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Recovery from addiction: behavioral economics and value-based decision-making

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Abstract

Behavioral economics provides a general framework to explain the shift in behavioral allocation from substance use to substance-free activities that characterizes recovery from addiction, but it does not attempt to explain the internal processes that prompt those behavioral changes. In this paper we outline a novel analysis of addiction recovery based on computational work on value-based decision-making (VBDM), which can explain how people with addiction are able to overcome the reinforcement pathologies and decision-making vulnerabilities that characterize the disorder. The central tenet of this account is that shifts in molar reinforcer preferences over time from substance use to substance-free activities can be attributed to changes in evidence accumulation rates and response thresholds in the context of choices involving substance use and substance-free alternatives. We discuss how this account can be reconciled with the established mechanisms of action of psychosocial interventions for addiction, and demonstrate how it has the potential to empirically address longstanding debates regarding the nature of impairments to self-control in addiction. We also highlight a number of conceptual and methodological issues that require careful consideration in translating VBDM to addiction and recovery.

Key words: Addiction; Behavioral economics; Decision-making; Recovery.

Despite influential depictions of addiction as a chronically relapsing brain disease that requires lifelong clinical management (Volkow, Koob, & McLellan, 2016), it is widely recognized that recovery is common among treatment-seeking and non-treatment-seeking persons with substance use disorders (Heyman, 2013; Lewis, 2017; Tucker & Simpson, 2010). Behavioral economics has made important contributions to our understanding of the nature and determinants of addiction, its treatment, and recovery (Murphy, MacKillop, Vuchinich, & Tucker, 2012). In the present paper we outline a speculative theoretical account that builds on established behavioral economic and cognitive neuroscience foundations to highlight the potential importance of value-based decision-making (VBDM) for recovery from addiction. This account yields new hypotheses that are amenable to empirical evaluation. The central tenet is that shifts in molar reinforcer preferences over time from substance use to substance-free activities can be attributed to changes in evidence accumulation rates and response thresholds in the context of choices involving substance use and substance-free alternatives. We identify some novel testable hypotheses about the mechanisms of action of established and emerging treatments in the context of VBDM, and describe empirical tests that can resolve disputes about the nature of self-control and related constructs.

Behavioral Economic Accounts of Addiction and Recovery

In accordance with Herrnstein's (1970) "matching law", behavioral economic explanations for substance use emphasize that, over extended periods of time, the proportion of behavior allocated to substance use will be a joint function of reinforcement gained from use of that substance and the reinforcement gained from all other sources. In other words, the value of (or demand for) substance use is determined by its benefit /

cost ratio in relation to the benefit / cost ratios of all other activities that a person might engage in (Murphy, MacKillop, et al., 2012).

The development and persistence of addiction can be attributed to 'reinforcement pathologies' (Ainslie, 2005; Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Heyman, 1996; Lamb & Ginsburg, 2018; Murphy, MacKillop, et al., 2012; Rachlin, 1995; Redish, Jensen, & Johnson, 2008), specifically distortion of valuation processes and hyperbolic discounting of delayed rewards. As addiction progresses, substances increase in value (hypervaluation) whereas alternative, substance-free reinforcers decrease in value (hypovaluation) (Rachlin, 2000). Alongside this, hyperbolic discounting (the phenomenon whereby reinforcers reduce in value with increasing delay to their receipt) increases (Ainslie, 1975; Madden & Bickel, 2010), thereby favoring more immediate reinforcers such as substance use over substance-free alternatives that typically have delayed and uncertain consequences. The combination of distorted valuations and increased hyperbolic discounting leaves people with addiction vulnerable to abrupt 'preference reversals': Substance-free activities may have a higher value than substance use when both are available after a delay. However, when the person is faced with an imminent opportunity to use the substance, hyperbolic discounting maximizes the value of the substance, leading to immediate use.

Evidence is broadly supportive of these claims, as reviewed elsewhere (Bickel et al., 2014; Madden & Bickel, 2010; Murphy, MacKillop, et al., 2012). For example, substance use is sensitive to its cost, and individual differences in price sensitivity are associated with individual differences in substance use (MacKillop et al., 2010; Murphy, MacKillop, Skidmore, & Pederson, 2009; Tucker, Roth, Vignolo, & Westfall, 2009). Addiction is associated with increased value of substance use compared to competing reinforcers (Hogarth & Hardy, 2018), and chronic substance use is characterised by diminished reward response to non-substance rewards (Lubman et al., 2009; Meshesha et al., 2017). A meta-analysis confirmed that addiction is robustly associated with elevated hyperbolic discounting (MacKillop et al., 2011). Individual differences in the value of substance use and in hyperbolic discounting are associated with the initiation of substance use (e.g., Audrain-McGovern et al., 2009; Fernie et al., 2013) and they are predictive of substance use outcomes after treatment (MacKillop & Kahler, 2009; MacKillop & Murphy, 2007) and natural recovery attempts (Tucker et al., 2016; Tucker et al., 2009).

