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Aberrant Cost–Benefit Integration During Effort-Based Decision Making Relates to Severity of Substance Use Disorders

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Abstract
Aberrant cost–benefit decision making is a key factor related to individual differences in the expression of substance use disorders (SUDs). Previous research highlights how delay-cost sensitivity affects variability in SUDs; however, other forms of cost–benefit decision making—effort-based choice—have received less attention. We administered the Effort Expenditure for Rewards Task (EEfRT) in an SUD-enriched community sample ($N = 80$). Individuals with more severe SUDs were less likely to use information about expected value when deciding between high-effort, high-reward and low-effort, low-reward options. Furthermore, individuals whose severity of use was primarily related to avoiding aversive affective states and individuals with heightened sensitivity to delay costs during intertemporal decision making were the least sensitive to expected value signals when making decisions to engage in effortful behavior. Together, these findings suggest that individuals with more severe SUDs have difficulty integrating multiple decision variables to guide behavior during effort-based decision making.

Keywords
substance use disorders, severity, cost–benefit decision making, effort, avoidance, delay discounting, open data

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Epidemiological data highlight substance use disorders (SUDs) as a leading cause of death and disability in the United States, and estimates of SUD-linked morbidity and mortality continue to rise (Mokdad et al., 2018). Current estimates suggest that as many as 9% of Americans meet criteria for SUDs (Kessler, Chiu, Demler, & Walters, 2005), and the cost of SUDs exceeds $740 billion annually in the United States (National Institute on Drug Abuse, 2016). Among those with SUDs, individuals with more severe disorders (i.e., those with more impairment, measured by greater SUD symptoms) carry the greatest burden of disease; they report more barriers to receiving treatment (Probst, Manthey, Martinez, & Rehm, 2015), exhibit higher rates of relapse or arrest following treatment (Kopak, Hoffmann, & Proctor, 2016), and experience a higher chance of accidental or early death and lower chance of survival compared with individuals with less severe SUDs (Maynard et al., 2016). Given the profound personal, social, and economic impact of SUDs, determining the cognitive mechanisms that underlie the observed variability in SUD severity is an essential step for advancing prevention and treatment development.

Although the factors that contribute to the expression of SUDs are multifaceted, impaired cost–benefit decision making has emerged as a key factor. Cost–benefit decision making is characterized by the need to integrate information about the diverse costs and benefits associated with different choice options. When faced with a decision and multiple choice options, an individual uses information about the estimated costs of each action to calculate its absolute value (i.e., the

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benefit; for review, see Rangel & Hare, 2010). One can differentiate distinct facets of cost–benefit decision making according to the specific costs that an individual must integrate to make optimal decisions (e.g., delay, probability, effort, and uncertainty; Rudebeck, Walton, Smyth, Bannerman, & Rushworth, 2006).

Of these distinct facets of cost–benefit decision making, heightened sensitivity to delay costs has received the most attention in the context of SUDs. Delay-cost sensitivity, or delay discounting, reflects a tendency to prefer small immediate rewards over larger delayed rewards. This tendency is inherent in many of the decisions made by individuals who use and abuse substances because benefits of substance use (e.g., the high experienced from use) often are realized immediately, whereas the larger benefits of abstinence (e.g., improved health) often are realized later in time (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014). Elevated delay-cost sensitivity is a core factor related to the initiation of substance use and recovery from SUDs (for review, see Mitchell & Potenza, 2014; Verdejo-García, Lawrence, & Clark, 2008). Moreover, delay-cost sensitivity is associated with reduced treatment retention (Stevens et al., 2014), reduced likelihood of achieving abstinence following treatment (Krishnan-Sarin et al., 2007; MacKillop & Kahler, 2009; Stanger et al., 2012; Washio et al., 2011), and increased likelihood of relapse following abstinence (Yoon et al., 2007). Delay-cost sensitivity is also associated with multiple indicators of substance use severity across a variety of substances (Amlung & MacKillop, 2011; Amlung, Vedelago, Acker, Balodis, & MacKillop, 2017; Claus, Kiehl, & Hutchison, 2011; E. N. Peters, Petry, LaPaglia, Reynolds, & Carroll, 2013). A wealth of empirical evidence illustrates how heightened sensitivity to delay costs increases risk for SUDs at multiple stages (Garrison & Potenza, 2014; Kreek, Nielsen, Butelman, & LaForge, 2005); there is strong evidence that this facet of cost–benefit decision making is related to individual differences in the expression of SUDs (Amlung et al., 2017).

Although previous research sheds important light on how delay-cost sensitivity relates to variability in SUDs, other forms of cost–benefit decision making—especially those involving effort-based choice—have received less attention. Effort-based decision making describes the process of choosing how much effort to invest to obtain a valued outcome and may involve choosing between options with varying work requirements (Chong, Bonnelle, & Husain, 2016; Salamone, Correa, Farrar, & Mingote, 2007). Every individual makes effort choices daily, whether deciding if it is "worth it" to invest effort and study hard for an exam, maintain a social relationship, or go to the gym after work. All other things being equal, individuals are generally effort-averse: When faced with a choice between completing two actions with equivalent reward outcomes, an individual will choose the one requiring less effort. Thus, within the framework of cost–benefit decision making, effort can be considered a cost (cf. Inzlicht, Shenhav, & Olivola, 2018). Consistent with the notion that adjusting effort expenditure according to expected value is an essential, evolutionarily conserved component of adaptive choice behavior (Salamone et al., 2007), effort-cost discounting of subjective value has been demonstrated across multiple species (Chong et al., 2016; Kurniawan, Guitart-Masip, & Dolan, 2011; Phillips, Walton, & Jhou, 2007; Walton, Rudebeck, Bannerman, & Rushworth, 2007).

Recent work using effort-based decision making tasks points to aberrant effort-based computations as a proximal cognitive mechanism underlying motivation-related symptoms in diverse forms of clinical disorders (Salamone et al., 2016; Treadway, Bossaller, Shelton, & Zald, 2012; Treadway & Zald, 2013). For example, individuals with schizophrenia demonstrate a relative insensitivity to information about reward magnitude and probability during effort-based decision making. Moreover, this insensitivity is associated with more severe negative symptoms and functional outcomes, which suggests effort-based computations may be related to variability in the expression of schizophrenia (see Culbreth, Moran, & Barch, 2018, for review). In addition, patients with major depressive disorder show similar deficits in effort-based decision making (Treadway, Bossaller et al., 2012), and the magnitude of these deficits tracks severity in anhedonic symptoms (Yang et al., 2014). Together, this work suggests that effort-based decision-making deficits may represent a transdiagnostic factor important for the expression and course of clinical disorders. However, despite evidence for cost–benefit decision-making deficits in individuals with severe SUDs, effort-based decision making remains relatively unexplored.

The goal of the present study was to examine the association between effort-based decision making and SUD severity. Previous research highlights dysfunction in other facets of cost–benefit decision making among individuals with SUDs as well as a striking overlap between (a) the circuitry involved in effort-based decision making—for example, the mesolimbic dopamine (DA) system (Treadway, Buckholtz, et al., 2012), the anterior cingulate cortex (ACC; Croxson, Walton, O'Reilly, Behrens, & Rushworth, 2009), the dorsolateral prefrontal cortex (DLPFC; Goldstein & Volkow, 2011)—and (b) circuit-level abnormalities associated with SUDs, such as DA system dysfunction (Everitt et al., 2008) and reductions in ACC and DLPFC gray matter and activity (Goldstein et al., 2009; Goldstein & Volkow, 2011; Volkow, Fowler, Wang, Baler, & Telang, 2009).

Together, these separate lines of research provide a premise for the hypothesis that integrating cost and benefit signals during effort-based decision making may be disrupted in individuals with SUDs. However, no work to date has examined effort-based choice in this population.

