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Affective Motivations for Substance Misuse Differentially Relate to Consideration of Multiple Costs During Effortful Decision Making

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Heightened sensitivity to costs during decision making consistently has been related to substance use. However, no work in this area has manipulated cost information to examine how people evaluate and compare multiple costs. Furthermore, limited work has examined how affective motivations for substance use modulate the evaluation of cost information. We administered a loss-frame variant of the Effort Expenditure for Rewards Task in a diverse community sample ($N = 126$). Individuals who use substances to avoid negative affect allocated comparable effort across varying likelihoods of loss and computational modeling parameters indicated that they did not systematically consider cost information, which ultimately led these individuals to exert effort when it was disadvantageous to do so. Individuals who use substances to enhance positive affect allocated effort when loss magnitudes were small, suggesting that they effectively compared costs and worked to minimize those costs. Motivations for substance use differentially relate to the comparison of costly information, ultimately influencing effective decision making.

General Scientific Summary
Substance use problems are a common issue in the United States, with over 100 million people engaging in problematic use in the past year. This study suggests that people who use substances to avoid negative feelings have difficulty comparing different costs, which paradoxically lead them to work harder for costlier choices. Conversely, people who use substances to feel good effectively compare costs and work to minimize those costs.

Keywords: decision making, loss aversion, substance use, avoidance, motivation

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In 2021, 60.0 million Americans binge-drank in the past month, 9.2 million misused opioids in the past year, and 46.3 million had a substance use disorder in the past year (Substance Abuse and Mental Health Services Administration, 2022). However, not all individuals engage in substance use for the same reasons. Theoretical models of substance use distinguish between use motivated by a desire to avoid negative affect (i.e., avoidance motivation) and use motivated by a desire to enhance positive affect (i.e., approach motivation; M. L. Cooper et al., 2015; Miglin et al., 2020). These affective motivations are associated with different substance use patterns, consequences from substance use, and treatment-related outcomes. For example, avoidance motivations relate to chronic and impairing use (often for coping), whereas approach motivations relate to use initiation (e.g., use primarily for excitement or pleasure; McHugh

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Sonia G. Ruiz served as lead for data curation, formal analysis, software, visualization, and writing–original draft and contributed equally to writing–review and editing. Ifat Levy served in a supporting role for investigation, supervision, visualization, and writing–review and editing. Arielle Baskin-Sommers served as lead for funding acquisition, resources, and supervision and served in a supporting role for formal analysis, visualization, writing–original draft, and writing–review and editing. Sonia G. Ruiz, Ifat Levy, and Arielle Baskin-Sommers contributed equally to conceptualization and methodology. Sonia G. Ruiz and Arielle Baskin-Sommers contributed equally to project administration and investigation.

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& Kneeland, 2019; Miglin et al., 2020; Sadeh et al., 2021). Additionally, consequences stemming from use related to avoidance motivations occur regardless of use frequency/severity, while consequences associated with approach motivations occur through changes in substance use frequency/severity (M. L. Cooper et al., 1995; Holahan et al., 2001; Magid et al., 2007; Merrill & Read, 2010; Simons et al., 2005). Finally, avoidance motivations for substance use are linked to poorer treatment-related outcomes such as earlier drop-out (Daughters, Lejuez, Bornovalova, et al., 2005), elevated craving levels during abstinence (Shorey et al., 2017), and higher relapse rates (Brown et al., 2009; Daughters, Lejuez, Kahler, et al., 2005). Motivations underlying substance misuse seem to impact why substances are used, when consequences are encountered, and how much consequences detract from desired effects of use. Thus, inherent in substance misuse appears to some comparison of different costs—what choice will someone make that incurs one cost (e.g., experiencing negative affect) over another (e.g., loss of familial support)? The goal of the present study was to examine how affective motivations for substance use may differentially relate to the choices people make in the context of comparing different costs.

A cost–benefit decision-making framework often is used to describe how individuals evaluate costs against desired benefits based on the available information. For example, the value of an action, such as using a substance, is modulated by costs including delay (e.g., preferring smaller effects sooner vs. larger later), risk (e.g., the probability of experiencing desired effects), and effort (e.g., drug availability). These costs are compared against desired effects (e.g., relief) to inform an "optimal" choice (Rudebeck et al., 2006). Extant research associates greater substance use severity with heightened sensitivity to delay (Amlung & MacKillop, 2011; Mitchell & Potenza, 2014), risk (often assessed via lottery-like paradigms explicitly stating outcome probabilities; Brand et al., 2008; Brevers et al., 2014; Wittwer et al., 2016), and effort (assessed via paradigms manipulating effort necessary to achieve varying rewards; Stuppy-Sullivan et al., 2020). However, limited work assesses how affective motivations for substance use impacts cost–benefit decision making. One study indicated that people with higher avoidance motivation for substance use were less likely to choose more costly (i.e., effortful) options despite their higher monetary value (Stuppy-Sullivan et al., 2020). Thus, affective motivations may differentially relate to the evaluation of cost variables given a desired benefit and could help explain when certain people repeatedly make "suboptimal" choices.

