in the United States, requiring a series of complex behavior changes that must be sustained for a lifetime (e.g., counting carbohydrates, self-monitoring blood glucose, adjusting insulin). Although complex, all of these tasks involve behavior, making them amenable targets for behavior analysts. In this article, the authors describe interventions that have focused on antecedent, consequent, multicomponent, and alternate procedures for the management of diabetes, highlighting ways in which technology has been used to overcome common barriers to the use of these intensive, evidence-based interventions. Additional variables relevant to poorly managed diabetes (e.g., delay discounting) are also discussed. Future research and practice should focus on harnessing continued advances in information technology while also considering underexplored behavioral technologies for the effective treatment of diabetes, with a focus on identifying sustainable, long-term solutions for maintaining proper diabetes management. Practical implementation of these interventions will depend on having qualified behavior analysts working in integrated primary care settings where the interventions are most likely to be used, which will require interdisciplinary training and collaboration.

Keywords Behavior analysis · Diabetes · Technology

Diabetes mellitus is the seventh leading cause of death in the United States and occurs when an individual experiences hyperglycemia (i.e., high levels of blood glucose), either as a result of insulin resistance (Type 2 diabetes) or because the pancreas does not produce insulin (Type 1 diabetes; American Diabetes Association, 2018a, b). In 2015, approximately 30.3 million U.S. citizens had diabetes, and 1.5 million new diagnoses were said to occur each year (American Diabetes Association, 2018c). Type 1 diabetes (T1D) occurs when the body's immune system destroys the beta cells that create insulin in the pancreas, either due to genetics or a virus, whereas Type 2 diabetes (T2D) is the result of genetic, lifestyle, and environmental factors (National Institute of Diabetes and Digestive and Kidney Diseases, 2016).

Regardless of type, if blood glucose is not maintained within a normal range, a host of health complications will arise, including

ketoacidosis, retinopathy, nephropathy (e.g., hypertension, renal failure, renal insufficiency), neuropathy, stroke, foot wounds, gangrene, cardiovascular disease (e.g., myocardial infarction, heart failure, atherosclerosis, aneurysm), and eventually death (Young et al., 2008). Diabetic foot ulceration represents the leading cause of hospitalization in patients with diabetes and—along with co-occurring peripheral arterial disease, which is present in nearly half of patients with poorly managed diabetes—represents the strongest predictor of limb amputation (Brownrigg, Apelqvist, Bakker, Schaper, & Hinchliffe, 2013; Newhall, Spangler, Dzebisashvili, Goodman, & Goodney, 2016). In 2017, diabetes-related health care and lost productivity costs were estimated to be \$327 billion dollars (American Diabetes Association, 2018c).

Hyperglycemia is the primary cause of health complications associated with diabetes (Crofford, 1995). Three common tests for determining blood glucose levels are (a) self-monitoring blood glucose (SMBG), typically measured via small drops of blood from a finger stick, which provides a short-term measure of glycemic control; (b) continuous glucose monitoring (CGM), measured via a device connected to the individual that periodically measures blood glucose automatically throughout the day and can alert the individual about

✉ Bethany R. Raiff
raiff@rowan.edu

¹ Department of Psychology, Rowan University, 201 Mullica Hill Road, Glassboro, NJ 08028, USA

high or low readings in real time; and (c) glycosylated hemoglobin (A1c), the gold standard measure of glycemic control measured via blood draw, typically in a clinical setting, which provides an estimate of diabetes management over a longer period of time (American Diabetes Association, 2018b). A1c is expressed in terms of the percentage of hemoglobin that is of the A1c subtype (Goldstein et al., 2004); target A1c levels for healthy adults are <7% but can range from $\leq 6.5\%$ to $\leq 8\%$ depending on the health history and age of the patient (American Diabetes Association, 2018b).

Intensive glycemic control can lead to a reduction in or postponement of diabetes-related health complications (The Diabetes Control and Complications Trial/Epidemiology of Diabetes Interventions and Complications (DCCT/EDIC) Study Research Group, 2005; White et al., 2001). For example, amputation rates among Medicaid patients with diabetes declined by more than 50% between 2002 and 2012, largely attributed to increased access to and consistency of hemoglobin A1c testing in poor communities and communities of color, who are disproportionately impacted by diabetes and related health outcomes (Suckow et al., 2016). However, recommendations for diabetes management can be labor intensive and complex (American Diabetes Association, 2018b; Silverstein et al., 2005). Individuals diagnosed with diabetes must be vigilant about the amount of carbohydrates they consume, the timing and dosage of insulin they self-administer (if insulin dependent) or antidiabetic medications they take (if T2D), the amount of exercise they engage in, and their overall stress management. Although complex, all of these tasks involve behavior, making them amenable targets for a behavioral science.