In the present study, we administered the Effort Expenditure for Rewards Task (EEfRT) in a sample enriched for SUDs. On the basis of previous work in other clinical populations linking symptom severity and dysfunction in effort-based decision making (e.g., individuals with depression, Treadway, Bossaller, et al., 2012; Yang et al., 2014; individuals with schizophrenia, Culbreth et al., 2018), we focused on examining individual variability in the severity of SUDs. Moreover, individuals with SUDs and other clinical disorders show severity-linked elevations in other facets of cost–benefit decision making, such as delay discounting (e.g., individuals with SUDs, Amlung et al., 2017; individuals with depression, Cáceda et al., 2014; Pulcu et al., 2014; individuals with schizophrenia, Brown, Hart, Snapper, Roffman, & Perlis, 2018; Heerey, Robinson, McMahon, & Gold, 2007). In addition, we used a self-report measure of specific motivational triggers for substance use to determine the relevance of different underlying motivations for substance use in effort-based decision making. Finally, given the known importance of delay-cost sensitivity for SUDs and overlap between delay- and effort-based decision making, we employed a self-report measure of delay discounting to identify potential moderating effects of this related and well-documented decision-making facet.

Method

Participants

Participants consisted of 94 adults recruited from the community through flyers soliciting risk-taking (e.g., substance use, crime, gambling, impulsive behavior, bullying) individuals in New Haven County, Connecticut (see Tables 1 and 2 for sample characteristics; for other psychiatric diagnoses in the current sample, see Table S1 in the Supplemental Material available online). A prescreen phone interview and in-person assessment materials were used to exclude individuals who were younger than 18 or older than 75; had performed below the fourth-grade level on a standardized measure of reading (Wide Range Achievement Test–III; Wilkinson, 1993); scored below 70 on a brief measure of IQ (Shipley Institute of Living Scale; Zachary, 1986); had diagnoses of schizophrenia, bipolar disorder, or psychosis, not otherwise specified (according to the Structured Clinical Interview for *DSM–5* Disorders [SCID-5]; First, Williams, Karg, & Spitzer, 2015); or had a history of medical problems (e.g., uncorrectable auditory or visual deficits, head injury with loss of consciousness greater than 30 min) that may affect their comprehension of the materials or performance on the task. All participants provided written informed consent according to the procedures set forth by the Yale University Human Investigation Committee. Participants earned \$10/hr for their completion of the self-report measures and the experimental task. Participants also were eligible to earn a bonus (range = \$2–\$8, rounded to the nearest dollar) depending on the sum of two randomly selected trials from the EEfRT task.

An a priori power analysis based on previous studies of individual differences in effort-based decision making (Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, Schwartzman, Lambert, & Zald, 2009) was conducted using GLIMMPSE Statistical Software (Kreidler et al., 2013). The power analysis indicated that a sample size of 48 to 80 participants would be required to have 80% power (α = .05) to detect an effect size comparable with those of other studies (i.e., a 15%–20% difference in hard task choices; Barch, Treadway, & Schoen, 2014; Treadway et al., 2009, Treadway, Bossaller, et al., 2012) that found three-way interactions among task variables (e.g., expected value, or EV, as a within-subjects repeated measure) and individual difference measures (e.g., SUD severity and moderator variables as between-subjects variables) in the EEfRT, controlling for covariates (see the Supplemental Material for a detailed account of the power analysis).

Below, we report all measures, conditions, and data exclusions. All deidentified data are available on the Open Science Framework website.

Measures

Structured Clinical Interview for* DSM–5 *Disorders. The SCID-5 (First et al., 2015) was used to determine SUD diagnoses in the following nine categories: alcohol; sedatives, hypnotics, and anxiolytics; cannabis; stimulants; opioids; inhalants; phencyclidine; hallucinogens; and other or unknown substances. In the present sample, the majority of participants met criteria for one or more SUDs (73.75%), and more than half met criteria for two or more SUDs (52.5%). Therefore, to represent the diagnostic degree of impairment related to SUDs for each participant, an average SUD severity measure was calculated by summing the severity of diagnoses across substance categories (0 = did not meet threshold for any SUD, zero or one symptom; 1 = mild SUD, two to three symptoms; 2 = moderate SUD, four to five symptoms; and 3 = severe SUD, six or more symptoms) and dividing the total severity by the sum of substance categories meeting diagnostic

Table 1. Sample Characteristics

Characteristic (*N* = 80)	Value
Age	
Mean	37.59 years
SD	12.88
Range	18–62 years
Sex	
Male	51
Female	29
Race	
White	33
Black	45
Asian	2
Ethnicity	
Hispanic	5
Not Hispanic	75
Education	
Junior high/middle school	2
Partial high school	16
High school graduate	23
Partial college	21
College education	11
Graduate degree	7
SCID-5 alcohol use disorder diagnosis	
No diagnosis	40
Past diagnosis	39
Current diagnosis	1
SCID-5 sedative use disorder diagnosis	
No diagnosis	75
Past diagnosis	4
Current diagnosis	1
SCID-5 cannabis use disorder diagnosis	
No diagnosis	34
Past diagnosis	39
Current diagnosis	7
SCID-5 stimulant use disorder diagnosis	
No diagnosis	58
Past diagnosis	19
Current diagnosis	3
SCID-5 opioid use disorder diagnosis	
No diagnosis	64
Past diagnosis	16
Current diagnosis	0
SCID-5 inhalant use disorder diagnosis	
No diagnosis	80
Past diagnosis	0
Current diagnosis	0
SCID-5 phencyclidine use disorder diagnosis	
No diagnosis	79
Past diagnosis	1
Current diagnosis	0
SCID-5 hallucinogen use disorder diagnosis	
No diagnosis	75
Past diagnosis	4
Current diagnosis	1

(*continued*)

Table 1. (Continued)

Characteristic (*N* = 80)	Value
SCID-5 other/unknown use disorder diagnosis	
No diagnosis	80
Past diagnosis	0
Current diagnosis	0

Note: Unless otherwise noted, values are not significant. SCID-5 = Structured Clinical Interview for *DSM–5* Disorders.

criteria. Average severity scores for individuals with no SUDs were entered as 0; average SUD severity could range from 0 to 3.

Risky, Impulsive, and Self-Destructive Behavior Questionnaire. The RISQ (Sadeh & Baskin-Sommers, 2017), a self-report questionnaire, was administered to tap motivations for substance misuse. Some researchers hypothesize that effort-based computations relate to individual differences in the motivation for substance use and the motivation for seeking and completing treatment (Trifilieff, Ducrocq, Van Der Veldt, & Martinez, 2017). Moreover, theoretical models of SUDs long distinguish between substance use evoked by a desire to avoid negative affect (i.e., avoid tendencies; e.g., Baker, Piper, McCarthy, Majeskie, & Fiore, 2004; Kassel et al., 2007) and substance use evoked by a desire to enhance positive affect (i.e., approach tendencies; e.g., Cheetham, Allen, Yücel, & Lubman, 2010; Volkow et al., 2005). In particular, avoidance motivations especially may be relevant for SUD recovery or relapse (Forster, Finn, & Brown, 2017; Gökbayrak, Paiva, Blissmer, & Prochaska, 2015; Lijffijt, Hu, & Swann, 2014; McCabe, Cranford, & Boyd, 2016; Venniro, Caprioli, & Shaham, 2016), and individuals with heightened avoidance tendencies experience more craving during periods of abstinence and worse treatment outcomes (Baker et al., 2004; Forsyth, Parker, & Finlay, 2003; Shorey et al., 2017).

The RISQ measured engagement in eight domains of risky and impulsive behavior; eight domain subscales reflected specific expressions of risky behaviors identified using factor analysis. In addition to assessing engagement in these behaviors, participants were asked to rate on a 5-point Likert-type scale (0 = *strongly disagree*, 4 = *strongly agree*) the extent to which they agreed with the following statements for each behavior endorsed: “I do this behavior to stop feeling upset, distressed, or overwhelmed” and “I do this behavior to feel excitement, to get a thrill, or to feel pleasure.” These last two questions assessed approach and avoid tendencies, respectively, encompassing both the automatic action tendency and the valence motivating these behaviors. For each domain of risky behavior, the

Table 2. Additional Sample Characteristics and Task Statistics

Statistic (N = 80)	Min	Max	*M*	*SD*
Lifetime SCID-5 substance use disorder				
Diagnosis total	0	6	1.70	1.50
Average severity	0	3	1.37	1.02
Discount rate (k)	0.0003	0.2500	0.0530	0.0562
ln(k)	–8.29	–1.39	–3.53	1.30
RISQ				
Approach score[a]	0.00	8.00	4.16	2.57
Avoid score[a]	0.00	7.71	3.00	2.38
EEfRT				
Number of trials	44.00	50.00	49.23	1.42
Proportion of hard task choices	0.00	1.00	0.39	0.21

Note: Min = minimum; Max = maximum; SCID-5 = Structured Clinical Interview for *DSM–5* Disorders; RISQ = Risky, Impulsive, and Self-Destructive Behavior Questionnaire; EEfRT = Effort Expenditure for Rewards Task.
[a]N = 76; four participants reported no lifetime substance use behaviors; therefore, they have missing data for the RISQ approach/avoid scales.

approach scale included positive basic emotions and approach motivational impulses, whereas the avoid scale included negative basic emotions (e.g., distress) and avoidance motivational impulses. For the present study, only the alcohol- and drug-use approach and avoid subscales were analyzed, given our focus on substance use motivations rather than the general tendency to engage in risky and impulsive behavior captured by the RISQ total score. For each alcohol and drug question, individuals provided a rating for the approach and avoid scales. On the RISQ, there were two questions assessing alcohol and eight assessing drug behaviors. Given our focus on average SUD severity across substance use categories, responses on motivation scales for each alcohol and drug question were summed to create total approach and total avoid scores, respectively. Higher total approach and avoid scores are associated with a greater tendency to be motivated by those specific tendencies. Note that 4 participants did not endorse any lifetime substance use; therefore, they have missing data for the RISQ approach and avoid scales (see Table 2).