Most cost–benefit decision-making paradigms assess how costs are evaluated against benefits. However, these paradigms do not include a manipulation of the cost information to model how cost comparisons inform choice. Cost–benefit decision-making tasks typically explore how people choose to incur costs in the context of rewards (Lloyd et al., 2021; Treadway et al., 2009; van den Bos & Hertwig, 2017). For example, during many effort-based decision-making and delay discounting tasks cost is manipulated in terms of how much effort (e.g., nondominant pinky presses; Treadway et al., 2009) or delay (e.g., smaller reward now, larger reward later; Lloyd et al., 2021) individuals are willing to endure for a reward. Other decision-making tasks focus on decisions in the context of losses, but the loss functions as an option individuals learn to avoid selecting altogether rather than evaluate (Blair et al., 2004; Collins & Shenhav, 2022; Hunter et al., 2022). For example, during counterfactual decision-making and passive avoidance learning tasks, loss information is manipulated by comparing outcomes of the alternative choice (e.g., winning $10 but if the other option was selected winning $20; Hunter et al., 2022) or receiving feedback about a stimulus associated with a loss (e.g., some stimulus always results in loss, so should always be avoided; Blair et al., 2004). Altogether, these paradigms do not test decision making among multiple unavoidable costs. There are well-documented differences in decision making among losses versus rewards using a variety of paradigms (i.e., effort-based, delay-discounting, lottery tasks; Byrne & Ghaiumy Anaraky, 2020; De Martino et al., 2006; Dora & Inzlicht, 2022; Kühberger, 1998; Mizak et al., 2021) and extensive work compares how people make choices between different rewards only (J. D. Cohen & Blum, 2002; O'Doherty et al., 2017). However, few studies probe how people make choices between different potential losses to incur without the confound of rewards or comparison between different losses (Massar et al., 2020). Consequently, we have limited understanding of how people compare costs, beyond their preference to avoid certain losses altogether (Nagaya, 2023). Manipulating cost information is important for understanding substance misuse because substance use occurs in a complex decision environment that inherently involves a cost comparison (e.g., expending resources to obtain a substance at the cost of responsibilities and relationships). Clarifying how individuals make cost comparisons may better explain which costs matter (e.g., loss of peer approval, withdrawal symptoms, distress), and for whom (i.e., related to specific affective experiences).

The present study aimed to specify how affective motivations for substance use differentially relate to the consideration and comparison of cost information during effort-based decision making. We administered a loss-frame variant of the Effort Expenditure for Rewards Task (EEfRT) in a community sample and a self-report measure of motivational triggers for substance use to determine the contribution of affective motivations to cost considerations. First, we examined choice preferences via regression analyses to determine the extent to which decision variables such as probability and loss magnitude are considered over the course of the task. Second, to identify choice strategies underlying choice preferences, we applied subjective value modeling. Subjective value modeling is used to determine the strategies individuals rely on to make choices; specifically, modeling the consistent (or inconsistent) evaluation of decision variables such as probability, reward, and effort on each trial (J. A. Cooper et al., 2019). Parameters here reflect sensitivity to decision variables indicative of a specific strategy—for example, consistently evaluating one variable, such as effort, but not others when making choices. Notably, our use of subjective value modeling represents a novel application of well-established decision-making models to characterize choice strategies people use when evaluating multiple unavoidable costs. Thus, our analyses allowed us to not only examine cost preferences overall (i.e., proportion of effortful choice), but also to explore how individuals arrived at their choices (i.e., whether they consistently used cost information).

Consistent with prior research on reward-based decision making, we hypothesized that lower expected values—that is, greater loss magnitude and probability—would predict decreased effort allocation, and that avoidance motivation for substance use would be associated with increased sensitivity to loss magnitude and probability during effort-based decision making (Stuppy-Sullivan et al., 2020). Because subjective value modeling analyses were exploratory and primarily used to interpret choice preference results, we did not have specific hypotheses about relationships between individual parameters and outcomes.

Method

Participants

Adults were recruited from New Haven County, Connecticut through flyers soliciting risk-taking behavior (e.g., substance use, impulsive behavior). A prescreen phone interview and in-person assessment materials were used to exclude individuals who were younger than 18 or older than 65; had performed below fourth-grade level on a standardized measure of reading; had scored below 70 on a standardized measure of IQ; were diagnosed with schizophrenia, bipolar disorder, or psychosis, not otherwise specified or had a family history of psychosis; took antipsychotic, anticonvulsant, or mood stabilizers; or had medical problems that could impede comprehension of or performance on the task (e.g., uncorrectable auditory or visual deficits, head injury with loss of consciousness greater than 30 min). All participants provided written informed consent. Participants earned $15/hr for their completion of the self-report measures and the experimental task. Participants also could earn a bonus (range = $0–$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 was conducted using two methods of simulation: estimating sample size given medium ($\beta = 0.3$) or small effects ($\beta = 0.1$) and a sensitivity analysis given a sample size of 106 (J. Cohen, 1992). We estimated power to detect interactions between task variables (e.g., loss magnitude and probability as two within-subjects variables) and individual difference measures (e.g., motivation for substance use as a between-subject variable) controlling for covariates (age, trial, sex) using a mixed effects logistic regression model (Olvera Astivia et al., 2019). The first simulation analysis showed that with 100 participants there would be 70% and 100% power to detect a small or medium effect for the three-way interaction, respectively (125 participants would have 80% power to detect a small effect). The sensitivity power analysis showed that with a sample of 106 there would be 85% and 77% power to detect two-way and three-way interactions, respectively, of effect size 0.1. We initially recruited 141 participants to account for potential data loss (see the online supplemental materials and https://osf.io/n95z3).

Measures

Correlations across sample demographics and measures are provided in Figure S1 in the online supplemental materials.