Recovery from addiction can also be understood through the lens of behavioral economics. Although 'recovery' is often equated with complete abstinence, here we include controlled substance use without problems if that is in line with the person's goals (Witkiewitz, 2013). Broadly speaking, people recover from addiction when the availability of substance-free rewarding activities increases (Tucker, Vuchinich, & Gladsjo, 1994; Tucker, Vuchinich, & Pukish, 1995; Tucker, Vuchinich, & Rippens, 2002) and as the costs of their addiction on physical and mental health, as well as interpersonal relationships, become more salient (McIntosh & McKeganey, 2000; Prins, 2008). Comparable findings have been demonstrated in animal models of addiction and recovery (see Lamb et al., 2016; Lamb & Ginsburg, 2018). The efficacy of psychosocial treatments may be partially dependent on the extent to which they can facilitate these changes (e.g., Dennhardt, Yurasek, & Murphy, 2015; McKay, 2017). Contingency management (CM), an efficacious addiction treatment in which participants receive small financial rewards for verified abstinence or other desirable behaviors (e.g., seeking employment), and related interventions such as employment-based reinforcement ('the therapeutic workplace'; Silverman et al., 2012) were directly informed by behavioral economic approaches to addiction (Petry, Martin, Cooney, & Kranzler, 2000; Petry et al., 2005; Petry et al., 2004; Stitzer & Petry, 2006). Recovery is also associated with adoption of situational and intrapersonal strategies that offer protection against preference reversals (e.g., Monterosso & Ainslie, 2007; Snoek, Levy, & Kennett, 2016) and by post-recovery changes in life circumstances that reinforce sobriety (King & Tucker 1998; Tucker et al., 1994, 1995, 2002).

Behavioral economic approaches explain substance use and addiction from a *molar* rather than a *molecular* perspective: they are concerned with *patterns* of behavior over time rather than individual *acts* (Rachlin, 1995), and with how proportional reinforcement from substance use versus competing activities changes over extended time periods (Murphy, MacKillop, et al., 2012). In the next section we describe computational neuroscience accounts of value-based decision-making that model the internal processes that contribute to discrete choices. We speculate that these research methods might be adapted to explain individual instances of substance use, i.e. individual *acts* (cf., Rachlin, 1995). Most importantly, we tentatively suggest that this approach could be extended to model the internal processes that determine shifting patterns of behavioral allocation over time, and by extension recovery from addiction.

Value-Based Decision-Making (VBDM) and Its Potential Role in Motivated Behavior and Addiction

VBDM provides a framework and set of experimental tools to explain the internal processes that underlie discrete choices. In a typical VBDM task (e.g., Polanía, Krajbich, Grueschow, & Ruff, 2014) participants first make value judgments about a set of pictorial stimuli (for example, different types of food) so that the stimulus set can be rank ordered from most valued to least valued. In a subsequent forced choice task, on each trial two stimuli are presented side-by-side on a computer screen, and participants are instructed to select their preferred item as quickly as possible. 'Errors' are inferred if choices are inconsistent with value judgments that were expressed before the forced choice task. VBDM assumes that participants' reaction time and error data arise from a process in which internal evidence for each possible decision accumulates over time, with the addition of random noise representing uncertainty, until the accumulated evidence for one decision crosses a threshold or 'decision boundary'. Weaker internal evidence results in slower evidence accumulation, and therefore longer response times. The accumulation of random noise along with evidence signals causes both occasional errors and the characteristic distribution of response times. This basic 'accumulation to threshold' concept is at the heart of a family of so-called 'sequential sampling models' of decision-making (Busemeyer, Gluth, Rieskamp, & Turner, 2019; Ratcliff, Smith, Brown, & McKoon, 2016).

By fitting these decision models to behavioral data, the VBDM approach permits the description of parameters that are hypothesized to underlie value-based choice. Specifically, it enables the quantification of the subjective value of different stimuli independently of other properties of the decision-maker, such as their response thresholds. Importantly, the decision process is hypothesized to be noisy and probabilistic. This means that any momentary change in favor of one choice option is determined by both random noise and the subjective value of that option. Computational models treat value signals as evidence for or against a particular choice. These value signals accumulate over time (hence, 'evidence accumulation' (EA) signals) until one of them crosses its response threshold, at which point the appropriate choice option is selected (see Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017). Decision modelling has been applied to delineate decision-making deficits and abnormalities in other psychological disorders (e.g., Moustafa et al., 2015; Pirrone, Dickinson, Gomez, Stafford, & Milne, 2017), and VBDM has been applied to the study of cognitive regulation of food choice (Tusche & Henderson, 2018).

The schematic in Figure 1 illustrates how VBDM could be applied to explain a person's decision-making when they are faced with an opportunity to drink alcohol (or not), or when they face a choice between drinking alcohol and pursuing an alternative, substance-free activity., For the sake of conceptual clarity and in common with Berkman et al., (2017), the Figure depicts the discrete choice between drinking alcohol versus an alternative substance-free activity as a 'race' to a single response threshold although we note that, in reality, each response option would have its own response threshold.

We speculatively suggest that if alcohol consumers were to complete a VBDM task that requires them to make value judgments about alcohol use and alcohol-free alternatives, this should permit extraction of individual differences in the VBDM parameters (EA rates and response thresholds) that may predict long-term patterns of behavioral allocation, irrespective of occasional acts or instances that contradict those long-term patterns (Ainslie, 2005; Rachlin, 1995). Substance-related VBDM in people with addiction has only recently been studied (see Lawn et al., 2019 for a study that investigated the neural substrates of smoking-related VBDM in tobacco smokers). However, the predictive validity of individual differences in VBDM for substance use and substance-free alternatives has not yet been investigated..

It is important to acknowledge other forced choice tasks in which participants choose between images that depict substance-related cues versus competing reinforcers, data from which have made important contributions to our understanding of addiction (e.g., Hardy, Parker, Hartley, & Hogarth, 2018; Moeller et al., 2018). There is an important distinction between conventional forced choice tasks and the VBDM tasks described here: both types of tasks can measure the overall proportion of (hypothetical) substance-related versus substance-free choice, and they are both considered measures of substance demand or value. However, only the decision modelling that is inherent to VBDM tasks is able to capture the internal processes that contribute to choice. We revisit this important distinction later.