Monetary Choice Questionnaire. The MCQ (Kirby, Petry, & Bickel, 1999), a 27-item questionnaire, was used to measure delay discounting. Delay-discounting behavior during intertemporal choice is associated with initiation of use, maintenance of use, SUD severity, recovery from SUDs, and relapse frequency. Previous studies identify both shared and cost-selective neurobiological mechanisms underlying delay discounting and effort-based decision making (J. Peters & Buchel, 2011; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010), which raises the possibility that variation in delay-cost sensitivity might influence effort-based computations. Note that decisions about effort allocation often involve an implicit consideration of delay. Tasks that require more effort typically take longer to complete and therefore provide delayed payouts.

For each binary choice item, participants indicated their preference between a larger amount of money ($25–$85) available at a delay (7–186 days) and a smaller amount of money ($11–$80) available immediately. Discount rates, k, were calculated according to a hyperbolic discounting function (Mazur, 1987), $V_d = r / (1 + kD)$; V_d was the subjective value of a delayed reward of magnitude r available at delay D. Distributions of k estimations were positively skewed and thus were natural log-transformed. Higher ln$k$ values are associated with a greater tendency to value immediate rewards over delayed rewards.

Effort Expenditure for Rewards Task. The EEfRT (Treadway et al., 2009), a multitrial computerized button-pressing game, measured the extent to which individuals were willing to incur greater effort costs to obtain larger, more probable rewards (e.g., see Barch et al., 2014; Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, et al., 2012). Participants made a series of choices between completing an easy task and a hard task for variable amounts of reward. The hard task always required 100 button presses to be made within 30 s with the nondominant pinkie finger. The easy task always required 30 button presses to be made within 7 s with the dominant index finger. Each trial started with an information/decision screen indicating the reward magnitude that could be earned for completing the easy task (always $1.00) and hard task ($1.24–$4.30) as well as the probability that completing either task would result in earning the reward (either a 12%, 50%, or 88% probability of being rewarded; see Fig. S1 in the Supplemental Material).

The participant had 5 s to make a choice between the easy and hard task for each trial. If the participant did not make a choice within 5 s, the computer randomly selected a task for the participant. After the choice period, a button-press screen appeared, and the participant completed button presses for the selected task. Individuals received feedback about whether they successfully completed the selected task and whether they earned a reward on each trial. Participants completed four practice trials before the task began and were monitored by research assistants via video camera to ensure proper execution of button presses and engagement with the EEfRT.

Following previous research (e.g., Treadway et al., 2009, Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, et al. 2012), trial-by-trial modeling was conducted to account for time-varying parameters; only the first 50 trials after practice were extracted for data analysis, and only trials in which the participant (not the computer) made a choice were analyzed. Moreover, participants were excluded completely if they had a physical feature that precluded complete engagement with the task (e.g., broken finger, arthritis in wrist), technical problems during their session (e.g., computer crash in the middle of the task), or behavior that indicated they were not making decisions or were not completing the selected tasks (i.e., timing out on over 10% of trials, failing to complete the selected task on over 20% of trials). The final sample consisted of 80 participants. Excluded participants did not differ significantly from included participants on average SUD severity.

The primary outcome from the EEfRT was choice (easy task vs. hard task). For each trial, two key variables were incorporated into analyses: the reward magnitude at stake for the hard task and the probability of earning a reward for successfully completing either task. In addition, the product of these two variables was calculated and used to represent the EV of the hard task for each trial. This third key variable, EV, thus represented the combined effect of reward magnitude and probability.

Results

Reward magnitude, probability, and EV influence effort-based choice

We first aimed to confirm that, consistent with prior studies, EV was a significant predictor of hard-task choice options regardless of SUD status. To confirm that participants' choices to select high- versus low-effort options were guided by EV, we ran a mixed-effects logistic regression model in STATA (Version 14). Choice was considered a binary outcome variable (0 = easy task, 1 = hard task), and EV, participant age, and trial number were considered continuous fixed-effect predictors.[1] Participant was treated as a random effect. Consistent with previous research, there was a significant main effect for EV (β = 0.801, *SE* = 0.041, 95% CI = [0.720, 0.882], z = 19.44, p < .001) on choice such that as the EV for the hard task increased, there was a greater likelihood of selecting the hard task. Overall, individuals used EV to inform their decisions to expend effort. Moreover, EV predicted choice behavior (β = 0.484, *SE* = 0.144, 95% CI = [0.203, 0.765], z = 3.37, p = .001) even after controlling for trial-wise variation in both reward magnitude (mean-centered; β = 0.562, *SE* = 0.045, 95% CI = [0.474, 0.51], z = 12.45, p < .001) and probability (mean-centered; β = 2.04, *SE* = 0.128, 95% CI = [1.787, 2.287], z = 15.97, p < .001). These data confirm that decisions about effort expenditure relied on the integration of multiple decision variables available at the time of choice to guide action value estimation and drive action selection (for additional analyses of task effects, see the Supplemental Material).

Individuals with more severe SUDs show diminished cost–benefit integration during effort-based choice

To determine whether the use of EV to guide choice behavior varied at different levels of SUD severity, we used a mixed-effect logistic regression model and included EV, average SUD severity, and the EV × SUD Severity interaction as continuous fixed-effects predictors. Consistent with our hypothesis, individuals with higher average SUD severity appeared less likely to use EV to modulate effort expenditure (β = −0.139, *SE* = 0.041, 95% CI = [−0.220, −0.059], z = −3.39, p = .001; Fig. 1).

This pattern of behavior is not necessarily evidence of a deficit in integrating effort costs and EV. It is possible that severity-linked differences in the use of EV information during effort-based choice could reflect blunted sensitivity to one or both of the decision variables used to calculate EV. It was thus important to identify any significant two-way interactions between our measure of SUD severity and reward magnitude or probability. Indeed, sensitivity to both reward magnitude and reward probability were blunted in individuals with more severe SUDs: Reward magnitude and probability showed independent interactions with SUD severity (Reward Magnitude × SUD Severity: β = −0.135, *SE* = 0.045, 95% CI = [−0.224, −0.047], z = −3.00, p = .003; Probability × SUD Severity: β = −0.327, *SE* = 0.128, 95% CI = [−0.577, −0.077], z = −2.56, p = .010).