Risky, Impulsive, and Self-Destructive Behavior Questionnaire (RISQ)

Motivation for substance use and misuse was estimated through the RISQ (Sadeh & Baskin-Sommers, 2017). The RISQ includes two subscales that ask participants to report lifetime frequency of alcohol (two questions) and drug use (eight questions), as well as how strongly they agreed with statements reflecting motivations for engaging in each endorsed behavior: to avoid distress ("I do this behavior to stop feeling upset, distressed, or overwhelmed"), or to enhance (i.e., approach) pleasure ("I do this behavior to feel excitement, to get a thrill, or to feel pleasure"; 5-point scale, 0 = *strongly disagree*, 4 = *strongly agree*). The frequency of use items were summed and included in models as a covariate to account for the amount of substance use when considering the motivations for use. Twenty participants did not endorse any lifetime substance use, so have missing data for the RISQ approach/avoid scales and were therefore excluded from substance use motivation analyses (see Table S3 and Figure S2 in the online supplemental materials). Excluded participants RISQ did not differ from those who did report substance use behaviors in terms of age, $t(25.43) = 1.40$, $p = .174$; sex, $\chi^2(1, N = 126) = 0.03$, $p = .856$; race/ethnicity, $\chi^2(5, N = 126) = 6.92$, $p = .227$; or proportion of trials completed, $t(32.96) = -1.03$, $p = .310$.

EEfRT

The EEfRT (Treadway et al., 2009) is a multitrial computerized button-pressing game that measures the extent to which individuals are willing to incur greater effort costs to earn larger, more probable rewards (Barch et al., 2014; Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, et al., 2012). In the present study, the EEfRT was adapted to a loss frame to assess effort cost preferences to avoid losses (e.g., Byrne & Ghaiumy Anaraky, 2020).

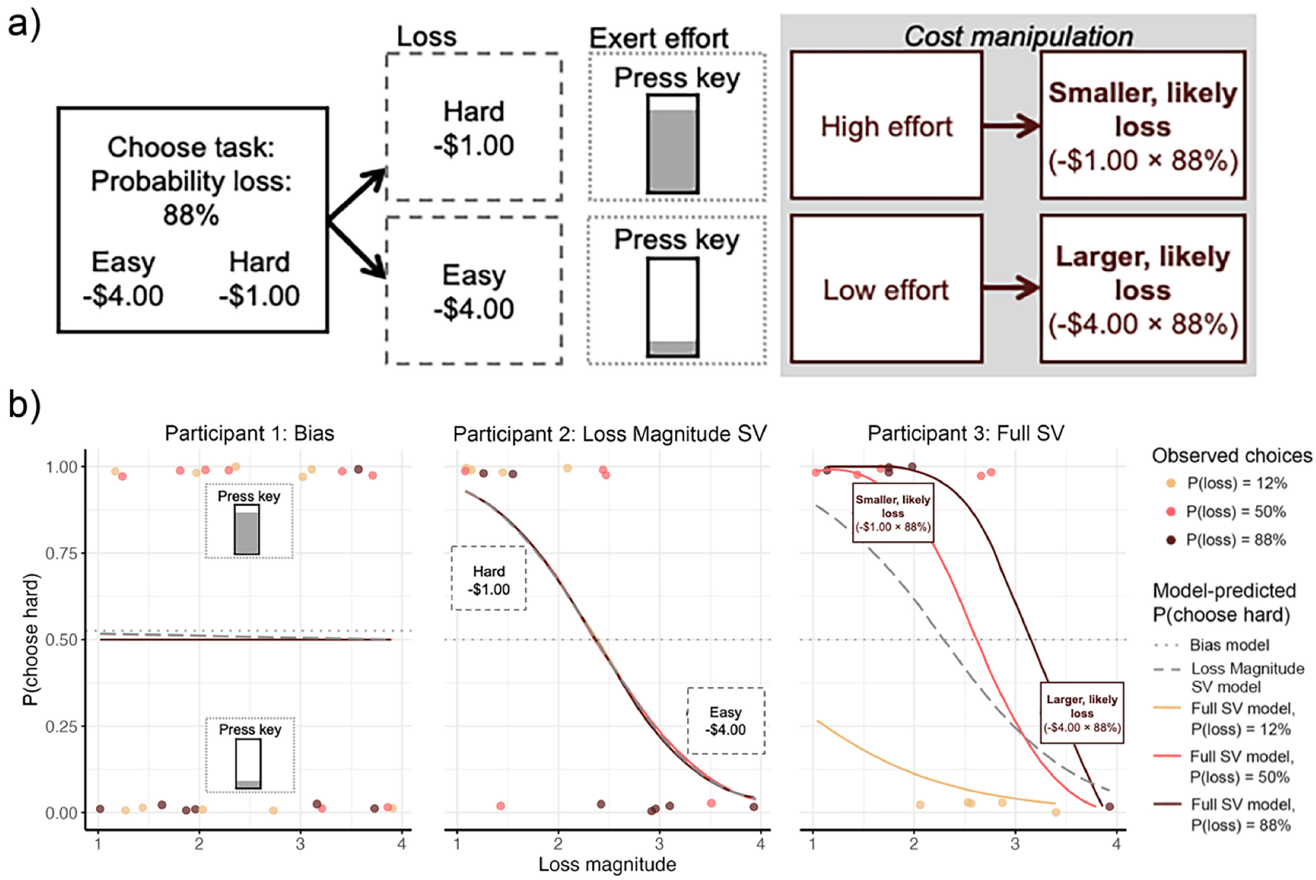
Participants chose between completing an easy task and a hard task for variable loss amounts. The hard task required 100 button presses (right arrow key 50 times, then left arrow key 50 times) to be made within 21 s with the nondominant pinkie finger. The easy task required 30 button presses (spacebar 30 times) to be made within 7 s with the dominant index finger.

For each of 40 trials, participants were presented with the amount that could be lost by completing the easy task (always $4.00) and hard task (between $1.00 and $3.95), and the probability of losing the amount indicated (12%, 50%, or 88%). If the selected task was not completed on any trial, participants were shown a screen indicating that they had lost $4.00. Participants did not have a limit on the amount of time to make a choice. After the choice period, participants completed button presses for the selected task. After each trial, participants received feedback informing them whether they had successfully completed the task and whether they had lost the amount indicated for that trial (Figure 1). Before beginning the task, participants were informed that the amounts lost on two trials would be randomly selected and subtracted from an $8.00 bonus, which would be added onto their hourly compensation.