Behavior Analysis and Diabetes Management

Successful diabetes management presents a unique challenge to patients, as it requires continuous adherence to a variety of health behaviors over the course of a lifetime. In addition, the benefits of implementing lifestyle changes can often be abstract, probabilistic, and temporally distant (i.e., reducing, but not eliminating, the probability of negative health outcomes in the long term). Diabetes management programs often require a substantial restructuring of daily routines, as noted previously (e.g., carbohydrate counting, adjusting insulin doses, SMBG). Individuals with diabetes are often required to make profound changes to their dietary behavior in order to control complex and often abstract physiological factors (Brazeau et al., 2013; Evert et al., 2013; Tay et al., 2014).

Furthermore, although A1c is the “gold standard” for evaluating successful diabetes management, it cannot be relied upon exclusively because it does not provide real-time guidance on how to maintain optimal blood glucose levels (Renard, 2005). To effectively manage blood glucose levels day to day, individuals who are insulin dependent (i.e., all

T1D and more severe cases of T2D) are told to conduct as many as 6 to 10 SMBG tests per day (American Diabetes Association, 2018b), at a minimum before and after meals, bed, and exercise. CGM was historically not reliable enough for making real-time treatment decisions (still requiring SMBG confirmation) and was not recommended for children and some adults; however, recent technological advances have changed this perspective, and with proper training, individuals can now use CGM to guide their decision making throughout the day to improve glycemic control (Pettus & Edelman, 2017). Taken together, these substantial lifestyle changes may not only interfere with an individual’s preestablished routine, but the activities themselves may also be aversive. In this sense, individuals who are noncompliant with these day-to-day lifestyle demands may view the immediate discomfort associated with exercise or SMBG tests as more aversive than the delayed and probabilistic discomfort associated with health complications resulting from poor management (i.e., the aversiveness of the delayed outcomes may be significantly discounted; Ostaszewski & Karzel, 2002).

Behavior analysts can conceptualize poor diabetes management as a combination of behavioral deficits and behavioral excesses. In either case, these challenging behaviors are associated with an increased risk for negative health outcomes. Behavioral deficits occur when health behaviors—such as SMBG testing (Murata et al., 2003), medication adherence (Rozenfeld, Hunt, Plauschinat, & Wong, 2008), exercise (Boulé, Haddad, Kenny, Wells, & Sigal, 2001), and carbohydrate counting (Mehta, Quinn, Volkening, & Laffel, 2009)—occur less often than advised by the patient’s diabetes care team (e.g., endocrinologists, nutritionists, dieticians). Behavioral excesses occur when a patient engages in a behavior at an inadvisably high frequency, which may in turn be predictive of negative health outcomes. Dietary habits are perhaps the clearest example of behavioral excesses for diabetes management (e.g., eating too many refined grains, sweets, chips; Nansel, Haynie, Lipsky, Laffel, & Mehta, 2012); however, compulsive blood glucose testing might also be a relevant concern in certain populations. For example, Franciosi et al. (2001) found that among non-insulin-dependent patients, higher frequency SMBG testing was associated with increased A1c (i.e., poorer outcomes) and higher levels of psychological distress.

Behavior analysts may be able to offer unique solutions to the challenges associated with poor diabetes management, whether they are a result of behavioral excesses or deficits, in addition to the ongoing work in related disciplines such as behavioral medicine that have become more integrated into mainstream health care (Hunter et al., 2018). Behavior analysis has long been concerned with the practical application of operant principles to issues relating to public health, and there is evidence to suggest that the methodology has shown success in a wide variety of domains, including drug abstinence, healthy eating, physical activity, and medication adherence (Dallery et al., 2016; Epstein, Paluch, Beecher, &

Roemmich, 2008; Lowe, Horne, Tapper, Bowdery, & Egerton, 2004; Morrill, Madden, Wengreen, Fargo, & Aguilar, 2016; Normand, 2008; Petry, Alessi, Olmstead, Rash, & Zajac, 2017; Rosen et al., 2007). Furthermore, because of advances in information technology, it is now possible to deliver high-intensity behavioral interventions for chronic health conditions such as diabetes in ways that were not previously possible.

The goals of this article are to (a) expose scientists and practitioners to examples of how diabetes management has been approached from a behavioral perspective, which is likely to be a novel area for many people practicing in the field, and (b) outline the contingencies that both help and hinder behavior analysts working in this area. The article is organized into sections based on the types of interventions that are typically used by behavior analysts (Cooper, Heron, & Heward, 2020): (a) antecedent-based interventions (e.g., stimulus control), (b) consequence-based interventions (e.g., reinforcement), (c) multicomponent interventions (e.g., combination of antecedent- and consequence-based interventions), and (d) alternative approaches (e.g., those that would be of interest to the audience but do not fit neatly into any of the aforementioned categories). The articles discussed herein are not meant to be exhaustive but were instead chosen because of their historical significance or because they highlighted how a particular behavioral approach has been applied previously. We conclude the article by discussing potential barriers to implementing these behavioral interventions, as well as areas for future research.