Contemporary accounts of VBDM posit that EA for a given choice option is the result of a value integration process that incorporates diverse sources of information about the overall utility of that response option, including its anticipated positive and negative consequences, financial and opportunity cost, effort, and so on (Berkman, 2018; Berkman et al., 2017; Levy & Glimcher, 2012; Rangel, Camerer, & Montague, 2008), although this is contentious (e.g., Busemeyer et al., 2019). According to one account (Berkman et al., 2017), delay to receipt of the outcome(s) of a response option is incorporated into this value integration process, such that evidence accumulates most rapidly for outcomes that are available immediately. This account of self-control as a form of value-based choice therefore provides a computational account for the effects of hyperbolic discounting on choice and preference reversals.

Our suggestion that VBDM could be applied to choices that involve substance use can be reconciled with many existing theories of addiction. For example, Redish et al., (2008) propose a unified framework for addiction that describes various 'vulnerabilities in the decision-process', the majority of which lead to a distortion of valuation processes during decision-making that can be directly equated with alterations to EA rates and response thresholds in the context of VBDM. For example, sensitization of dopamine neurons as a consequence of chronic drug use increases the 'incentive salience' of drugs and drug-related cues (Robinson & Berridge, 1993) which should correspond to an amplification of EA for substance use. Chronic substance use also leads to neuroadaptations that result in anhedonia (Koob & Le Moal, 1997) that should correspond to a suppression of EA for substance-free alternatives. During VBDM, when a person faces multiple choice options, selective attention plays an important role: attentional allocation to stimuli is influenced by the degree to which those stimuli were previously associated with reward (Della Libera & Chelazzi, 2009), and the amount of attention directed at each response option amplifies the EA rate for that response option, making it more likely to be chosen (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011). This may explain the development of attentional biases for substance cues and the influence of attentional biases on substance use (Field et al., 2016; Rose, Brown, MacKillop, Field, & Hogarth, 2018).

In this section and in Figure 1 we have sketched out a speculative account of the role of VBDM in substance use and addiction. Although this account awaits empirical testing, it complements much of what is already known about the behavioral changes that characterize the development and persistence of the disorder, and the neurobiological underpinnings of those changes. However, as previously noted, complete recovery from addiction is a common outcome (Heyman, 2013) and most theories of addiction that emphasize the importance of compulsion and habit struggle to explain why this is so (see Heather, 2017). As such, we believe that the most important contribution of the present account may be its potential to explain how people overcome the 'reinforcement pathologies' (Bickel et al., 2014) and diverse 'vulnerabilities in the decision process' (Redish et al., 2008) as they recover from addiction. This is the focus of the next section. In the subsequent section we consider challenges to this approach and how it might be reconciled with other theoretical perspectives. In the final section of the paper we outline the clinical implications of our approach and offer some suggestions for future research.

Recovery, Relapse, and Mechanisms of Treatment Action

In this section we outline a novel analysis of recovery from addiction that was inspired by Berkman and colleagues' (2017) account of self-control as value-based choice and that yields new hypotheses that are amenable to empirical testing. Our central claim is that recovery can be attributed to any of the following changes in VBDM parameters, either alone or in combination: (1) suppression of EA for the substance, such that it is less likely to be first to cross the response threshold; (2) augmentation of EA for substance-free activities, such that they are more likely to be first to cross the response threshold, and (3) a gradual upwards shift in the response threshold when faced with a choice set that includes substance use. These hypothesized changes in EA rates and response thresholds are depicted in Figure 2.

According to this account, people remain vulnerable to lapses during the early stages of recovery because EA rates are noisy and probabilistic, so it is always possible that EA for substance use will cross the response threshold first (cf. the 'cusp catastrophe' model of relapse and recovery; Hufford, Witkiewitz, Shields, Kodya, & Caruso, 2003; Witkiewitz, Van Der Maas, Hufford, & Marlatt, 2007). As depicted in Figure 2, lapses may be more likely to occur when response thresholds are low. However, assuming that the 'direction of travel' of VBDM parameters over extended periods of time favors recovery from addiction (as depicted in Figure 2), the likelihood of lapse should decline, eventually approaching zero.

This tentative account of the changes in VBDM that underlie recovery from addiction awaits empirical testing. This could initially be achieved by conducting cross-sectional comparisons of people who have achieved stable recovery versus those who have not yet sought to reduce their substance use and related problems. In the remainder of this section, we demonstrate how this account can be reconciled with the broader literature on recovery and the mechanisms of action of established treatments. We suggest that treatments will be effective to the extent that they directly or indirectly support the hypothesized changes in VBDM parameters that are depicted in Figure 2.

Recovery from a behavioral economic perspective: The effectiveness of contingency management demonstrates that directly increasing the monetary value of abstinence and other desirable behaviors and outcomes is an effective treatment for addiction, even when the monetary value of the reinforcers offered is very low (Petry et al., 2000; Petry et al., 2005; Petry et al., 2004; Stitzer & Petry, 2006). In principle, the effectiveness of CM and related interventions (e.g., Silverman et al., 2012) should be dependent on the extent to which they are able to rebalance the relative value of substance use versus substance-free behaviours. Consistent with this claim, Goelz et al (2014) found that people who successfully quit smoking showed increases in substance-free reinforcement eight weeks following their quit attempt, whereas Rogers et al. (2008) found CM that included vouchers redeemable for substance-free items/activities increased both abstinence and engagement in substance-free activities relative to abstinent-contingent pharmacotherapy, in a sample of cocaine and heroin users (see also Higgins et al 2003).

The proposed VDBM account suggests that the effectiveness of CM on substance-use outcomes may be mediated by a suppression of EA for substance use combined with augmentation of EA for substance-free alternatives. An alternative explanation for the clinical effectiveness of CM suggests that it "engages deliberative processes … and improves the ability of those deliberative processes to attend to non-drug options" (Regier & Redish, 2015). This provides an alternative mechanism of action: an increase in the response threshold combined with potentiation of EA for substance-free alternatives that is mediated by changes in selective attention (cf., Krajbich et al., 2010; Krajbich & Rangel, 2011).