Participants completed four practice trials before the task began and were monitored by research assistants to ensure proper execution of button presses and task engagement. Participants were excluded if they had a physical feature that prevented complete engagement with the task (e.g., fused finger joints or shoulder issues, $N = 2$), technical issues during the task (e.g., computer froze midway through task, $N = 1$), or behavior that indicated they were not completing the selected tasks (i.e., failing to complete the selected task on over 20% of trials, $N = 12$; Stuppy-Sullivan et al., 2020; Treadway, Bossaller, et al., 2012; Treadway, Buckholtz, et al., 2012; Treadway et al., 2009). Excluded participants did not differ significantly from included participants in terms of age, sex, race/ethnicity, or RISQ approach/avoid or lifetime substance use measures, all $ps > .076$.

The final sample for the basic task effects was 126 participants and the final sample for substance use motivation analyses was 106 (see Table S3 in the online supplemental materials). The EEfRT loss adaptation was programmed in PsychoPy (PsychoPy3 Version 2022.1.1; Peirce et al., 2019).

Figure 1
Subjective Value Modeling of Loss-Frame EEfRT



Note. (a) Diagram of an example trial of the loss-frame EEfRT. (b) Plots showing EEfRT trial information from panel (a) alongside data best fit by each model type (bias, loss magnitude SV, and full SV). We display three sample participants with similar proportions of choosing the hard task (on 50%–53% of trials). Observed choices are overlaid with model-predicted probabilities of choosing hard for 12%, 50%, and 88% probability of loss trials from the full SV model; loss magnitude SV model; and bias model. The participant best fit by the bias model (left) showed little modulation of their hard task choices given variation in loss magnitude and probability (full SV, loss magnitude SV, and bias predicted lines all overlap). The participant best fit by the loss magnitude SV model (middle) chose the hard task less frequently as loss magnitude increased without an effect of probability (full SV and loss magnitude SV predicted lines overlap). The participant best fit by the full SV model (right) chose the hard task less frequently as loss magnitude increased, with different rates for the probability conditions. EEfRT = Effort Expenditure for Rewards Task; SV = subjective value. See the online article for the color version of this figure.

Data Analysis

Choice Preference Analysis

Mixed-effects logistic regressions assessed preference for allocating effort given cost information. Trials with reaction times less than 200 ms (i.e., premature responses; $N = 1$ trial) were removed from individual participants' data before analysis (Ratcliff et al., 2018). Trial-by-trial choice (hard task vs. easy task) was considered a binary outcome variable; potential loss magnitude for the hard task, probability of loss for the amount indicated, and the interaction of loss magnitude and probability (i.e., expected value) were considered continuous fixed-effect predictors. All analyses controlled for participant age (mean-centered), sex (mean-centered), and trial number (Dawson, 2023). Participant was treated as a random effect.

To determine whether consideration of cost information varied according to affective motivations for substance use, analyses tested for interactions between affective motivations for substance use and loss magnitude, probability of loss, and the Loss Magnitude × Probability interaction, controlling for total lifetime substance use (z-scored). Approach and Avoid scales from the RISQ (Spearman's $\rho = .52$, $p < .001$) were entered into separate models; participants with missing approach/avoid data were excluded. Significant interactions were followed up on with simple slopes analyses as outlined by Preacher et al. (2006). For additional analyses probing the specific contributions of avoid versus approach motivations and for participants high on both motivations, see the online supplemental materials. Given that some researchers may be interested in the effects of sex and age on motivations for substance use, exploratory analyses with sex and age as a moderator were run; see the online supplemental materials.

Analyses were conducted using the lme4, lmerTest, and interactions packages in R Version 4.2.2 (Bates et al., 2015; Kuznetsova et al., 2017; Long, 2019; R Core Team, 2022).

Choice Strategy: Subjective Value Modeling

To assess participants' decision-making strategies for allocating effort given varying costs, seven subjective value model variants were fit to EEfRT task data and compared; the three models that were best fit by a reasonable number of participants are described here. For details about additional model variants, see the online supplemental materials. Briefly, models were: (a) a full subjective value (SV) model, which reflects consistent trial-wise consideration of both loss magnitude and probability; (b) a loss magnitude SV model, which reflects systematic consideration of only loss magnitude, and (c) a bias model, which reflects the lack of consideration of loss magnitude or probability information (i.e., only consideration of effort aversion). Similar models have been used to describe decision strategies in temporal delay tasks and effort-based decision-making tasks (J. A. Cooper et al., 2019; Frederick et al., 2002; Green & Myerson, 2004; Hartmann et al., 2013; Klein-Flugge et al., 2015; Pessiglione et al., 2018).

Model parameters were fit using maximum likelihood estimation (fminsearch in MATLAB Version R2022a; MathWorks Inc., 2022). For parameter and model recovery analyses, see the online supplemental materials.

Model 1: Full SV Model. The full SV model best fit participants who considered loss magnitude and probability information consistently across trials when deciding to allocate effort. Trial-by-trial subjective value was calculated as a function of the loss magnitude, L ($1–$3.95, normalized between 0 and 1) as modulated by probability, p (.12, .50, or .88), and reduced by the effort (E) required to avoid loss (0.3 for easy task, 1.0 for hard task). Individual differences in the weighting of probability and discounting of effort were reflected in the free parameters h and k, respectively (Equation 1).

$$\mathrm{SV} = \mathrm{L} \times p^{h} - k\mathrm{E}. \tag{1}$$

Subjective values were transformed into choice probabilities using the Softmax decision rule, where the inverse temperature parameter t reflected a preference for the option with a higher subjective value (Sutton & Barto, 2018; Equation 2).

$$p(\mathrm{hard}) = \frac{1}{1 + e^{-t(\mathrm{SVhard} - \mathrm{SVeasy})}}. \tag{2}$$

Higher values for k indicated a tendency to perceive effort as more costly or undesirable, higher values of h captured the tendency to under-weight the probability of loss (i.e., support riskier choices), and higher values for t reflected a tendency to select higher-value options (i.e., value differences between choices mattered more). Following previous studies (J. A. Cooper et al., 2019), the effort aversion k parameter was bounded between 0 and 10, the probability weighting h parameter between 0 and 10, and the inverse temperature t parameter between 0 and 20 (to avoid ceiling effects).