Antecedent-Based Approaches

Antecedent procedures are those that occur before the behavior, such as adding prompts or altering the context in which the behavior occurs (Cooper et al., 2020). Antecedent interventions have been found to be effective in improving self-management tasks among children with severe intellectual disabilities (Lancioni, O'Reilly, Campodonico, Oliva, & Groeneweg, 2002), increasing compliance in a variety of settings and with different populations (Lipschultz & Wilder, 2017), and decreasing undesirable behavior maintained by positive and negative reinforcement (Kettering, Fisher, Kelley, & LaRue, 2018; McComas, Thompson, & Johnson, 2003). Although the efficacy of these approaches has been documented in a range of settings, few studies to date have examined the effectiveness of antecedent interventions in improving treatment adherence to prescribed medical regimens.

A prompt is a conditioned supplemental stimulus that increases the probability of performing a desired response (Dietz & Malone, 1985) and might involve a written or vocal reminder to set the occasion for a specific diabetes management task (e.g., SMBG). In one of the earliest behavioral studies on treatment adherence among individuals with diabetes,

Lowe and Lutzker (1979) used a multiple-baseline design across diabetes care behaviors (i.e., urine testing, foot care, and dietary-related tasks) to examine the effects of adding a written memo to increase adherence in a noncompliant 9-year-old girl diagnosed with T1D. The written memo was posted in easy-to-find locations, including the kitchen and bathroom, and contained a list of “self-care tasks” that needed to be completed on a daily basis. An additional vocal prompt was added if the child did not complete the tasks. The use of both written and vocal prompts resulted in improvements in adherence to dietary-related tasks (mean baseline = 72% vs. mean prompts = 99%). Improvements in foot care (mean baseline = 19% vs. mean prompts = 35%) and urine testing (mean baseline and prompts = 72%) only increased with the addition of contingent points exchangeable for tangible items (foot care = 97%, urine testing = 100%; Lowe & Lutzker, 1979). More recently, Wong, Seroka, and Ogisi (2000) used a written checklist prompt with a memory-impaired patient with T1D to increase her percentage of correctly completed independent SMBG steps (baseline = ~70% vs. checklist = ~90%).

Because of advances in technology, these early findings using vocal and written prompts have been extended to technology-based prompts in the form of short message service (SMS) text message reminders, and more recently via notifications on smartphone devices, to increase glucose monitoring and medication adherence (Herbert, Owen, Pascarella, & Streisand, 2013; Markowitz et al., 2014; Vervloet et al., 2012). For example, Vervloet et al. (2012) found that text message reminders improved medication adherence of patients with T2D. Participants were more likely to take the appropriate amount of medication, and missed fewer doses, within a specified 1-hr time window (control group = 39% vs. SMS prompt group = 50%). Additionally, the use of text messages was viewed favorably among participants, indicating that mobile prompts may present a socially valid approach to prompting individuals to adhere with medical regimens, especially among young people with T1D who are especially at risk for noncompliance (Herbert et al., 2013).

Other antecedent approaches that have been explored in the context of diabetes management include exposure therapy and response prevention (Allen & Evans, 2001; Green, Feher, & Catalan, 2000). For example, Allen and Evans (2001) assessed the efficacy of exposure therapy and response prevention on excessive SMBG testing in a case study. The participant tested her blood sugar upward of 80 to 95 times per day, versus the recommended 6 to 12 times per day, presumably to prevent the aversive effects of hypoglycemia. During the treatment, access to blood glucose testing strips was gradually decreased using a changing criterion design, with SMBG goals set by the participant's parents, exposing the participant and her parents to the possibility of the adverse effects of a hypoglycemic episode. The criterion was reduced

until SMBG testing was taking place 20 or fewer times per day. Exposure therapy and response prevention have also been identified as potential strategies for reducing overeating (Havermans, 2013; Jansen et al., 2003).

Another antecedent intervention involves restructuring the environment to increase or decrease the likelihood of a particular response by making discriminative stimuli more or less apparent (Smith & Iwata, 1997). In our search of the literature, there were no examples of this approach published in a behavioral science journal. However, conceptually, this is related to studies conducted on consumer choice in the supermarket, where it has been shown that placing healthy foods near the checkout counter can lead to an increase in healthy food purchases relative to placing healthy food elsewhere in the supermarket (Sigurdsson, Larsen, & Gunnarsson, 2013). Another, related, antecedent manipulation shown to impact healthy eating is the traffic light method, which involves putting food into categories based on its energy density (green = <10% vs. yellow = 10%–25% vs. red = >25% calories per serving). In one study, youth who were told to eat more green category items had greater weight loss than youth who were told to eat fewer red category items (Epstein et al., 2008). Although these studies were not conducted with individuals diagnosed with diabetes per se, the impact of restructuring the environment in a way that promotes healthy eating does have implications for this population. Similar antecedent approaches such as these could be explored for improving other diabetes-relevant behavior as well, such as putting SMBG testing supplies in easily accessible locations to increase their salience and reduce the response cost associated with testing.