Qualitative research indirectly implicates the importance of changes in valuations for recovery from addiction: people attribute their recovery to regaining interest in competing rewards that used to hold value, such as spending time with family, satisfaction at work, and so on (Klingemann, Sobell, & Sobell, 2010; McIntosh & McKeganey, 2000; Prins, 2008), and a person might be considered to have 'recovered' when these evaluative shifts cement into a stable change in identity (Best et al., 2016). These findings are complemented by studies of non-treatment seeking heavy drinkers that used behavioral economic simulations (such as hypothetical purchase tasks) and demonstrated that receipt of brief motivational intervention or pharmacotherapy prompted changes in drug demand, which in turn predicted the likelihood of sustained behavior change (Bujarski, MacKillop, & Ray, 2012; Dennhardt et al., 2015). In a recent study, changes in proportionate reinforcement from substance-related to substance-free activities partially mediated the effects of a brief motivational intervention on alcohol use and problems (Murphy et al., 2019).

These findings raise a number of possibilities about the role of changes in VBDM during the transition to recovery. We speculate that the initial shift in VBDM parameters as depicted in Figure 2 may initially arise from changing life circumstances or receipt of treatment, including brief intervention. Subsequently these shifting trajectories in VBDM parameters that support recovery are potentiated each time the person resists an opportunity to use the substance and engages in an alternative substance-free activity. These predictions could be tested in longitudinal studies in which life experiences, treatment completion, episodes of substance use, and shifts in VBDM parameters are repeatedly measured from the early stages of recovery forward in time, in order to model the temporal relationships between these variables.

Recovery from addiction is often difficult because, as a result of economic or social deprivation or the effects of chronic substance use, people may initially have no viable alternative sources of reinforcement in their lives other than substance use. A number of novel treatment interventions such as behavioral activation (Daughters et al., 2018; Martínez-Vispo, Martínez, López-Durán, Fernández del Río, & Becoña, 2018) and substance-free activity sessions (Murphy et al., 2019; Murphy, Dennhardt, et al., 2012; Yurasek, Dennhardt, & Murphy, 2015) aim to restructure the environment in order to provide alternative sources of reinforcement. There is emerging evidence for the effectiveness of these interventions which may be mediated by the extent to which they increase reinforcement from substance-free activities (Fazzino et al., 2019; Murphy et al., 2019). In the context of our VBDM account, we hypothesize that potentiation of EA for substance-free activities will mediate the effects of these interventions on substance use outcomes.

Reconciliation with mechanisms of action of established psychosocial treatments: The psychological mechanisms of action of efficacious treatments, such as cognitive-behavior therapy (CBT), motivational interviewing (MI) or motivational enhancement therapy, and Alcoholics' Anonymous (AA) and related therapies, are increasingly well understood. For example, improvements in 'coping skills' in participants who receive CBT may be related to post-treatment drinking outcomes (Roos, Maisto, & Witkiewitz, 2017), whereas MI may prompt recovery because "clients talk themselves into changing" (Magill et al., 2014; Magill & Hallgren, 2019). The effects of AA attendance on recovery are mediated by a number of factors, including facilitation of adaptive social network changes, increasing abstinence self-efficacy and coping skills, and helping people to maintain their recovery motivation over time (Kelly, 2017). Alongside these demonstrations about how specific treatments exert their therapeutic effects are examples of how some therapist behaviors (Gaume, Heather, Tober, & McCambridge, 2018; Magill et al., 2016) and psychological changes in clients (for example, self-reported motivation to change; Cook, Heather, & McCambridge, 2015) are observed across treatments and are associated with treatment outcome, regardless of the type of treatment that was provided.

An important question for future research is to clarify the relationships between the aforementioned mechanisms of behavior change and the VBDM parameters that are posited to represent the final pathway to behavior because they determine whether a person will prefer a substance or an alternative substance-free activity at any given choice point (Berkman et al., 2017; Rangel et al., 2008). For example, negative social network changes (in which people drop heavy drinkers from their social networks) might be associated with a suppression of EA for alcohol, whereas positive social network changes (in which people in stable recovery are added to the social network) (Kelly, 2017) might be associated with a potentiation of EA for substance-free activities. Generating predictions about other mechanisms of behavior change is more complicated. For example, 'coping skills' and 'coping repertoire' are multifaceted and include specific skills, some of which might plausibly be related to suppression of EA for alcohol (e.g., thinking about how drinking is hurting others, and actively avoiding drinking situations), whereas the role of other coping skills (e.g. counterconditioning) may be more closely related to augmentation of EA for substance-free alternatives (Roos et al., 2017). A further possibility is that acquisition of a broad coping repertoire raises response thresholds when the person has a substance use opportunity.

Mindfulness-based relapse prevention and related approaches may exert their beneficial effects on substance use via their influence on VBDM. Specifically, the focus on "acceptance of uncomfortable states or challenging situations without reacting automatically" (Witkiewitz, Lustyk, & Bowen, 2013) can be understood as providing participants with the skills needed to raise the response threshold when they face an opportunity to use a substance. Alternatively, mindfulness techniques that train people to 'savor' positive, substance-free options in their lives (Garland, Roberts-Lewis, Tronnier, Graves, & Kelley, 2016) might amplify EA for substance-free activities.