Model 2: Loss Magnitude SV Model. The loss magnitude SV model best fit participants who allocated effort only according to the potential loss (i.e., they did not integrate information about probability). Like the full SV model, subjective value was determined by the loss magnitude discounted by effort, but h was set at zero such that probability of loss did not influence choice (Equation 3). Again, the effort aversion k parameter was bounded between 0 and 10 and the inverse temperature t parameter between 0 and 20.

$$\mathrm{SV} = \mathrm{L} - k\mathrm{E}. \tag{3}$$

Model 3: Bias Model. The bias model best fit participants who highly favored one option (i.e., did not use trial-specific information), responded inconsistently, or selected options contrary to the SV model assumptions (i.e., allocating effort for greater loss magnitudes). The bias model was the simplest model, with one free parameter, b, which represented a consistent bias toward the low-effort option, regardless of variation in probability or loss (Equation 4). Here, the bias b parameter was bounded between 0 and 1.

$$p(\mathrm{hard}) = 1 - b. \tag{4}$$

Model Fitting. Model fit for each participant was assessed using Bayesian Information Criterion (BIC). BIC penalizes models with additional flexibility (i.e., more free parameters), favoring more parsimonious models when the log likelihood is the same or similar. BIC considers goodness of fit (likelihood, L_i), number of free parameters (V_i), and the number of observations (i.e., number of trials, n; Equation 5):

$$\mathrm{BIC}_i = -2\ln(L_i) + V_i\ln(n). \tag{5}$$

Importantly, comparing the fit of the three models determined which participants used a decision-making strategy that considered trial-wise cost information when allocating effort (i.e., full SV model or loss magnitude SV model), and those who did not (i.e., bias model). Figure 1 illustrates these decision-making strategies with data from three participants with similar effort allocation (proportion selected hard task is 50%–53%) best fit by each model, overlaid with model-predicted probabilities of choosing the hard task.

BIC difference scores (ΔBIC) captured the improvement in model fit that models considering trial-wise cost information (i.e., the full SV and loss magnitude SV models) provided over the simpler bias model (Ahn et al., 2008; Dai et al., 2015; Lefebvre et al., 2017). BIC for the full SV and loss magnitude SV models were used (Equations 6 and 7; J. A. Cooper et al., 2019).

$$\Delta\mathrm{BIC} = \mathrm{BIC}_{\mathrm{Bias}} - \mathrm{BIC}_{\mathrm{SV.}} \tag{6}$$

$$\Delta\mathrm{BIC} = \mathrm{BIC}_{\mathrm{Bias}} - \mathrm{BIC}_{\mathrm{Loss\ only}}. \tag{7}$$

Positive ΔBIC values indicated better fit to the SV model such that choice behavior was better explained by incorporating trial-by-trial variability in loss magnitude and probability, and negative ΔBIC values reflected effort allocation better explained by the simpler bias model.

To determine whether decision-making strategies (systematic consideration of cost information vs. effort bias) varied by affective motivations for substance use, three logistic regressions with the best-fitting model as a binary outcome (e.g., 1 = *full SV model was the best-fitting model*, 0 = *otherwise*) and affective motivation as the independent variable were run. To examine how affective motivations for substance use associated with the contribution of trial-wise cost information to choice behavior, regressions included the ΔBIC (i.e., the improvement in fit attributable to consideration of trial-wise cost information) as the dependent variable and affective motivation as the independent variable. Among individuals best fit by each model (bias, loss magnitude SV, full SV), regressions with affective motivation predicting free parameters from that model probed individual differences in associations between model parameters reflecting decision processes and affective motivations for substance use. All analyses controlled for participant age (mean-centered), sex (mean-centered), and total lifetime substance use (z-scored). Approach and avoid scales from the RISQ were entered into separate models; participants with missing approach/avoid data were excluded. For differences in sample characteristics among best-fitting models, see the online supplemental materials.

Transparency and Openness

We report how we determined our sample size, data exclusions, manipulations, and measures included in the study, and we follow JARS (Kazak, 2018). All deidentified data and analysis code have been made publicly available via Open Science Framework at https://osf.io/n95z3 (Ruiz et al., 2023). Data were analyzed using R Version 4.2.2 and MATLAB (MathWorks Inc., 2022; R Core Team, 2022). This study's design and its analyses were not preregistered. All procedures complied with American Psychological Association ethical standards and were approved by the Yale University Institutional Review Board (Protocol 1408014485).