To our knowledge, other types of antecedent interventions commonly employed by behavior analysts, such as manipulating motivating operations (e.g., establishing diabetes management as a reinforcing activity) and exploring high-probability procedures (i.e., behavioral momentum), have not yet been investigated in the context of diabetes management and might serve as worthwhile directions for future research. Furthermore, advances in information technology might offer exciting avenues for manipulating antecedent conditions. For example, simulating environments via virtual reality may allow researchers to rigorously study a number of antecedent interventions for improving diabetes management, similar to how it has been used in other areas (e.g., Morina, Ijntema, Meyerbroker, & Emmelkamp, 2015).

Consequence-Based Approaches

Consequence-based interventions have most often involved positive-reinforcement approaches. One specific type of positive-reinforcement approach that involves delivering desirable consequences contingent on adherence with diabetes management recommendations is referred to as contingency management (CM), and literature in this category of

consequence-based interventions comprises the bulk of this section. CM has been widely used in the treatment of addiction, such as cocaine- and opioid-use disorders (DeFulio et al., 2012; Festinger, Dugosh, Kirby, & Seymour, 2014; Jarvis et al., 2017; Olmstead & Petry, 2009), but has also been used to increase other health behaviors, such as asthma medication adherence in children (Burkhart, Rayens, Oakley, Abshire, & Zhang, 2007) and compliance with cardiac rehabilitation in adults (Gaalema et al., 2016).

CM has also shown promise for improving diabetes management as it relates to a wide array of behaviors that can improve glycemic control. One of the earliest studies applying CM to diabetes management was conducted by Carney, Schecheter, and Davis (1983), in which they found large increases in adherence to diabetes regimen recommendations when parents were told to deliver praise and points exchangeable for privileges contingent on their children with T1D adhering with glucose-monitoring recommendations. During baseline, participants adhered approximately 5% of the time, compared to an increase to about 90% during the 5-week CM intervention. Importantly, at a 4-month follow-up, A1c was reduced by a mean of 2.4%, which is a clinically meaningful outcome. Although this study was a promising first step, it was limited by the method of verifying glucose testing (i.e., used test strips [permanent product]), which also introduced inevitable delays between the behavior and its putative reinforcing consequences (i.e., praise/points). CM is most effective when the consequences are delivered immediately (Lussier, Heil, Mongeon, Badger, & Higgins, 2006; Roll, Reilly, & Johanson, 2000) and contingent on objective evidence of the behavior (Petry, 2000). These limitations can be readily addressed by advancements in information technology.

In an early stage pilot study conducted by Raiff and Dallery (2010), four adolescents with poorly managed T1D were enrolled in an Internet-based CM program where they could earn monetary incentives for each SMBG test conducted as long as they adhered with testing at least four times per day, up to a maximum of eight times per day (\$1 per test plus a \$3 bonus for meeting the minimum of four tests). Participants recorded videos going through the SMBG process, or they showed the log from their glucose meter for that day, to earn the monetary incentives. Using a brief A-B-A reversal design, this Internet-based CM intervention was shown to be effective in increasing the frequency of blood glucose testing from 1.7 times per day during baseline conditions to 5.7 times per day during the 5-day CM condition. A longer duration follow-up study was also conducted, showing that Internet-based monetary incentives, when combined with motivational interviewing, increased the frequency of blood glucose testing, and the trajectory of these changes maintained during a 21-day follow-up period, particularly in older (vs. younger) adolescents diagnosed with T1D (Raiff, Barry, Ridenour, & Jitnarin, 2016).

Another pilot study conducted by Lansing, Stanger, Budney, Christiano, and Casella (2016) found that an Internet-delivered intervention involving teens with T1D and their parents, who delivered incentives contingent on SMBG adherence, was effective at improving SMBG adherence and A1c outcomes. Adolescent participants increased SMBG adherence from an average of 3.73 tests per day to an average of nearly 7 tests per day within 3 months, and A1c levels decreased by the end of treatment (mean change = -0.8%). These findings were recently replicated in a randomized controlled trial with T1D adolescent–parent dyads ($N = 61$; Stanger et al., 2018).

Although diabetes management was not the focus of the paper, a meta-analysis conducted by Petry, Rash, Byrne, Ashraf, and White (2012) suggested that CM interventions may also be effective at increasing medication compliance. CM interventions were more effective than control conditions at increasing medication compliance, with an effect size of .77, 95% CI [.70, .84], indicating a medium-high impact of the intervention on behavior. Historically, medication adherence has been based on pill counts, prescription refills, or direct observation, all of which have limitations (Cramer, 2004; Odegard & Capoccia, 2007; Rudd et al., 1989); however, recent technological advances, such as medication event monitoring (MEM) and telemonitoring, have made medication compliance a more viable target in CM interventions for diabetes management (Petry, Alessi, Byrne, & White, 2015; Raiff, Jarvis, & Dallery, 2016; Rosen et al., 2007).