To confirm that the EV × SUD interaction (reflecting the integration of two decision variables) accounted for variance in choice behavior over and above that which could be explained by the interactions between SUD severity and the two "simple" decision variables (reward magnitude and probability), we included the three-way

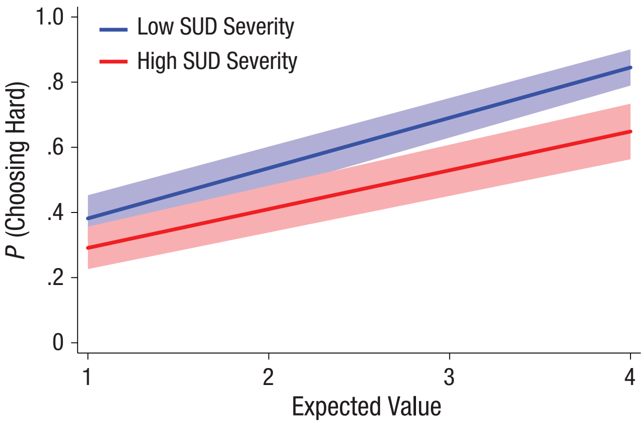

Fig. 1. Expected value (EV) by substance use disorder (SUD) severity. Individuals with more severe SUDs were less likely to use EV to modulate effort expenditure. Lines represent ±1 *SD* from the mean. Shading around lines represents 95% confidence intervals for point estimates.

interaction between reward, probability, and SUD severity as a continuous fixed-effect predictor. If the SUD Severity × EV interaction truly signifies an integration deficit, rather than simply reflecting an insensitivity to reward magnitude and/or probability that is carried over into the EV term, the three-way interaction between reward, probability, and SUD severity should predict choice even when two-way interactions between the simple decision variables and SUD are modeled. In fact, a significant three-way interaction between reward magnitude, probability, and SUD severity was observed ($\beta = 0.250$, $SE = 0.085$, 95% CI = [0.083, 0.417], $z = 2.94$, $p = .003$; see Fig. 2). This pattern of results is consistent with the notion that more severe SUDs are associated with a relative deficit in the capacity to integrate available decisions variables—here, reward magnitude and probability of reward receipt—to modulate action valuation and selection during cost–benefit decisions involving effort allocation. Having confirmed that the effects of SUD severity on EV use during effort-based choice reflect an integration deficit rather than simply recapitulating the independent effects of SUDs on the use of reward magnitude and probability information, we used EV in subsequent analyses of motivation for substance use and delay discounting.

EV sensitivity during effort-based decision making varies by motivational triggers for substance use

The relationships among effort-based decision making, motivation, and SUD severity suggest that variation in approach/avoidance tendencies might moderate the relationship between SUDs and effort-based choice (Baker et al., 2004; Cheetham et al., 2010; Kassel et al., 2007; Treadway, Buckholtz, et al., 2012; Volkow et al., 2005). To explore this possible relationship, we first tested for two-way interactions between EV sensitivity and individual differences in approach and avoidance motivations for substance use. Approach and avoid scales from the RISQ were entered into separate models. We found significant effects for both the Approach × EV ($\beta = 0.057$, $SE = 0.016$, 95% CI = [0.025, 0.089], $z = 3.49$, $p < .001$) and Avoid × EV interaction terms ($\beta = -0.037$, $SE = 0.018$, 95% CI = [−0.072, −0.002], $z = -2.09$, $p = .037$) that indicate that approach and avoidance motivation exerted independent and opposing influences on EV use during effort-based decision making. Specifically, individuals who tend to seek substances to enhance positive affect were more sensitive to EV information during effort-based computations, whereas those who use drugs to avoid negative affect exhibited decreased sensitivity to EV.

Next, we sought to determine whether approach/avoidance motivation modulated the relationship between EV sensitivity and SUD severity. Models included all first- and second-order terms and the three-way interaction term. The Approach × EV × SUD Severity interaction was not significant ($\beta = -0.020$, $SE = 0.018$, 95% CI = [−0.055, 0.014], $z = -1.14$, $p = .253$). However, the Avoid × EV × SUD Severity interaction was significant ($\beta = -0.058$, $SE = 0.020$, 95% CI = [−0.097, −0.018], $z = -2.84$, $p = .004$; see Fig. 3). These results indicate that EV sensitivity was weaker in the individuals with more severe SUDs whose use was primarily motivated by a desire to avoid negative affect.

Delay-cost sensitivity predicts effort and blunted EV sensitivity during effort-based decision making

Cost–benefit decisions involving effort costs may also inherently involve considerations of delay costs, given that the outcomes of more effortful choices frequently are realized with greater time delays compared with time delays associated with less effortful options. This tendency suggests that individuals who more steeply discount delayed rewards also should avoid high-effort–high-reward options. We found a negative relationship between ln*k* values calculated from the MCQ and the probability of making high-effort–high-reward choices ($\beta = -0.225$, $SE = -0.099$, 95% CI = [−0.419, −0.031], $z = -2.28$, $p = .023$). This result indicates that participants with higher levels of delay discounting exhibited increased effort aversion during decision making.

Next, we examined whether the use of EV signals to make effort-based choices varied as a function of delay discounting. A significant ln*k* × EV interaction was observed ($\beta = -0.153$, $SE = 0.035$, 95% CI = [−0.221, −0.085], $z = -4.42$, $p < .001$); EV use during effort-based decision making diminished with greater levels of delay

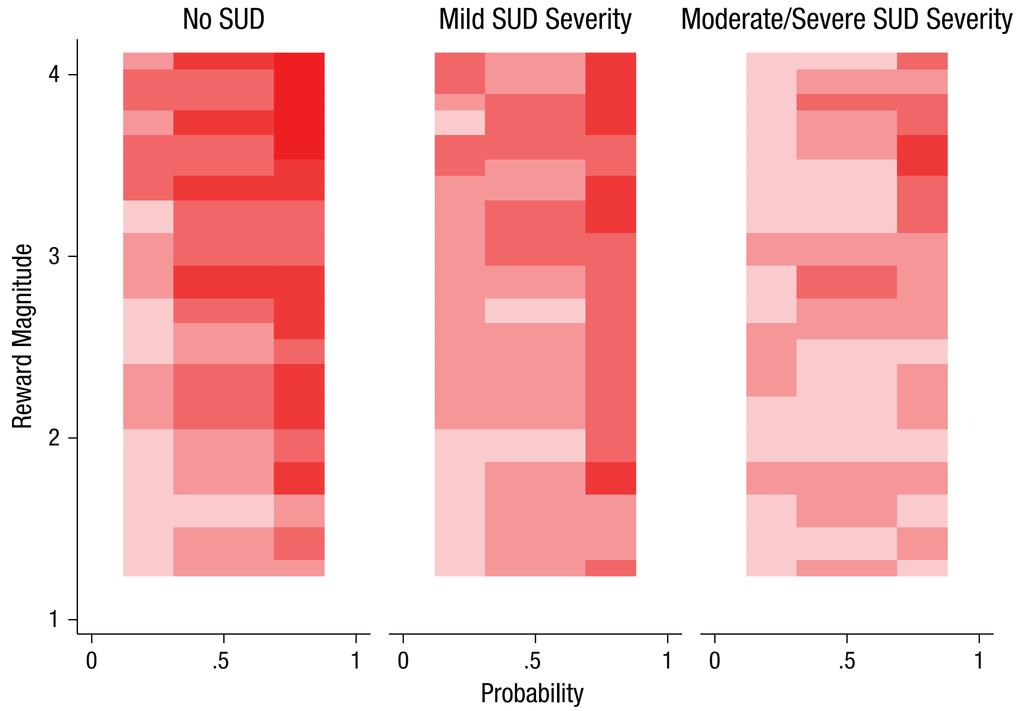

Fig. 2. Heat map showing the effects of reward magnitude and probability on choice at each level of substance use disorder (SUD) severity. Individuals with more severe SUDs displayed a relative deficit in the capacity to integrate reward magnitude and probability to modulate effort expenditure. For display, average SUD severity: no diagnosis = 21 participants, mild (two or three symptoms) = 17 participants, moderate (four or five symptoms) = 13 participants, and severe (six or more symptoms) = 29 participants. Heat maps indicate that the likelihood of choosing the hard task increases (i.e., shading becomes darker red) as probability increases (horizontally from left to right across each heat map), as reward magnitude increases (vertically from the bottom to the top of each heat map), and as expected value (EV) increases (diagonally from bottom left to top right of each heat map). However, looking at the separate panels by SUD severity, each of these effects (probability, reward magnitude, EV) is diminished among individuals with more severe SUDs (i.e., individuals with moderate or severe SUDs transition to red shading that is lighter compared with those with no or mild SUDs).

discounting. Together, these findings are consistent with the notion that effort-based decision making and delay discounting rely on common cognitive mechanisms (see the Supplemental Material for follow-up analyses examining integration of probability and reward).