Assuming that relationships exist between VBDM parameters and the psychological and social changes referred to above (coping skills, motivation to change, changes in social networks), a crucial task will be to delineate the temporal and causal relationships between these constructs. For example, self-reported motivation to change and 'change talk' might reflect participants' awareness of shifting EA for alcohol versus valued substance-free alternatives, resulting from treatment related changes to their social/environmental context or via pharmacotherapy, with the implication that the subjective reports would not play a meaningful causal role in treatment outcome. An alternative possibility is that these subjective changes arise in response to treatment and they play a critical role in recovery but exert their beneficial effects on substance use by modulating EA rates when the person is faced with an opportunity to use the substance. In other words, if recovery ultimately arises because people learn to modulate EA rates and response thresholds when they have an opportunity to use the substance or engage in a substance-free activity, established mechanisms of behavior change may provide essential scaffolding that supports these changes.

Emerging treatments: Interventions such as working memory training (Bickel, Yi, Landes, Hill, & Baxter, 2011; Rass et al., 2015) and non-invasive brain stimulation (Song, Zilverstand, Gui, Li, & Zhou, 2019) that are intended to partially compensate for neurocognitive deficits arising from chronic substance use should exert their beneficial effects by raising response thresholds. Similarly, experimental interventions that are intended to mitigate hyperbolic discounting processes, including reward bundling (Ainslie & Monterosso, 2003; Hofmeyr, Ainslie, Charlton, & Ross, 2011) and episodic future thinking (Rung & Madden, 2018; Stein et al., 2016), might initially raise response thresholds before amplifying the EA signal for substance-free activities. Cognitive bias modification (CBM; see Boffo et al., 2019) might influence substance use through a number of mechanisms. For instance, given that selective attention to choice options amplifies value signals (Krajbich et al., 2010; Krajbich & Rangel, 2011), attenuation of attentional-biases for substance-related cues after attentional bias modification would be expected to suppress EA for substance use (Field et al., 2016). By contrast, approach bias modification (e.g., Rinck, Wiers, Becker, & Lindenmeyer, 2018), which reverses automatic approach tendencies evoked by substance-related cues, could suppress the substance-related EA signal more directly.

In this section we have outlined a tentative account that describes how VBDM could be applied to explain how people recover from addiction, and how addiction treatments might exert their beneficial effects on substance use by changing the VBDM parameters that influence behavior when the person faces a substance use opportunity. Our account is offered as a heuristic to guide new research questions that may inform a more comprehensive account of recovery than is provided by extant theories of addiction. In anticipation of conceptual and methodological objections, in the final section we consider this tentative account in the broader context.

Challenges and Reconciliation with Other Perspectives

Does this account offer anything that conventional behavioral economic accounts do not? Behavioral economic accounts attribute recovery from addiction to a reduction in the value or utility (benefit / cost ratio) of substance use that may be combined with an increase in the value or utility of competing substance-free activities (see Murphy, MacKillop, et al., 2012). The novel account outlined here develops those constructs and articulates them in the language of the internal processes that contribute to VBDM, and putative changes in those processes over time as a person recovers from addiction.

This focus could be informative regarding that person's likelihood of recovering from addiction before any change in overt substance use is observed. Consider the schematic in Figure 2: In a person who is currently receiving treatment, their EA for substance-free activities might shift upwards and to the left over the course of a treatment program, which would be a beneficial 'direction of travel' for that particular parameter. Unfortunately, this person's response threshold might be low, and EA for substance use may not be suppressed. As a consequence, the person might consistently favor substance use over alternative substance-free activities, both in terms of their overt behavior but also in terms of their responding on a conventional forced choice task (e.g., Hardy et al., 2018; Moeller et al., 2018). The potential advantage of the current approach is its ability to identify when the internal processes that support decision-making in favor of recovery from addiction are moving in the right direction, even in the absence of overt behavior change.

Is this a molar or a molecular account of behavior and behavior change? Although there is increasing enthusiasm for computational approaches to psychological disorders and their treatment (Huys, Maia, & Frank, 2016), the literature on VBDM is primarily concerned with the internal processes that contribute to discrete choices (Berkman et al., 2017; Rangel et al., 2008). As such, the focus of VBDM on individual 'acts' is incompatible with the focus on longer-term patterns of behavior as favored by traditional behavioral economics (e.g. Rachlin, 1995; for a critique of attempts to explain individual acts in isolation from broader patterns of behavior, see Tucker & Vuchinich, 2015).

It may be possible to use the VBDM tasks described here to predict the likelihood of substance use in the near future and, by extension, as an 'early warning system' to predict the risk of lapses during or after treatment. (cf. Marhe, Waters, Van De Wetering, & Franken, 2013). However, measures obtained from a single assessment of VBDM may be too 'noisy' to have reliable predictive validity for individual acts (e.g. a lapse in the near future), although this is an empirical question that is worthy of investigation. More importantly, because we believe that it is important to view recovery from addiction from a molar perspective, we suggest that the primary application of this account to understanding recovery from addiction may be its ability to track changes in VBDM parameters (EA for substance use, EA for substance-free activities, and response thresholds for those particular choice sets) over time. We speculate that repeated administration of VBDM tasks as people progress through treatment and into stable recovery (or relapse) will permit monitoring of the internal processes that contribute to molar behavioral allocation. Adoption of VBDM methods may facilitate understanding of how changes in those internal processes over extended periods of time precede and determine changes in observable behavior, including substance use and engagement in substance-free activities. It is also important to determine the correspondence between VBDM task parameters and behavioral economic measures of delay discounting and demand, which may also change dynamically in response to internal processes and predict subsequent changes in behavioral patterns (Murphy et al., 2015; Rung & Madden, 2018). Additionally, it is important to consider the role of the *availability* of substance-free rewards in an individual's environment, which can exert substantial influence on substance use independent of any decision making process (Higgins et al., 2004).