The utility of CM extends to the management of other behavioral deficits as well. Not only is engaging in exercise associated with improved glycemic control among those already diagnosed with diabetes (especially in T2D), but it can also prevent an individual from progressing beyond prediabetes (American Diabetes Association, 2004; Bird & Hawley, 2012; Riddell et al., 2017), and CM has been shown to be effective at increasing physical activity in sedentary adults (Andrade, Barry, Litt, & Petry, 2014; Kurti & Dallery, 2013; Petry, Andrade, Barry, & Byrne, 2013). For example, Kurti and Dallery (2013) found a 182% increase in steps taken when monetary incentives were made contingent on sedentary adults meeting increasing step goals, measured via a Fitbit activity tracker and verified by Internet-based video confirmation. Washington, Banna, and Gibson (2014) used a similar approach and found that a prize-based monetary incentive was also effective, suggesting a potentially lower cost alternative.

With any CM intervention, it is important, especially early on, to select an appropriate target behavior (Meredith et al., 2014). Dividing the target into small, frequent, manageable steps is critical to ensuring that it will contact the reinforcer early during treatment, especially with a complex, long-term lifestyle change such as diabetes management. This procedural necessity may have contributed to the null outcomes reported by Long, Jahnle, Richardson, Loewenstein, and Volpp

(2012), who did not find improvements in glycemic control when \$100 and \$200 financial incentives were made contingent on one- or two-point A1c reductions, respectively, 6 months later. Because A1c is a long-term measure of diabetes management over a 2- to 3-month period and is the result of a complex series of behavior that must occur throughout most days during that period, the contingencies were likely ineffective due to the incentives being delayed and not linked to concrete, day-to-day behavior. CM interventions for chronic illnesses, requiring long-term lifestyle changes, need to be developed in consideration of these basic principles of behavior.

Using the Internet to deliver consequence-based interventions, guided by the basic principles of behavior, can overcome a number of potential barriers to evidence-based behavioral treatments. First, many of the studies discussed in this section involved patients who were geographically isolated, in some cases living in rural areas where the closest diabetes clinic was over 75 miles (121 kilometers) away. When CM interventions are developed in a way that is guided by behavioral science principles, they are intensive, typically requiring daily check-ins at first, which would not be possible if face-to-face meetings with clinical staff were required. Second, conducting these studies remotely, via the Internet or mobile devices, allows for the immediate delivery of reinforcers. Because people with poorly controlled diabetes have been shown to be more sensitive to immediate rewards (i.e., display more impulsive choice; Stoianova, Tampke, Lansing, & Stanger, 2018), providing immediate rewards for effective diabetes management can tip the balance in favor of these healthy decisions even when the outcomes would typically be delayed.

To our knowledge, consequence-based approaches involving punishment and/or extinction for behavioral excesses related to diabetes management have not been explored. Extinction would be impossible if the function of the behavior were not first identified, and even then, the reinforcer would have to be something that could be controlled (e.g., it is not possible to remove the reinforcing properties of foods high in carbohydrates). Reinforcement of alternative behaviors that compete with behavioral excesses is typically preferred to punishment procedures, making punishment a less desirable treatment approach as well.

Multicomponent Approaches

Multicomponent approaches have also been explored with behavior related to diabetes management. For example, Stock and Milan (1993) used a multicomponent behavioral intervention designed to improve dietary choices among elderly individuals living in a residential facility. Menus were designed to provide contextual cues indicating healthy dining options, and the cafeteria staff prompted participants to select

heart-healthy options (antecedents). If healthy items were selected, the staff provided social reinforcement (i.e., verbal praise from the cafeteria staff). Participants selected healthy dining options at higher rates during the prompting and verbal praise condition than during either prompting or verbal praise in isolation, suggesting that this might be a simple approach toward improving dietary choices among individuals diagnosed with diabetes.

More recently, Morrill et al. (2016) demonstrated the efficacy of the Food Dudes program in the U.S. school system. The approach combined antecedent prompting with contingent rewards to produce an increase in fruit and vegetable consumption among children. Food Dudes media (i.e., videos, letters, and branded toys) were used to create a story around the Food Dudes characters, establishing them as conditioned motivating operations, and they provided prompts for fruit and vegetable consumption. Children assigned to either the tangible reward (e.g., small toys) group or the praise reward group consumed significantly more fruits and vegetables relative to control participants; however, the tangible rewards were found to be more effective than praise. Lorenz, Van der Mars, Kulinna, Ainsworth, and Hovell (2017) also used a multicomponent approach to increase school-wide physical activity among junior high school students. Rates of total student engagement in moderate to vigorous physical activity were shown to increase during a lunchtime program when prompts (e.g., signs and verbal cues), as well as verbal and token reinforcement, were employed. Although these studies did not specifically target individuals diagnosed with diabetes, lifestyle interventions aimed at reducing obesity have been shown to reduce the risk of developing metabolic syndromes, such as diabetes, in children and adolescents (Reinehr, Kleber, & Toschke, 2009).