Results

Choice Preference Analysis

Basic Tasks Effects: Cost Information and Effort Allocation

Results indicated that loss magnitude ($\beta = -0.553$, $SE = 0.040$, 95% CI [−0.632, −0.474], $z = -13.74$, $p < .001$), probability ($\beta = 1.465$, $SE = 0.111$, 95% CI [1.248, 1.682], $z = 13.26$, $p < .001$), and the Loss Magnitude × Probability interaction ($\beta = -0.429$, $SE = 0.132$, 95% CI [−0.688, −0.170], $z = -3.25$, $p = .001$) predicted choice behavior, such that participants were less likely to select the hard task as the losses grew larger, particularly when losses were more likely (Figure S3 in the online supplemental materials). Furthermore, this pattern of results predicted choice behavior even after controlling for a loss outcome experienced on the previous trial (loss magnitude $\beta = -0.570$, $SE = 0.041$, 95% CI [−0.650, −0.489], $z = -13.86$, $p < .001$; probability $\beta = 1.530$, $SE = 0.113$, 95% CI [1.309, 1.751], $z = 13.56$, $p < .001$; Loss Magnitude × Probability interaction $\beta = -0.416$, $SE = 0.135$, 95% CI [−0.680, −0.152], $z = -3.09$, $p = .002$) and after controlling for the total choice reaction time (loss magnitude $\beta = -0.552$, $SE = 0.040$, 95% CI [−0.631, −0.472], $z = -13.65$, $p < .001$; probability $\beta = 1.470$, $SE = 0.111$, 95% CI [1.253, 1.687], $z = 13.25$, $p < .001$; Loss Magnitude × Probability interaction $\beta = -0.435$, $SE = 0.133$, 95% CI [−0.695, −0.175], $z = -3.28$, $p = .001$), suggesting that cost consideration remained consistent in explaining effort allocation given reactions to previous losses and time spent considering effort allocation. Together, these results indicate that decisions about effort allocation relied on the integration of multiple cost variables to guide cost preferences.

Considering Affective Motivations for Substance Use

Avoidance Motivation. Analyses indicated significant effects for the Avoid × Probability interaction term ($\beta = -0.121$, $SE = 0.052$, 95% CI [−0.223, −0.019], $z = -2.33$, $p = .020$), but not the Avoid × Loss Magnitude ($\beta = 0.029$, $SE = 0.019$, 95% CI [−0.008, 0.066], $z = 1.55$, $p = .122$) or the Avoid × Loss Magnitude × Probability interactions ($\beta = 0.016$, $SE = 0.062$, 95% CI [−0.105, 0.137], $z = 0.26$, $p = .795$; Figure 2). Simple slopes for the association between probability of loss and effort allocation were tested for low (−1 SD below the mean), moderate (mean), and high (+1 SD above the mean) levels of avoidance motivation. Individuals were more likely to allocate effort at higher probabilities of loss across all levels of avoidance motivation (all ps $< .001$; see Table S4 in the online supplemental materials). As the probability of loss increased, the likelihood of choosing hard increased by 1.18% for every standard deviation increase in avoidance motivation. In fact, people with higher avoidance (point estimate at 1.5 SD above mean) displayed a greater likelihood of choosing hard (40%) when the probability of loss was 12% than people with lower avoidance (1.5 SD below mean; 23% likely). These results suggest that individuals who used substances to avoid negative affect showed less discrimination among levels of probability relative to those lower on avoidance motivation (i.e., those who were less likely to allocate effort when losses were less likely).

Approach Motivation. Analyses revealed a significant effect for the Approach × Loss Magnitude ($\beta = -0.056$, $SE = 0.018$, 95% CI [−0.092, −0.021], $z = -3.15$, $p = .002$), but not the Approach × Probability ($\beta = -0.025$, $SE = 0.049$, 95% CI [−0.121, 0.071], $z = -0.51$, $p = .608$) or the Approach × Loss Magnitude × Probability ($\beta = -0.109$, $SE = 0.059$, 95% CI [−0.225, 0.007], $z = -1.85$, $p = .065$) interaction terms (Figure 2), suggesting that the effect of approach motivation on effort allocation depended on the level of loss magnitude. Simple slopes for the association between loss magnitude and effort allocation were tested for low (−1 SD below the mean), moderate (mean), and high (+1 SD above the mean) levels of approach motivation. Individuals were less likely to allocate effort for greater magnitudes of loss across all levels of approach motivation (all ps $< .01$; Table S4 in the online supplemental materials). As the loss magnitude increased, the likelihood of choosing hard decreased by 0.67% for every standard deviation increase in approach motivation. In fact, people with higher approach (point estimate at 1.5 SD above mean) displayed a greater likelihood of choosing hard (64%) when loss magnitude was low than people with lower approach (1.5 SD below mean; 46% likely). These results indicate that individuals who used substances to enhance positive affect showed greater sensitivity to loss magnitudes relative to those lower on approach motivation, such that they allocated effort for lower loss magnitudes but less effort for higher loss magnitudes.