These findings also raise the possibility that a known risk factor for SUDs (steeper delay discounting) might amplify the effect of SUD severity on effort-based computations. To test this possibility, we ran a model that included all first- and second-order terms and the three-way interaction term. However, we did not observe significant interactions between delay discounting and SUD severity on effort allocation preferences (ln*k* × SUD Severity: $\beta = -0.121$, $SE = 0.130$, 95% CI = [−0.376, −0.134], $z = -0.93$, $p = .354$). The three-way interaction between ln*k*, EV, and SUD severity likewise was not significant (ln*k* × EV × SUD Severity: $\beta = 0.037$, $SE = 0.039$, 95% CI = [−0.040, 0.114], $z = 0.95$, $p = .343$). On the whole, this pattern of results indicated that delay discounting affects effort-based computations by interfering with the use of EV information during effort-based decision making. However, evidence supporting the relevance of this relationship for SUDs was not compelling given that we did not observe interactions between delay discounting, EV, and SUD severity.

Discussion

In a community sample enriched for SUDs, we found evidence that aberrant cost–benefit computations are associated with the expression of SUDs. Specifically, individuals with more severe SUDs displayed decreased sensitivity to EV information during effort-based decision making. Note that the significant three-way interaction between reward magnitude, probability, and SUD severity reflected deficits in the integration of multiple decision variables during effort-based decision making. These integration deficits had motivational specificity; in particular, the individuals with more severe SUDs

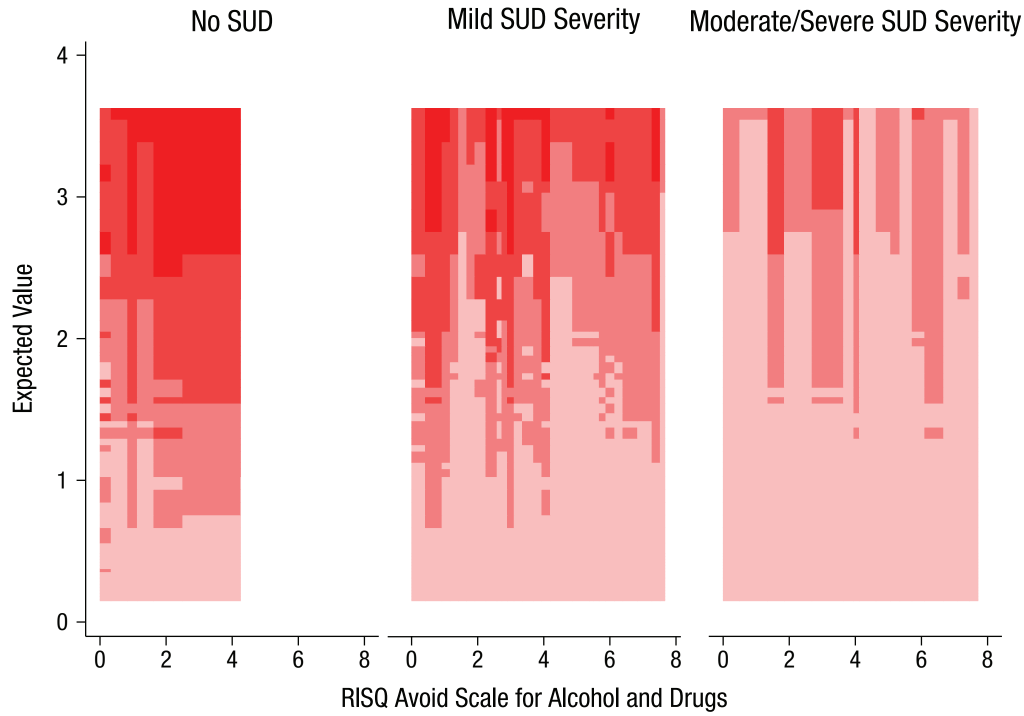

Fig. 3. Heat map showing the two-way interaction between expected value (EV) and Risky, Impulsive, and Self-Destructive Behavior Questionnaire (RISQ) avoid at each level of substance use disorder (SUD) severity, allowing for a visualization of the three-way interaction. Individuals with more severe SUDs and higher avoidance motivations were less likely to use EV information during effort-based computations. For display, average SUD severity: no diagnosis = 21 participants, mild (two or three symptoms) = 17 participants, moderate (four or five symptoms) = 13 participants, and severe (six or more symptoms) = 29 participants. Heat maps indicate that the likelihood of choosing the hard task increases (i.e., shading becomes darker red) as EV increases (moving from bottom to top across each heat map). However, the separate panel for individuals with moderate to severe SUDs indicates that the EV effect is diminished (i.e., shading transitions to a lighter red) among those with higher avoid tendencies.

who used substances primarily to avoid experiencing negative affect exhibited the most pronounced cost–benefit decision-making integration deficits during effort-based choice. These data provide evidence that the capacity to integrate information from multiple decision-making variables to estimate EV and guide action selection is compromised in individuals with more severe SUDs, especially among those whose SUDs are driven by avoidance motivations.

The finding that individuals with more severe SUDs were less able to integrate information about reward magnitude and probability into an EV signal that was used to guide effort expenditure is especially interesting given that the brain circuit mechanisms underlying cost–benefit decision making broadly and effort-based decision making specifically appear dramatically compromised in individuals with SUDs. For instance, decrements in striatal DA transmission were reported in individuals with both SUDs and a preference for low effort-low cost choices during effort-based decision making (Martinez et al., 2007; Treadway, Buckholtz, et al., 2012). Note that these deficits also are associated with symptom severity in other clinical populations (e.g., Culbreth et al., 2018; Treadway, Bossaller, et al., 2012; Yang et al., 2014). DA dysfunction also predicts SUD treatment outcomes, and some researchers suggest a link between blunted striatal DA transmission, SUD relapse, and effort-based decision making (Martinez et al., 2011). Our finding that individuals with severe SUDs show deficits in decision variable integration during effort-based choice is consistent with the possibility that aberrant decision-making preferences may play a particularly strong role in the maintenance and modifiability of more severe SUDs.

Furthermore, the motivationally specific deficit in decision variable integration highlights the importance of considering negative affect as a determinant of the modulation of effort expenditure. Research in rodents and humans documents that negative affect, from acute stress to clinical levels of depression, impairs effort-based decision making (Shafiei, Gray, Viau, & Floresco, 2012; Treadway et al., 2009). The relationship between negative affect and SUDs also is well documented; considerable evidence from population-based and clinical studies supports a positive association between negative affect, chronic distress, and SUDs. In fact, difficulty tolerating distress (i.e., heightened perception of unpleasant states and difficulty persisting in goal-directed activity when experiencing distress) increases risk for experiencing negative emotional states, withdrawal symptoms, use of avoidance-based coping strategies, and treatment dropout in individuals with SUDs (Baskin-Sommers & Hearon, 2015; Daughters, Lejuez, Bornovalova, et al., 2005; Daughters, Lejuez, Kahler, Strong, & Brown, 2005; McHugh, Hearon, & Otto, 2010). In the EEfRT, it is possible that individuals with more severe SUDs and strong avoidance tendencies may have less tolerance for the distress involved in completing effortful tasks and may thus be less willing to expend effort, regardless of the rewards at stake or their probabilities. Taken together, these findings suggest that negative affect not only influences effort-based decision making but also that individual differences in the avoidance of negative affect may further constrain integration of decision variables during effort-based choice among individuals with more severe SUDs.

Another important cost–benefit decision-making factor related to SUDs is delay discounting. Delay-cost sensitivity is a robust predictor of multiple stages of SUDs. Here, we found that participants with steeper delay discounting during intertemporal choice showed a consistent preference for low effort and low reward options and were less sensitive to information about expected value during effort-based choice. This finding, to our knowledge, is the first report of a link between these facets of cost–benefit decision making in humans. However, this relationship is perhaps not surprising given the overlap in mechanisms contributing to both effort and delay-based discounting (Croxson et al., 2009; J. Peters & Buchel, 2011; Westbrook, Kester, & Braver, 2013). It is often the case that rewards that require more effort to obtain also are received at greater temporal delays. It is possible that the shortsightedness about the future present in individuals who discount delayed rewards more steeply prevents them from appropriately estimating the value of exerting effort to obtain future rewards. In other words, steeper delay discounting may reflect not only a bias toward the present but also an intolerance or aversion to delays that precede rewards requiring a high amount of effort (Pattij & Vanderschuren, 2008). This could be the case with the task in this study, given the longer duration of the hard task delays the delivery of feedback about reward earnings relative to the easy task. However, the relationship between delay- and effort-based preferences may not have specific relevance for SUD severity.