Technological advances have also made it possible to seamlessly integrate antecedent and behavioral interventions into a single, packaged treatment. For example, Raiff, Jarvis, et al. (2016) used an electronic medication-monitoring device similar to MEM (i.e., Wisepill electronic pill dispenser) to increase medication adherence among three nonadherent adults diagnosed with T2D, similar to the study described earlier by Vervloet et al. (2012). Participants were sent text message prompts at specific times throughout the day (personalized to the needs of the individuals) if they had not yet taken their medication. Monetary incentives were delivered contingent on medication adherence as measured via the Wisepill device (i.e., a signal was sent to the server when the container was opened). This technology-delivered multicomponent approach improved medication adherence with all three participants in the study (adherence increased by 45%–71%). Technology allowed this intervention to be personalized and sustained for an extended period of time (approximately 30 days). Furthermore, the prompts were only sent when individuals were noncompliant, thereby reducing the likelihood of habituation to the antecedent prompts.

Two limitations with the Raiff et al. (2016) study should be noted. First, the device measured container openings, which served as a proxy for medication taking. Petry et al. (2015) asked participants to submit a mobile-phone-recorded video directly showing medication ingestion, which addresses this concern but introduces other logistical limitations in terms of added patient and clinician burden. Although controversial, another solution may be the use of “digital pills,” the first of which was approved by the U.S. Food and Drug Administration in 2017 (Lee, Farchione, Mathis, Muniz, & Muoio, 2018). Digital pills embedded with a chip send a signal to a skin patch worn by the patient when the pill is digested, which then communicates to a web portal that can be monitored by clinicians or family members. If this approach becomes more widely available, it may serve as a more objective measure of medication adherence. Second, because of the multicomponent approach used in all of the studies discussed in this section, it is not clear which components of the interventions were needed to produce the observed changes in behavior. This interpretive limitation is present with any multicomponent intervention, and future research may focus on exploring which features are both necessary and sufficient to produce desirable changes in diabetes management with minimal resources (Ward-Horner & Sturme, 2010).

Alternative Targets and Approaches

It is important for effective diabetes management protocols to consider other behavioral excesses and deficits that may co-occur with diabetes and may inadvertently influence the individual’s effective management. For example, individuals diagnosed with diabetes have been shown to use substances at a higher rate than the general population, and this is relatively underexplored (Petry et al., 2018; Walter, Wagner, Cengiz, Tamborlane, & Petry, 2017). In one promising study, CM targeting substance use disorder was more effective with individuals diagnosed with diabetes than with individuals who were not diagnosed with diabetes (Walter & Petry, 2015). Furthermore, individuals diagnosed with diabetes were also more likely to remain drug abstinent at a 9-month follow-up.

Gamification is another area for intervention research that has been broadly applied and can be easily translated to technology. Morford, Witts, Killingsworth, and Alavosius (2014) provided a detailed analysis of gamification from a behavioral perspective, defining it as the extension of elements of game design into nongaming contexts. Models of gamification might combine antecedent- and consequence-based behavioral approaches with modes of delivery that draw inspiration from the field of game design. Along the same lines, the term “serious games” has been used to refer to video games that make meaningful, real-life changes for the player outside of the game context (McCallum, 2012). Gamified interventions have been explored on a variety of platforms,

including traditional gaming consoles, but also more recently on mobile devices and in the context of social media (Wattanasoontorn, Boada, Garcia, & Sbert, 2013). In 2018, 60% of Americans played video games daily on a variety of devices, the most popular of which were personal computers (41%), smartphones (36%), and dedicated consoles (36%). The average age of video game players was 33, and 46% of U.S. video game players were female (Entertainment Software Association, 2019). The ubiquity of mobile technology and game playing indicates that it may be both an accessible and appealing method for disseminating behavioral interventions.

A number of serious games for diabetes management have been investigated (Lieberman, 2012). One of the earliest studies assessed the effectiveness of an educational video game called Packy & Marlon in addressing diabetes management skills in children (Brown et al., 1997). Game players were presented with diabetes management challenges for their fictional characters with the end goal being that these skills would generalize to the children's own behavior outside of the game. The outcomes were promising, with an approximately 20% decrease in urgent care hospital visits among participants who played Packy & Marlon when compared to a control group exposed to a general educational video game.

Unfortunately, most of the games developed for diabetes management are not designed with consideration of the basic principles of behavior. However, Raiff, Jarvis, and Rapoza (2012) found widespread acceptability among health care providers, as well as smokers, when asked about translating a traditional CM intervention involving monetary incentives into a “gamified” intervention involving virtual game-based incentives for smoking cessation. At least two “serious games” for diabetes management have used in-game rewards to reinforce real-life diabetes management. For example, Kumar, Wentzell, Mikkelsen, Pentland, and Laffel (2004) compared diabetes management software to diabetes management software plus a “predict your blood glucose level” game in which participants would guess their blood glucose level after having collected three earlier readings. Blood glucose data, insulin doses, and carbohydrate intake were displayed graphically to help players make effective estimates. The game group transmitted more glucose values, had significantly less hyperglycemia, and had a significant increase in diabetes management knowledge over a 4-week trial. There was also a trend toward improved A1c in the game group. Likewise, Glucoboy was a blood glucose meter developed to work with the Nintendo Gameboy Advance or DS, to provide video game-based rewards for SMBG adherence and for meeting target blood glucose levels. To our knowledge, Glucoboy was never rigorously tested in a research study and never went to market in the United States, but conceptually the approach is consistent with CM.