Can this account model patterns, or only acts? Figures 1 and 2 depict a choice between two specific acts: drinking alcohol, or spending time with one's children. This illustrative choice set is our attempt to mirror the typical VBDM experimental setup, in which participants choose between two alternative reinforcers (e.g. chocolate versus peanuts; see Polanía et al., 2014). However, molar behavioral economic perspectives emphasize that this discrete choice (between two mutually exclusive acts) must be understood in the context of broader patterns of behavior (Rachlin, 1995). The relative valuation of parenting vs. drinking can be determined by observing the distribution of these behaviors over time. Thus, a pattern of increasing engagement in parenting behavior by a person early in recovery may reflect increasing reinforcement from parenting (perhaps due to improving parenting skills or increased identification with one's role/identity as a parent), which over time, will reduce the relative valuation of substance use. Empirical testing of our VBDM account relies on the assumption that, if participants were to complete a VBDM task as depicted in Figures 1 and 2, the two response options are either representative of the broader pattern (rather than the specific act that is depicted), or, at the very least, that EA for the specific choice options is determined by the underlying patterns, and therefore it can capture variation in those patterns. Modifications to the experimental procedure, such as priming participants with their identity as a conscientious parent before they complete a VBDM task (cf. Tusche & Hutcherson, 2018) might be required in order to achieve this goal.

Akrasia: According to our account, when a person in recovery is faced with the choice between substance use and a substance-free activity, EA in favor of the substance free option should *consistently* cross the response threshold before EA in favor of substance use. Another implication is that, when a person in recovery experiences a lapse, they do so because, at the time that the decision was made, the momentary valuation of substance use was higher than the momentary valuation of not using the substance. They may regret that decision in hindsight, but this does not imply that the decision was not based on a higher valuation at the time that it was made. This view is consistent with conventional behavioral economic accounts of the 'preference reversals' that underlie loss of control (Ainslie, 2005; Bickel & Marsch, 2001), and other accounts of short-lived changes in valuations as determinants of apparent 'loss of control' (Berkman et al., 2017; Dill & Holton, 2014; Levy, 2018; Yaffe, 2014).

However, this view is rejected by many on philosophical grounds (see Levy, 2014). In particular, the phenomenon of akrasia – in which a person "acts intentionally counter to his own best judgment" (Heather & Segal, 2013) – highlights some conceptual problems with any attempt to implicate overt behavior as a direct outcome of valuation processes. For example, Kennett and Smith (1996) attributed self-control failures to 'failures of orthonomy' in which momentary desires (for substance use) overwhelm "all things considered" judgments about what is the most valued option. Indeed, the majority of models of addiction from neuroscience (Redish et al., 2008) philosophy (Dill & Holton, 2014) and psychology (Stacy & Wiers, 2010) emphasize that habitual or automatic processes can effectively bypass valuation processes, thereby explaining loss of control. Even without appeal to habitual or automatic processes, self-control can be seen as a decision *not* to choose the behavioral option that is most highly valued, implying the existence of an additional process beyond VBDM that determines overt choice (Holton, 2009).

By contrast, in common with conventional behavioral economic accounts, the VBDM account of recovery that we have outlined yields the straightforward hypothesis that recovery arises when people consistently value substance use less than substance-free activities, and lapses occur when that general pattern is disrupted such that valuations favor substance use over alternatives, even if that reversal is only temporary and subsequently regretted (cf. Berkman et al., 2017). This issue has been difficult to resolve empirically because it is very difficult to know what people were thinking at the moment they relapsed: retrospective claims that people relapsed to substance use against their better judgment might reflect self-serving justifications rather than an accurate account of why the person acted the way that they did (Davies, 1997). Alternatively, if preference reversals are extremely brief (before reverting back to long-term patterns), the person might sincerely believe that when they used the substance they were acting against their own better judgment.

Fortunately, the account proposed here offers a way to empirically distinguish these competing accounts about why people in treatment or stable recovery sometimes experience lapses to substance use, and indeed in the broader sense why people are prone to failures of self-control. Although we believe that the primary advantage of our account is its ability to capture the internal processes that predict molar behavioral allocation over extended periods of time, it also yields some testable hypotheses about the psychological precursors of lapses to substance use (that do not typically derail that person's recovery in the longer-term, because lapses are a common part of the recovery process; Witkiewitz & Masyn, 2008). Specifically, if one were to take a sample of people in treatment or stable recovery and repeatedly administer a VBDM task using EMA methods (e.g., Marhe et al., 2013), then one should expect lapses to substance use to be preceded by predictable changes in VBDM parameters. Compared to longer-term trends for that person, we would expect to see increased EA for substance use, suppression of EA for substance-free alternatives, or a lowered response threshold, as precursors of a lapse. If such a pattern was not identified soon before a lapse, this would demonstrate that substance use occurred contrary to what one would expect on the basis of VBDM, which would disconfirm the account proposed here.

What is the outcome of value-based decision-making? In the context of most VBDM studies, the moment that EA in favor of one response option crosses a response threshold, that response is immediately enacted (see Rangel et al., 2008). An influential view is that diverse influences on behavior, including weighting of short-term versus longer-term goals, exercising self-control, and so on, all work to either amplify or suppress a unified value signal (see Hare, Camerer, & Rangel, 2009; Levy & Glimcher, 2012), a view that has been explicitly endorsed in recent attempts to apply VBDM to health behavior (Berkman, 2018) and self-control choices (Berkman et al., 2017). However some empirical data (e.g. (Tusche & Hutcherson, 2018) and alternative theoretical accounts question this view. For example, the outcome of valuations may determine the formation of intentions which, in turn, determine actions. Addiction may primarily involve weaknesses or sources of bias in the latter (intention formation and action implementation) (Dill & Holton, 2014; Redish et al., 2008; Verdejo-Garcia, Chong, Stout, Yücel, & London, 2018). If these latter accounts are correct, self-regulation or executive functioning ability may be an important moderator of the association between VBDM parameters and relapse and recovery after addiction treatment. These competing predictions could be tested in future research.