We found no evidence that delay discounting moderated the relationship between effort-based computations and severity of SUDs. Both SUD severity and delay discounting exerted independent influences on effort-based decision making. Follow-up analyses on our EV findings indicated that individuals with more severe SUDs showed reduced sensitivity to multiple decision variables (probability, reward, and their combination, EV), which suggests integration deficits. By contrast, elevated delay discounting was associated with diminished sensitivity to probability but not with differences in sensitivity to reward magnitude (see the Supplemental Results in the Supplemental Material). This latter finding is consistent with prior studies linking delay-cost sensitivity with abnormal probability-cost sensitivity (Green & Myerson, 2013). More broadly, though, these independent influences on effort-based decision making reflect how multiple factors can result in similar decision-making aberrations. Overall, these findings highlight the importance of considering not only specific facets of cost–benefit decision making but also component processes within types of decision costs and individual differences that relate to them (Green & Myerson, 2013).

The present study is not without limitations. First, although we used a well-characterized sample of individuals with SUDs, we included individuals with both current (past 12 months) and past (before past 12 months) diagnoses. On the basis of existing research, there was no reason to believe SUD recency or remission status would affect effort-based decision making, and previous research has shown cost–benefit decision-making deficits across stages of SUDs (initiation, maintenance, recovery, and relapse). Second, we included individuals with SUDs across several substance categories. Our choice to measure SUD severity across substance categories was based on well-documented rates of polysubstance use, particularly among more severe users. Third, although it is hypothesized that effort-based decision making is important for treatment outcomes among individuals with SUDs, we did not have measures of treatment in the present sample. Fourth, our cross-sectional design precluded the ability to rule out whether decreased use of EV to modulate effort occurs as a consequence of more severe SUDs rather than as a mechanism supporting the development of more severe SUDs. Although our effects were robust to various measures of SUD severity (see the Supplemental Results in the Supplemental Material), future studies replicating the found associations between effort-based decision making and SUD-related impairment and studies connecting effort-based decision making to stage of illness and treatment outcomes in SUDs are needed to increase confidence in our results and extend them in meaningful ways.

Finally, the goal of the present study was to examine the influence of decision variables on effort-based computations; however, we did not measure effort discounting (Botvinick, Huffstetler, & McGuire, 2009). The EEfRT is designed to look at basic effort-based decision making, but it does not measure effort discounting because there was no parametric variation in the amount of effort required over trials. Future studies that sample from a wider distribution of effort options would be useful for testing alterations in effort-based decision making among individuals with SUDs.

In sum, our findings indicate that individuals with more severe SUDs show aberrations in the integration of multiple decision variables to guide action selection during effort-based decision making. Moreover, these integration deficits appear to be closely linked to motivations to avoid negative affect. Decisions regarding effort define many real-world choices confronted by individuals with SUDs. Whether they are deciding to make an effort to find a sober driver or overcome perceived barriers to attending treatment (Probst et al., 2015), these choices require the integration of information regarding the probabilities of different outcomes and their potential benefits (e.g., the greater likelihood of safety despite the cost of the ride, the greater likelihood of abstaining from substance use despite the time and money spent on therapy, the greater likelihood of improving physical health despite the initial discomfort of withdrawal). Failure to integrate this information can result in a choice that yields problematic outcomes (e.g., arrest, physical harm) for the individual and other members of society.

More broadly, these findings are particularly interesting given mounting evidence for cost–benefit integration deficits in other disorders highly comorbid with SUDs, from internalizing disorders (e.g., depression) to externalizing disorders (e.g., antisocial personality disorder; Buckholtz, 2015). Although we know of no studies to date that look specifically at effort-based decision making in other externalizing disorders, the present findings raise the intriguing possibility that such deficits may constitute a common mechanism across several forms of psychopathology. An exciting avenue for future research will be to examine whether findings related to cost–benefit decision making reflect common factors that influence risk for psychopathology more generally or whether specific combinations of decision-making abnormalities confer risk for specific disorders (e.g., SUDs, depression, schizophrenia) or specific aspects of their expression (e.g., course of illness, severity). Future studies examining multiple facets of cost–benefit decision making systematically across heterogeneous samples may help to identify and specify transdiagnostic features of clinical disorders.

Action Editor

John J. Curtin served as action editor for this article.

Author Contributions

All of the authors developed the study concept and contributed to the study design. Data collection was performed by A. M. Stuppy-Sullivan and A. Baskin-Sommers, and all of the authors contributed to analysis and interpretation. A. M. Stuppy-Sullivan drafted the manuscript, and A. Baskin-Sommers and J. W. Buckholtz provided critical revisions. All of the authors approved the final manuscript for submission.

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Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/2167702619868155

Open Practices

All data have been made publicly available via Open Science Framework and can be accessed at https://osf.io/uz32c. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/2167702619868155. This article has received the badge for Open Data. More information about the Open Practices badges can be found at https://www.psychologicalscience.org/publications/badges.

Note

1. Consistent with prior studies using the EEfRT, age and trial number were included in all analyses to account for potential confounding effects of fatigue, including those associated with age (Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, et al., 2012; Treadway et al., 2009; Wardle et al., 2011). For all results, age was a significant predictor of fewer hard-task choices (all ps $< .01$), and trial number was either a significant predictor of fewer hard choices or predicted fewer hard choices at trend levels (all ps $< .08$). However, all effects reported in the article remained significant when age and trial number were not included as covariates.

References

Amlung, M., & MacKillop, J. (2011). Delayed reward discounting and alcohol misuse: The roles of response consistency and reward magnitude. *Journal of Experimental Psychopathology*, *2*, 418–431.

Amlung, M., Vedelago, L., Acker, J., Balodis, I., & MacKillop, J. (2017). Steep delay discounting and addictive behavior: A meta-analysis of continuous associations. *Addiction*, *112*, 51–62.

Baker, T. B., Piper, M. E., McCarthy, D. E., Majeskie, M. R., & Fiore, M. C. (2004). Addiction motivation reformulated: An affective processing model of negative reinforcement. *Psychological Review*, *111*, 33–51.

Barch, D. M., Treadway, M. T., & Schoen, N. (2014). Effort, anhedonia, and function in schizophrenia: Reduced effort allocation predicts amotivation and functional impairment. *Journal of Abnormal Psychology*, *123*, 387–397.

Baskin-Sommers, A. R., & Hearon, B. A. (2015). The intersection between neurobiological and psychological theories of substance use disorders. In H. H. Brownstein (Ed.), *The handbook of drugs and society* (pp. 218–235). Hoboken, NJ: John Wiley & Sons.

Bickel, W. K., Johnson, M. W., Koffarnus, M. N., MacKillop, J., & Murphy, J. G. (2014). The behavioral economics of substance use disorders: Reinforcement pathologies and their repair. *Annual Review of Clinical Psychology*, *10*, 641–677.

Botvinick, M. M., Huffstetler, S., & McGuire, J. T. (2009). Effort discounting in human nucleus accumbens. *Cognitive, Affective, & Behavioral Neuroscience*, *9*, 16–27.

Brown, H. E., Hart, K. L., Snapper, L. A., Roffman, J. L., & Perlis, R. H. (2018). Impairment in delay discounting in schizophrenia and schizoaffective disorder but not primary mood disorders. *npj Schizophrenia*, *4*, Article 9. doi:10.1038/s41537-018-0050-z.

Buckholtz, J. W. (2015). Social norms, self-control, and the value of antisocial behavior. *Current Opinion in Behavioral Sciences*, *3*, 122–129. doi:10.1016/j.cobeha.2015.03.004

Cáceda, R., Durand, D., Cortes, E., Prendes-Alvarez, S., Moskovciak, T., Harvey, P. D., & Nemeroff, C. B. (2014). Impulsive choice and psychological pain in acutely suicidal depressed patients. *Psychosomatic Medicine*, *76*, 445–451.

Cheetham, A., Allen, N. B., Yücel, M., & Lubman, D. I. (2010). The role of affective dysregulation in drug addiction. *Clinical Psychology Review*, *30*, 621–634.

Chong, T.-J., Bonnelle, V., & Husain, M. (2016). Quantifying motivation with effort-based decision-making paradigms in health and disease In B. Studer & S. Knecht (Eds.), *Progress in brain research* (Vol. 229, pp. 71–100). Amsterdam, The Netherlands: Elsevier.