Finally, exergaming refers to video games designed to track and increase physical activity by providing in-game

virtual rewards contingent on physical activity. Exergames have been shown to increase physical activity among inactive children during gym classes (Fogel, Miltenberger, Graves, & Koehler, 2010), increase physical activity and promote weight loss in overweight/obese adolescents (Staiano, Abraham, & Calvert, 2013), and improve balance in older adults (Agmon, Perry, Phelan, Demiris, & Nguyen, 2011). One of the most commercially successful exergames to date is Pokémon Go, which was recently found to increase self-reported walking, and decrease self-reported sedentary behavior, in a college student sample (Barkley, Lepp, & Glickman, 2017). Thus far, the literature shows promise for incorporating gamification into diabetes management procedures, but more rigorous scientific research is still needed.

Future Directions

Technological Advances

Over the past several decades, advances in information technology have facilitated the translation of these, often intensive, behavioral interventions to the application of diabetes management by overcoming barriers to adoption. Mobile interventions can be accessed almost anytime, anywhere, by just about anyone and have opened up opportunities for targeting behavior that could not previously be reliably and consistently measured (e.g., blood glucose testing, medication adherence, physical activity). Behavioral interventions could be used to complement the just-in-time adaptive interventions that are gaining popularity within the mobile health sector (Schembre et al., 2018).

Advances in information technology will continue to present exciting new opportunities for researchers and clinicians wishing to integrate behavioral interventions with diabetes management outcomes (e.g., artificial pancreas, noninvasive glucose monitoring via sensor-based contact lenses, digital pills; Doyle, Huyett, Lee, Zisser, & Dassau, 2014; Liao, Yao, Lingley, Parviz, & Otis, 2012). Physiological and activity-monitoring devices, in conjunction with the growing ubiquity of social media platforms, represent a promising avenue by which near-immediate social reinforcement can be delivered contingent on objective measures of behavior. However, some words of caution regarding the use of technology-based interventions are warranted. There are estimated to be over 1,000 smartphone applications (apps) related to diabetes in the Apple and Google Play app stores (Jahns, 2014). Releasing an app does not require any rigorous testing, and therefore many of them have not been formally evaluated. Unless otherwise noted, all of the technology-based interventions described in this article did go through some form of empirical testing, but additional research would further support the use of these approaches. Some researchers have

evaluated the usability and clinical efficacy of diabetes apps that have undergone empirical validation (Fu, McMahon, Gross, Adam, & Wyman, 2017); however, any of the apps that have not undergone formal empirical testing should be approached with caution.

In addition to future research and dissemination guided by advances in information technology, there are many applications of behavioral technologies that have not yet been explored in the context of diabetes management. Some of the interventions that have been shown to produce profound effects in populations that are more often targeted by behavior analytic interventions (e.g., autism, developmental disabilities) may also be worth exploring in individuals diagnosed with diabetes, such as using antecedent interventions to reduce the aversiveness, or increase the reinforcing value, of highly aversive diabetes management tasks. Because diabetes management requires long-term solutions, it will also be important to explore the technology of behavior maintenance and generalization in producing lasting changes (Stokes & Baer, 1977). Additionally, exploring the implications of behavioral theories of decision making, such as delay discounting, matching theory, and operant theories of behavioral economic demand (e.g., Hursh, 1984, Hursh & Silberberg, 2008), may be useful in guiding future interventions.

Dissemination and Implementation

In order to effectively disseminate these empirically supported behavioral technologies to clinical settings, it will be important for behavior analysts to be working in primary care settings where these interventions are likely to be implemented. Having clinical behavior analysts working in integrated primary care settings could provide a number of benefits to the effective assessment and treatment of diabetes, as well as other health behaviors. For example, behavior analysts might be able to identify and intervene upon behavior associated with prediabetes, conduct functional assessments to identify the putative reinforcers maintaining risky health behaviors, develop treatment protocols sensitive to individual differences, and recommend effective and empirically validated behavioral interventions.

However, it is important to remember that the Behavior Analyst Certification Board and state licensure laws require behavior analysts to work within their scope of practice and competence (Brodhead, Quigley, & Wilczynski, 2018). Most behavior analysts are unlikely to have training in the management of diabetes; therefore, to extend their practice to this novel, socially significant issue would require expanding opportunities for learning. Brodhead et al. (2018) provided a number of suggestions about how behavior analysts might acquire such competencies, such as getting additional field experience with qualified supervisors, reading the literature, attending

workshops and trainings, and working on interdisciplinary teams that include individuals with the expertise missing from the behavior analyst's repertoire.