Future Directions and Implications for Treatment

Some methodological issues should be considered before incorporating VBDM methods into addiction research and treatment. For example, it will be important to assess whether participants can 'fake' responding on these tasks and if so, if faking is easy to detect and quantify. It will also be important to assess participants' perspectives and whether participants find it aversive or helpful to complete VBDM tasks during treatment. In addition to prediction of relapse and recovery, VBDM could be explicitly incorporated into the treatment of addiction via traditional methods and via mobile platforms. For example, if a person in treatment repeatedly completed a VBDM task at the start of each treatment session, then the treatment provider could use these data to predict likelihood of lapses in between sessions. For a person who is at a higher risk of lapse we might expect increased EA for substance use, suppression of EA for alternatives, or a lowered response threshold. Treatment providers could use these data to discuss upcoming opportunities for substance use (addressing response threshold and EA for substance use), alongside commitment to change and availability of substance-free alternatives (decreasing the suppression of EA for alternatives).

VBDM could also be used to inform and improve recovery support delivered via smartphone applications. For example, VBDM tasks could be incorporated in the Addiction-Comprehensive Health Enhancement Support System (A-CHESS) mobile health recovery support system (Gustafson et al., 2014) to predict in near real-time the EA for substance use and substance-free activities, as well as the response threshold. This could be used to predict probability of lapsing and the parameters that are most likely to increase risk of lapse. Updated probabilities could be shown to the person and also sent to a supportive significant other or treatment provider.

Summary and Conclusions

Based on the diverse 'reinforcement pathologies' (Bickel et al., 2014) and 'vulnerabilities in the decision process' (Redish et al., 2008) that characterize addiction, it would be reasonable to expect recovery from addiction to be uncommon. Yet, recovery is a common outcome (Heyman, 2013), and a coherent theoretical account of the internal processes that are involved when a person transitions from being addicted to being recovered is lacking. Behavioral economics can explain the external factors that facilitate recovery, but does not attempt to model the internal processes that predict changes in overt behavior. In the present article we argued that recent work on VBDM might be able to fill that gap, and we have specified how changes in valuation of substance use versus substance-free activities, and response thresholds when people are faced with choices involving those options, might be important outcomes of established and emerging psychosocial treatments. Our account is necessarily tentative and provisional, and there are a number of methodological and conceptual challenges ahead. However, we suggest that this account generates a number of hypotheses that should be tested in future empirical research. The results of this research will enhance our understanding of the internal processes that support recovery from addiction, and either confirm or falsify the central tenets of this account.

Figure 1: Schematic illustration of value-based decision making (VBDM) parameters that may determine the behavior of alcohol consumers when faced with the choice between drinking alcohol (dashed lines) or an alternative, substance-free activity that is incompatible with drinking

alcohol, such as spending time with one's children (solid lines). Panel A depicts a frequent drinker who is not alcohol-dependent. During the early stages of deliberation (left side of graph), the rate of evidence accumulation (EA) is roughly comparable for alcohol versus the substance-free alternative, so if the response threshold is low (for example, if the decision is made under time pressure), either could cross the threshold first, although in this example EA for alcohol is first to cross the response threshold. However, if the response threshold were higher, EA for the substance-free alternative would cross the threshold first. Note that EA rates are noisy and probabilistic and response thresholds are likely to vary across situations, therefore even minor variations in any of these parameters could result in a different 'winner' and therefore a different behavior being enacted. Panel B depicts a person who is alcohol-dependent: when faced with this choice set, the response threshold is typically low, EA for alcohol is augmented (shifted upwards and to the left) whereas EA for the substance-free alternative is suppressed (shifted downwards and to the right), making it probable that EA for alcohol will be first to cross the response threshold. Schematics are adapted from those in Berkman et al. (2017), images are reproduced from Unsplash.com.