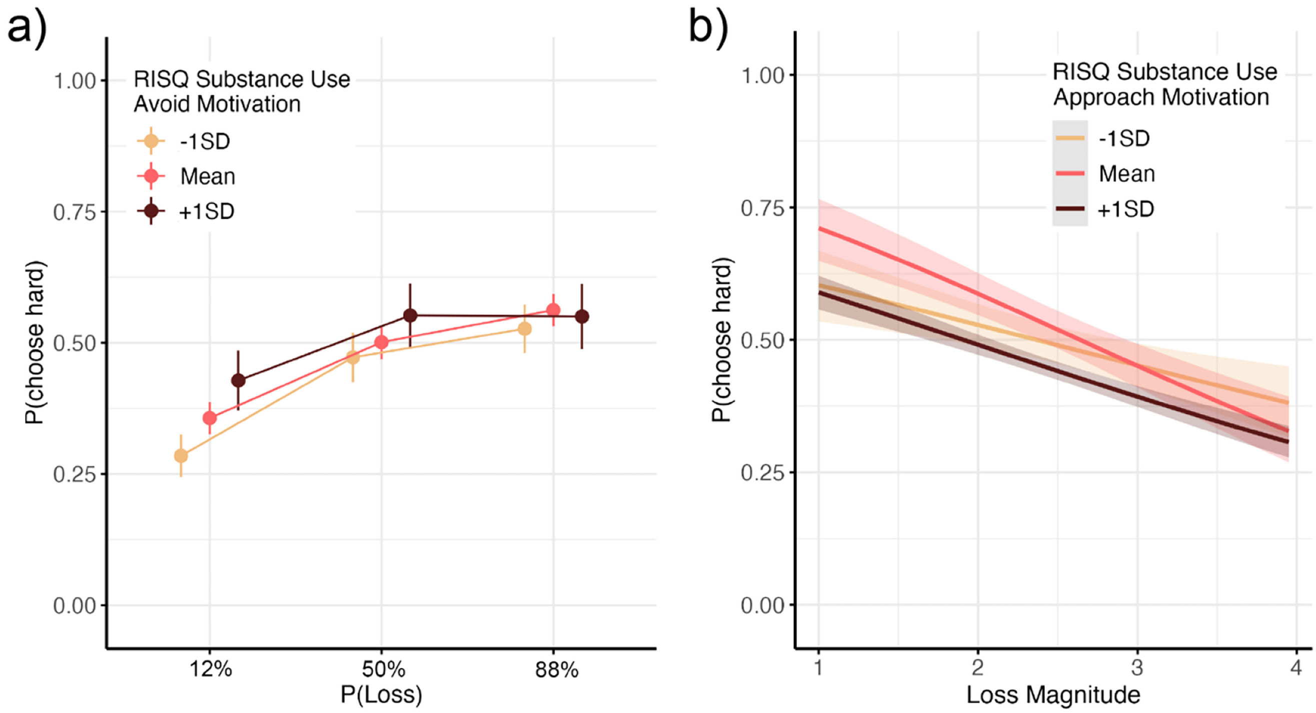
Choice Strategy (Subjective Value Modeling) Analysis

The majority of participants were best fit by the bias model ($N = 67$), followed by the full SV model ($N = 39$), then the loss magnitude SV model ($N = 20$). For parameter and fit statistics, see Table S5 in the online supplemental materials. For characteristics of participants best fit by each model, see Table S6 in the online supplemental materials. For a visual comparison of observed and model-predicted choice data, see Figure S6 in the online supplemental materials.

Best-Fitting Model Considering Affective Motivations for Substance Use

Individuals higher on avoidance motivation for substance use were more likely to be better fit by the bias model ($\beta = 0.252$,

Figure 2
Cost Considerations Interact With Affective Motivations to Predict Choice



Note. Line plots showing interactions between affective motivation and cost variables. (a) Two-way interaction between RISQ avoid score and loss probability. (b) Two-way interaction between RISQ approach score and loss magnitude. To aid visualization, RISQ motivation scores were binned (and represented by each line) to values 1 *SD* above, within 1 *SD*, and 1 *SD* below the mean score across subjects. Shading around lines represents 95% confidence intervals for point estimates. RISQ = Risky, Impulsive, and Self-Destructive Behavior Questionnaire. See the online article for the color version of this figure.

SE = 0.125, 95% CI [0.018, 0.512], z = 2.01, p = .044) and less likely to be better fit by the full SV model (β = −0.294, *SE* = 0.136, 95% CI [−0.579, −0.043], z = −2.17, p = .030), and were not more or less likely to be better fit by the loss magnitude SV model (β = 0.016, *SE* = 0.153, 95% CI [−0.298, 0.310], z = 0.10, p = .917), relative to those lower on avoidance (Figure 3).

Variation in approach motivation did not categorically predict any decision-making strategy as characterized by model fit (bias model: β = −0.057, *SE* = 0.096, 95% CI [−0.248, 0.131], z = −0.60, p = .551; loss magnitude SV model: β = 0.206, *SE* = 0.136, 95% CI [−0.054, 0.488], z = 1.51, p = .132; full SV model: β = −0.050, *SE* = 0.099, 95% CI [−0.248, 0.144], z = −0.51, p = .614). Therefore, subjective value modeling analyses focused on avoidance motivation.

Improvement in Fit Considering Affective Motivations for Substance Use

Greater avoidance motivation was associated with less model fit improvement (ΔBIC) for the full SV model relative to the bias model (β = −1.268, *SE* = 0.517, 95% CI [−2.295, −0.242], t = −2.45, p = .016), and for the full SV model relative to the loss magnitude SV model (β = −0.905, *SE* = 0.418, 95% CI [−1.733, −0.076], t = −2.17, p = .033), but not the loss magnitude SV model relative to the bias model (β = −0.364, *SE* = 0.286, 95% CI [−0.930, 0.203], t = −1.27, p = .206). Here, the inclusion of trial-by-trial loss and probability information did not more accurately explain effort allocation for those high on avoidance (Figure 3). Together, these results suggest that individuals who use substances to avoid negative affect are less likely to track and use cost information (e.g., loss values and probabilities) to guide their effort allocation.