In the case of diabetes management, the ambitious behavior analyst looking to broaden his or her scope of competence might seek additional training and collaboration in the areas of endocrinology, nutrition, dietetics, exercise science, and/or primary care. Interdisciplinary trainings and collaborations will help behavior analysts identify appropriate behavior change targets (e.g., SMBG frequency, diet, medication adherence). Behavior analysts have a history of successful interdisciplinary collaborations in other areas, such as working in schools with teachers and school administrators (Donaldson, Matter, & Wiskow, 2018; Luiselli, Putnam, Handler, & Feinberg, 2005; Pence & St. Peter, 2018) and working in medical research centers, drug treatment centers, and primary care settings with medical professionals (Allen, Barone, & Kuhn, 1993; Brady, 1993; Kirby, Amass, & McLellan, 1998; Stitzer et al., 2019). All of the work described in the preceding sections of this article published by the authors was conducted in interdisciplinary settings in close collaboration with nurses and doctors with expertise in endocrinology (e.g., Raiff, Barry, et al., 2016; Raiff & Dallery, 2010; Raiff, Jarvis, et al., 2016; the Naomi Berrie Diabetes Center in New York City and the Shands Hospital in Gainesville, Florida).

If behavior analysts are going to expand their scope of practice and competence to diabetes management, it will also be important that their skills are seen as valuable. A number of thoughtful articles, talks, and task forces have been dedicated to identifying strategies for increasing the demand for behavior-analytic services in new areas (e.g., addiction, geriatrics, exercise). It will be important for universities offering behavior analysis coursework to accept people with different training histories and backgrounds who are interested in extending the basic principles to their existing repertoires. Likewise, it might be necessary for behavior analysts to seek out further training after completing behavior-analytic coursework (e.g., medical school). Behavior analysts interested in practicing or conducting research in these novel areas will also need to (a) stay current on research being published about diabetes, (b) publish their research in journals being read by those who focus on diabetes (e.g., *Preventive Medicine*, *Diabetes Care*, *Journal of the American Medical Association*), and (c) attend conferences focused on behavioral health broadly, and diabetes specifically (e.g., Society for Behavioral Medicine, American Diabetes Association Clinical Conference on Diabetes; Seniuk, Cihon, Benson, & Luke, 2019; Vyse, 2013).

Potential Barriers

There are also barriers that behavior analysts might encounter when attempting to broaden their experience to the area of

diabetes management. First, having our work accepted in non-behavior-analytic journals and conferences will necessarily mean broadening the types of research we are willing to conduct, often requiring the use of group designs and inferential statistics, which can make some behavior analysts uncomfortable (Baron, 1999; Crosbie, 1999; Perone, 1999). However, if our tools are as robust as we believe them to be, they will survive these minor transgressions and allow our science to have a broader impact.

Second, as practitioners, there may be barriers to implementing behavioral interventions in these new settings caused by resistance from medical professionals and families when it comes to some of our procedures. For example, critics of the use of reinforcement procedures report concerns about the impact of “extrinsic reinforcers” on “intrinsic motivation” for health behavior (Deci, 1971; Promberger & Marteau, 2013). Some medical professionals and family members may also have misunderstandings about what behavior analysis actually represents, such as assuming it only applies to individuals with autism, that it results in “robotic” behavior, or that it might be harmful or uncomfortable for those receiving services (Kelly, 2012). Finally, once families and medical professionals are convinced to use behavioral interventions, their behavior will also be subject to the contingencies and may require additional training to ensure compliance (Koegel, Glahn, & Nieminen, 1978; Postorino et al., 2017). Fortunately, behavior analysts have a long history of responding to these common criticisms and working collaboratively with other disciplines, as noted earlier, showing that we can successfully overcome these barriers.

Conclusion

In conclusion, diabetes management is composed of multiple complex behavioral patterns requiring long-term, sustainable solutions that fall within the realm of behavior-analytic and behavioral medicine approaches to managing behavior. A number of antecedent, consequent, multicomponent, and alternative approaches have shown promise in improving diabetes management either directly (e.g., increasing glucose monitoring) or indirectly (e.g., increasing physical activity). In order to broaden our scope of practice and competence to diabetes management, behavior analysts will need to seek out additional training, professional development opportunities, and interdisciplinary collaborations, thereby creating demand for the unique skills the field has to offer.

Author Note This article is dedicated to Dr. Nancy Petry, for being an innovator and an inspiration. Dr. Petry paved the way toward using information technologies to disseminate effective behavioral technologies, and she had a personal interest in improving the lives of people living with diabetes. Her articles comprise about 10% of the citations found in this review (more than any other single author) and account for just a

small fraction of her impact on the field. Her contributions will always be valued, and the research community feels her loss. We also thank Jesse Dallery and three anonymous reviewers for their helpful comments on an earlier draft of this manuscript.

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