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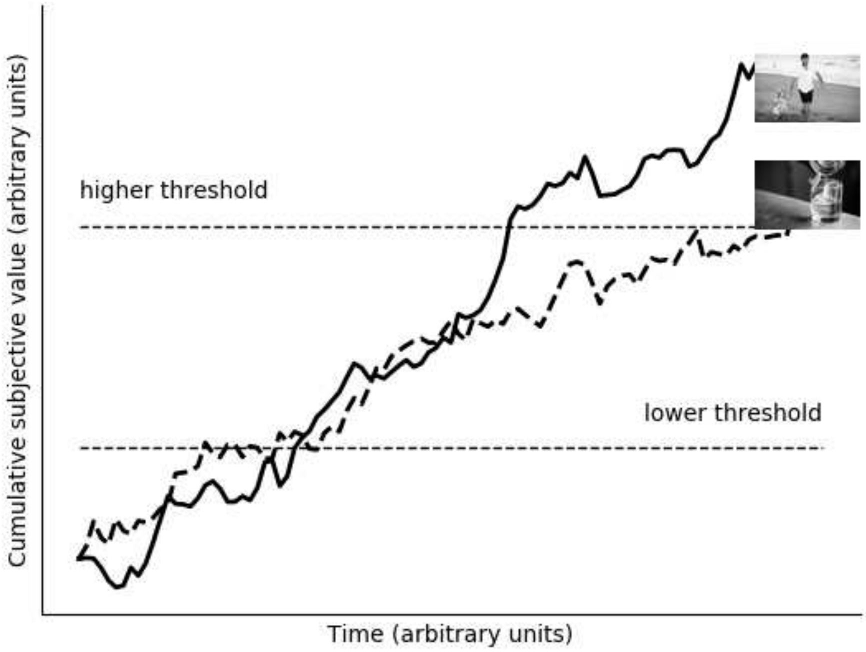
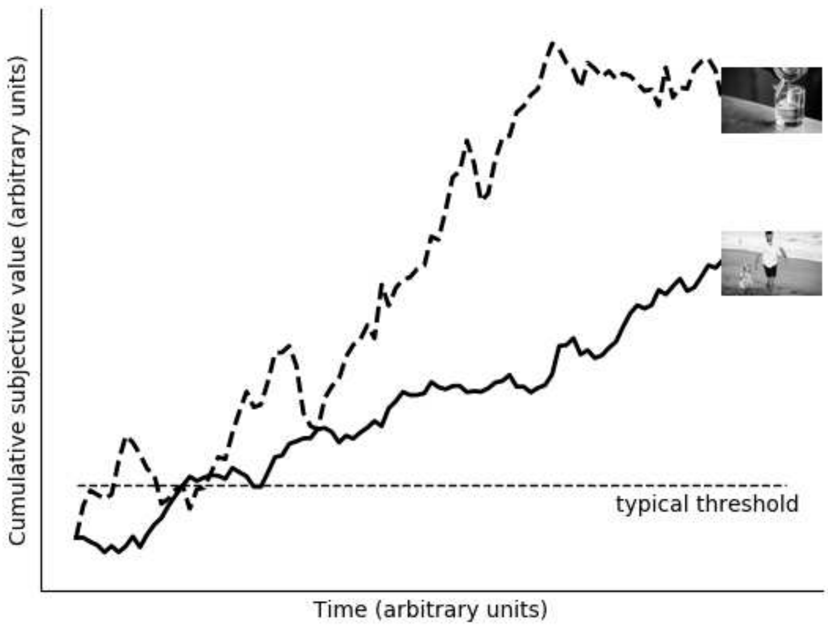
A. Frequent but non-dependent drinker



B. Dependent drinker



<u>Figure 2:</u> Schematic illustration of the changes in VBDM parameters that may underlie recovery from addiction and lapses during the recovery process. As people progress through recovery they

acquire skills that enable them to take more time to consider their options when faced with opportunities to drink alcohol, so the typical response threshold increases (the transition from the lower to the upper horizontal response threshold line). Furthermore, EA for alcohol shifts downwards and to the right (the transition from the dashed black line to the dashed grey line), whereas EA for substance-free alternatives shifts upwards and to the left (the transition from the solid black line to the solid grey line). Each of these changes (or any individual change in isolation) increase the probability that EA for the substance-free activity will be first to cross the response threshold as recovery stabilizes. However, these changes are fragile: lapses could occur in response to a downwards shift in the response threshold (if the person is required to make a decision quickly) or because of the noisy and probabilistic nature of EA rates which make it possible that either could cross the response threshold first. However, as recovery stabilizes, the likelihood of (re)lapse approaches zero because the trajectories of EA rates continue to separate, people are able to adopt strategies to amplify these changes, and they are able to adopt different strategies that raise the response threshold when they are faced with an opportunity to use the substance. See text for details. Schematics are adapted from those in Berkman et al. (2017), images are reproduced from Unsplash.com.

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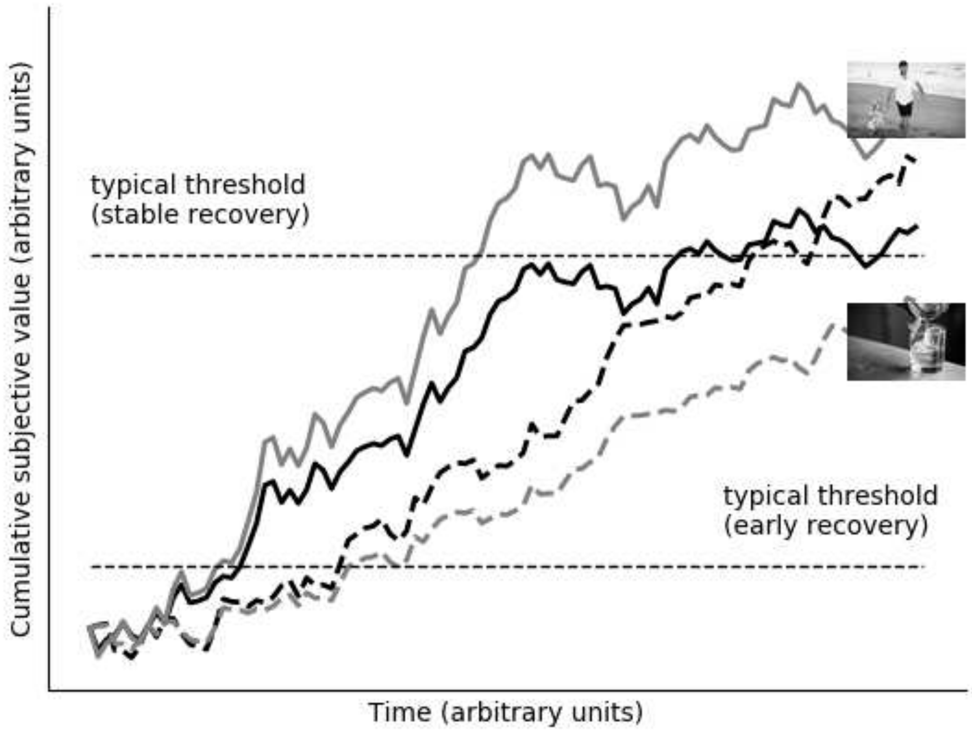
Cumulative subjective value (arbitrary units)
typical threshold
(stable recovery)
typical threshold
(early recovery)
Time (arbitrary units)

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