Claus, E. D., Kiehl, K. A., & Hutchison, K. E. (2011). Neural and behavioral mechanisms of impulsive choice in alcohol use disorder. *Alcoholism: Clinical and Experimental Research*, *35*, 1209–1219.

Croxson, P. L., Walton, M. E., O'Reilly, J. X., Behrens, T. E., & Rushworth, M. F. (2009). Effort-based cost–benefit valuation and the human brain. *The Journal of Neuroscience*, *29*, 4531–4541.

Culbreth, A., Moran, E., & Barch, D. (2018). Effort-cost decision-making in psychosis and depression: Could a similar behavioral deficit arise from disparate psychological and neural mechanisms? *Psychological Medicine*, *48*, 889–904.

Daughters, S. B., Lejuez, C., Bornovalova, M. A., Kahler, C. W., Strong, D. R., & Brown, R. A. (2005). Distress tolerance as a predictor of early treatment dropout in a residential substance abuse treatment facility. *Journal of Abnormal Psychology*, *114*, 729–734.

Daughters, S. B., Lejuez, C. W., Kahler, C. W., Strong, D. R., & Brown, R. A. (2005). Psychological distress tolerance and duration of most recent abstinence attempt among residential treatment-seeking substance abusers. *Psychology of Addictive Behaviors*, *19*, 208–211.

Everitt, B. J., Belin, D., Economidou, D., Pelloux, Y., Dalley, J. W., & Robbins, T. W. (2008). Neural mechanisms underlying the vulnerability to develop compulsive drug-seeking habits and addiction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*, 3125–3135.

First, M. B., Williams, J. B. W., Karg, R. S., & Spitzer, R. L. (2015). *Structured clinical interview for* DSM-5*—Research version (SCID-5 for DSM-5, research version; SCID-5-RV)*. Washington, DC: American Psychiatric Association.

Forster, S. E., Finn, P. R., & Brown, J. W. (2017). Neural responses to negative outcomes predict success in community-based substance use treatment. *Addiction*, *112*, 884–896.

Forsyth, J. P., Parker, J. D., & Finlay, C. G. (2003). Anxiety sensitivity, controllability, and experiential avoidance and their relation to drug of choice and addiction severity in a residential sample of substance-abusing veterans. *Addictive Behaviors*, *28*, 851–870.

Garrison, K. A., & Potenza, M. N. (2014). Neuroimaging and biomarkers in addiction treatment. *Current Psychiatry Reports*, *16*, Article 513. doi:10.1007/s11920-014-0513-5

Gökbayrak, N., Paiva, A., Blissmer, B., & Prochaska, J. (2015). Predictors of relapse among smokers: Transtheoretical effort variables, demographics, and smoking severity. *Addictive Behaviors*, *42*, 176–179.

Goldstein, R. Z., Alia-Klein, N., Tomasi, D., Carrillo, J. H., Maloney, T., Woicik, P. A., . . . Volkow, N. D. (2009). Anterior cingulate cortex hypoactivations to an emotionally salient task in cocaine addiction. *Proceedings of the National Academy of Sciences, USA*, *106*, 9453–9458.

Goldstein, R. Z., & Volkow, N. D. (2011). Dysfunction of the prefrontal cortex in addiction: Neuroimaging findings and clinical implications. *Nature Reviews Neuroscience*, *12*, 652–669.

Green, L., & Myerson, J. (2013). How many impulsivities? A discounting perspective. *Journal of the Experimental Analysis of Behavior*, *99*, 3–13.

Heerey, E. A., Robinson, B. M., McMahon, R. P., & Gold, J. M. (2007). Delay discounting in schizophrenia. *Cognitive Neuropsychiatry*, *12*, 213–221.

Inzlicht, M., Shenhav, A., & Olivola, C. Y. (2018). The effort paradox: Effort is both costly and valued. *Trends in Cognitive Sciences*, *22*, 337–349.

Kassel, J. D., Greenstein, J. E., Evatt, D. P., Roesch, L. L., Veilleux, J. C., Wardle, M. C., & Yates, M. C. (2007).

Negative affect and addiction. In M. Al'Absi (Ed.), *Stress and addiction: Biological and psychological mechanisms* (pp. 171–189). San Diego, CA: Elsevier Academic Press.

Kessler, R. C., Chiu, W. T., Demler, O., & Walters, E. E. (2005). Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry*, *62*, 617–627.

Kirby, K. N., Petry, N. M., & Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology: General*, *128*, 78–87.

Kopak, A. M., Hoffmann, N. G., & Proctor, S. L. (2016). Key risk factors for relapse and rearrest among substance use treatment patients involved in the criminal justice system. *American Journal of Criminal Justice*, *41*, 14–30.

Kreek, M. J., Nielsen, D. A., Butelman, E. R., & LaForge, K. S. (2005). Genetic influences on impulsivity, risk taking, stress responsivity and vulnerability to drug abuse and addiction. *Nature Neuroscience*, *8*, 1450–1457.

Kreidler, S. M., Muller, K. E., Grunwald, G. K., Ringham, B. M., Coker-Dukowitz, Z. T., Sakhadeo, U. R., . . . Glueck, D. H. (2013). GLIMMPSE: Online power computation for linear models with and without a baseline covariate. *Journal of Statistical Software*, *54*(10), Article i10. Retrieved from https://www.jstatsoft.org/article/view/v054i10

Krishnan-Sarin, S., Reynolds, B., Duhig, A. M., Smith, A., Liss, T., McFetridge, A., . . . Potenza, M. N. (2007). Behavioral impulsivity predicts treatment outcome in a smoking cessation program for adolescent smokers. *Drug and Alcohol Dependence*, *88*, 79–82.

Kurniawan, I. T., Guitart-Masip, M., & Dolan, R. J. (2011). Dopamine and effort-based decision making. *Frontiers in Neuroscience*, *5*, Article 81. doi:10.3389/fnins.2011.00081

Lijffijt, M., Hu, K., & Swann, A. C. (2014). Stress modulates illness-course of substance use disorders: A translational review. *Frontiers in Psychiatry*, *5*, Article 83. doi:10.3389/fpsyt.2014.00083

MacKillop, J., & Kahler, C. W. (2009). Delayed reward discounting predicts treatment response for heavy drinkers receiving smoking cessation treatment. *Drug and Alcohol Dependence*, *104*, 197–203.

Martinez, D., Carpenter, K. M., Liu, F., Slifstein, M., Broft, A., Friedman, A. C., . . . Nunes, E. (2011). Imaging dopamine transmission in cocaine dependence: Link between neurochemistry and response to treatment. *American Journal of Psychiatry*, *168*, 634–641.

Martinez, D., Narendran, R., Foltin, R. W., Slifstein, M., Hwang, D.-R., Broft, A., . . . Kleber, H. D. (2007). Amphetamine-induced dopamine release: Markedly blunted in cocaine dependence and predictive of the choice to self-administer cocaine. *American Journal of Psychiatry*, *164*, 622–629.

Maynard, C., Graves, M. C., West, I. I., Bumgardner, K., Krupski, A., & Roy-Byrne, P. (2016). Drug use severity, mortality, and cause of death in primary care patients with substance use disorders. *SAGE Open*, *6*(1). doi:10.1177/2158244015626225

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In M. L. Commons, J. E. Mazur, J. A. Nevin, & H. Rachlin (Eds.), *Quantitative analyses of behavior, Vol. V. The effect of delay and of intervening events on reinforcement value* (pp. 55–73). Hillsdale, NJ: Erlbaum.

McCabe, S. E., Cranford, J. A., & Boyd, C. J. (2016). Stressful events and other predictors of remission from drug dependence in the United States: Longitudinal results from a national survey. *Journal of Substance Abuse Treatment*, *71*, 41–47.

McHugh, R. K., Hearon, B. A., & Otto, M. W. (2010). Cognitive behavioral therapy for substance use disorders. *Psychiatric Clinics of North America*, *33*, 511–525. doi:10.1016/j.psc.2010.04.012

Mitchell, M. R., & Potenza, M. N. (2014). Addictions and personality traits: Impulsivity and related constructs. *Current Behavioral Neuroscience Reports*, *1*, 1–12.

Mokdad, A. H., Ballestros, K., Echko, M., Glenn, S., Olsen, H. E., Mullany, E., . . . Ferrari, A. J. (2018). The state of US health, 1990-2016: Burden of diseases, injuries, and risk factors among US states. *JAMA: Journal of the American Medical Association*, *319*, 1444–1472.

National Institute on Drug Abuse. (2016). *Trends & statistics*. Retrieved from https://www.drugabuse.gov/related-topics/trends-statistics

Pattij, T., & Vanderschuren, L. J. (2008). The neuropharmacology of impulsive behaviour. *Trends in Pharmacological Sciences*, *29*, 192–199.

Peters, E. N., Petry, N. M., LaPaglia, D. M., Reynolds, B., & Carroll, K. M. (2013). Delay discounting in adults receiving treatment for marijuana dependence. *Experimental and Clinical Psychopharmacology*, *21*, 46–54.

Peters, J., & Buchel, C. (2011). The neural mechanisms of inter-temporal decision-making: Understanding variability. *Trends in Cognitive Sciences*, *15*, 227–239. doi:10.1016/j.tics.2011.03.002

Phillips, P. E., Walton, M. E., & Jhou, T. C. (2007). Calculating utility: Preclinical evidence for cost–benefit analysis by mesolimbic dopamine. *Psychopharmacology*, *191*, 483–495.

Prévost, C., Pessiglione, M., Météreau, E., Cléry-Melin, M.-L., & Dreher, J.-C. (2010). Separate valuation subsystems for delay and effort decision costs. *The Journal of Neuroscience*, *30*, 14080–14090.

Probst, C., Manthey, J., Martinez, A., & Rehm, J. (2015). Alcohol use disorder severity and reported reasons not to seek treatment: A cross-sectional study in European primary care practices. *Substance Abuse Treatment, Prevention, and Policy*, *10*(1), Article 32. doi:10.1186/s13011-015-0028-z

Pulcu, E., Trotter, P., Thomas, E., McFarquhar, M., Juhász, G., Sahakian, B., . . . Elliott, R. (2014). Temporal discounting in major depressive disorder. *Psychological Medicine*, *44*, 1825–1834.

Rangel, A., & Hare, T. (2010). Neural computations associated with goal-directed choice. *Current Opinion in Neurobiology*, *20*, 262–270.

Rudebeck, P. H., Walton, M. E., Smyth, A. N., Bannerman, D. M., & Rushworth, M. F. (2006). Separate neural pathways process different decision costs. *Nature Neuroscience*, *9*, 1161–1168.

Sadeh, N., & Baskin-Sommers, A. (2017). Risky, Impulsive, and Self-Destructive Behavior Questionnaire (RISQ): A validation study. *Assessment*, *24*, 1080–1094. doi:10.1177/1073191116640356

Salamone, J. D., Correa, M., Farrar, A., & Mingote, S. M. (2007). Effort-related functions of nucleus accumbens dopamine and associated forebrain circuits. *Psychopharmacology*, *191*, 461–482.

Salamone, J. D., Correa, M., Yohn, S., Cruz, L. L., San Miguel, N., & Alatorre, L. (2016). The pharmacology of effort-related choice behavior: Dopamine, depression, and individual differences. *Behavioural Processes*, *127*, 3–17.

Shafiei, N., Gray, M., Viau, V., & Floresco, S. B. (2012). Acute stress induces selective alterations in cost/benefit decision-making. *Neuropsychopharmacology*, *37*, 2194–2209.

Shorey, R. C., Gawrysiak, M. J., Elmquist, J., Brem, M., Anderson, S., & Stuart, G. L. (2017). Experiential avoidance, distress tolerance, and substance use cravings among adults in residential treatment for substance use disorders. *Journal of Addictive Diseases*, *36*, 151–157.

Stanger, C., Ryan, S. R., Fu, H., Landes, R. D., Jones, B. A., Bickel, W. K., & Budney, A. J. (2012). Delay discounting predicts adolescent substance abuse treatment outcome. *Experimental and Clinical Psychopharmacology*, *20*, 205–212.

Stevens, L., Verdejo-García, A., Goudriaan, A. E., Roeyers, H., Dom, G., & Vanderplasschen, W. (2014). Impulsivity as a vulnerability factor for poor addiction treatment outcomes: A review of neurocognitive findings among individuals with substance use disorders. *Journal of Substance Abuse Treatment*, *47*, 58–72.

Treadway, M. T., Bossaller, N. A., Shelton, R. C., & Zald, D. H. (2012). Effort-based decision-making in major depressive disorder: A translational model of motivational anhedonia. *Journal of Abnormal Psychology*, *121*, 553–558.

Treadway, M. T., Buckholtz, J. W., Cowan, R. L., Woodward, N. D., Li, R., Ansari, M. S., . . . Zald, D. H. (2012). Dopaminergic mechanisms of individual differences in human effort-based decision-making. *The Journal of Neuroscience*, *32*, 6170–6176.

Treadway, M. T., Buckholtz, J. W., Schwartzman, A. N., Lambert, W. E., & Zald, D. H. (2009). Worth the 'EEfRT'? The effort expenditure for rewards task as an objective measure of motivation and anhedonia. *PLOS ONE*, *4*(8), Article e6598. doi:10.1371/journal.pone.0006598

Treadway, M. T., & Zald, D. H. (2013). Parsing anhedonia: Translational models of reward-processing deficits in psychopathology. *Current Directions in Psychological Science*, *22*, 244–249.

Trifilieff, P., Ducrocq, F., van der Veldt, S., & Martinez, D. (2017). Blunted dopamine transmission in addiction: potential mechanisms and implications for behavior. *Seminars in Nuclear Medicine*, *47*, 64–74.

Venniro, M., Caprioli, D., & Shaham, Y. (2016). Animal models of drug relapse and craving: From drug priming-induced reinstatement to incubation of craving after voluntary abstinence. *Progress in Brain Research*, *224*, 25–52.

Verdejo-García, A., Lawrence, A. J., & Clark, L. (2008). Impulsivity as a vulnerability marker for substance-use disorders: Review of findings from high-risk research, problem gamblers and genetic association studies. *Neuroscience & Biobehavioral Reviews*, *32*, 777–810.

Volkow, N. D., Fowler, J., Wang, G., Baler, R., & Telang, F. (2009). Imaging dopamine's role in drug abuse and addiction. *Neuropharmacology*, *56*, 3–8.

Volkow, N. D., Wang, G.-J., Ma, Y., Fowler, J. S., Wong, C., Ding, Y.-S., . . . Kalivas, P. (2005). Activation of orbital and medial prefrontal cortex by methylphenidate in cocaine-addicted subjects but not in controls: Relevance to addiction. *The Journal of Neuroscience*, *25*, 3932–3939.

Walton, M. E., Rudebeck, P. H., Bannerman, D. M., & Rushworth, M. F. (2007). Calculating the cost of acting in frontal cortex. *Annals of the New York Academy of Sciences*, *1104*, 340–356.

Wardle, M. C., Treadway, M. T., Mayo, L. M., Zald, D. H., & de Wit, H. (2011). Amping up effort: Effects of d-amphetamine on human effort-based decision-making. *The Journal of Neuroscience*, *31*, 16597–16602.

Washio, Y., Higgins, S. T., Heil, S. H., McKerchar, T. L., Badger, G. J., Skelly, J. M., & Dantona, R. L. (2011). Delay discounting is associated with treatment response among cocaine-dependent outpatients. *Experimental and Clinical Psychopharmacology*, *19*, 243–248.

Westbrook, A., Kester, D., & Braver, T. S. (2013). What is the subjective cost of cognitive effort? Load, trait, and aging effects revealed by economic preference. *PLOS ONE*, *8*(7), Article e68210. doi:10.1371/journal.pone.0068210

Wilkinson, G. S. (1993). *The Wide Range Achievement Test: Manual* (3rd ed.). Wilmington, DE: Wide Range Inc.

Yang, X.-h., Huang, J., Zhu, C.-y., Wang, Y.-f., Cheung, E. F., Chan, R. C., & Xie, G.-r. (2014). Motivational deficits in effort-based decision making in individuals with subsyndromal depression, first-episode and remitted depression patients. *Psychiatry Research*, *220*, 874–882.

Yoon, J. H., Higgins, S. T., Heil, S. H., Sugarbaker, R. J., Thomas, C. S., & Badger, G. J. (2007). Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women. *Experimental and Clinical Psychopharmacology*, *15*, 176–186.

Zachary, R. A. (1986). *Shipley Institute of Living Scale: Revised manual*. Los Angeles, CA: Western Psychological Services.