Associations Between Model Parameters and Affective Motivation for Substance Use

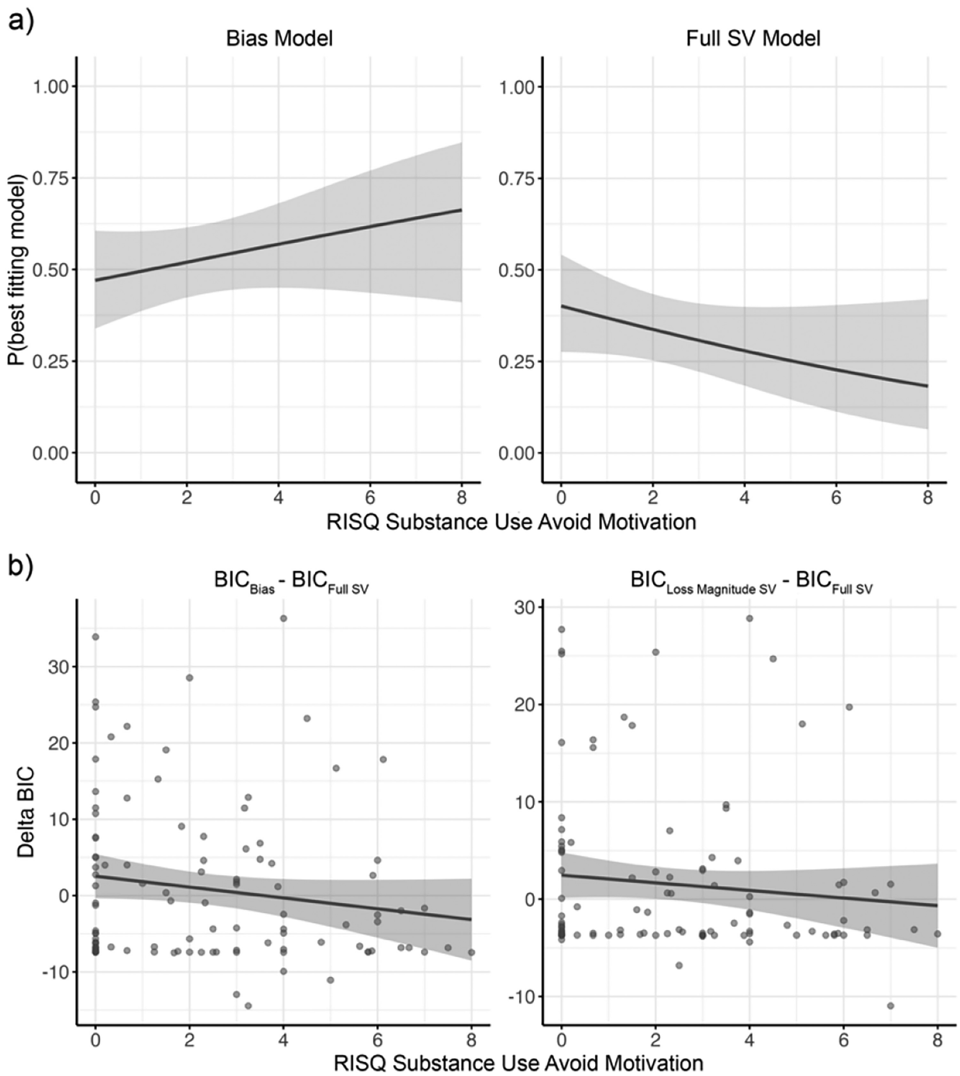
Among individuals best fit by the bias model, avoidance motivation did not predict the effort sensitivity parameter b (β = −0.009, *SE* = 0.019, 95% CI [−0.047, 0.028], t = −0.51, p = .613), suggesting that an overall decision-making style that does not consider loss information, rather than individual differences in effort sensitivity, contribute to choice behavior.

Discussion

The present study extends our understanding of how affective motivations for substance use contribute to decision making regarding costs via an experimental approach in a community sample. Consistent with previous research (Byrne & Ghaiumy Anaraky, 2020), individuals used cost information (i.e., loss magnitude and probability) to inform their choices, becoming less likely to allocate effort as losses grew larger and likelier. However, motivations for substance use differentially related to how individuals evaluated

Figure 3

Avoidance Motivation Predicts Best Fit by the Bias Model



Note. Line plots showing relationship between RISQ avoid score and model fits. (a) Those higher on avoid were more likely to be best fit by the bias model and less likely to be best fit by the full SV model. (b) Those higher on avoid showed less fit improvement reflected by the ΔBIC between the full SV model and bias model, and full SV model and loss magnitude SV model. Positive ΔBIC values reflect greater improvement in model fit explained by the consistent evaluation of cost information (i.e., the full SV model). Shading around lines represents 95% confidence intervals for point estimates. SV = subjective value; RISQ = Risky, Impulsive, and Self-Destructive Behavior Questionnaire; BIC = Bayesian Information Criterion.

cost information. Individuals higher on avoidance motivations allocated comparable effort across varying likelihoods of loss (choice preference analysis), appeared to not consider costs, and were more willing to expend effort overall (subjective value analysis). By contrast, greater approach motivation for substance use was associated with increased distinction between levels of loss magnitude (choice preference analysis), such that individuals with greater approach motivation allocated effort when loss magnitudes were low. These results were robust to the inclusion of covariates and moderators. Different affective motivations for substance use are differentially related to cost comparisons.

People who use substances to avoid negative affect appear less sensitive to comparing information about costs, ultimately making costlier choices. One explanation for this finding is that these individuals may engage in efforts to avoid losses altogether without considering how likely they will be to succeed (in the present study, selecting the hard task). When faced with negative information, these individuals may have constrained capacity (Wills et al., 2001) to consider the costs of their preferences (e.g., avoiding negative affect via substance use) relative to nonavoidance alternatives, such that avoidance is valued more. For example, research suggests that in the context of negative affect, relative changes in the value of substance-related options (increased) compared to alternative options (decreased) may underlie substance use motivated by avoidance (Dora et al., 2023; Field et al., 2020; Hogarth, 2020). Another interpretation of this finding is that individuals who use substances to avoid negative affect may have different criteria for evaluating cost information. They may value effortful but familiar choices known to deliver a desired outcome (i.e., exploiting one coping strategy; Morris et al., 2016), may have higher thresholds for valuing alternative options (i.e., valuing certainty vs. magnitude of relief; Smith et al., 2020), or may only perceive differences in costs when they are exaggerated (i.e., when significant costs are already present). Future research should tease apart the different cognitive processes contributing to choice criteria among those who use substances based on avoidance motivation.

In contrast, those who use substances for approach motivations appear to allocate effort in contexts where the risk is calculated; in the present study, when loss magnitude is low. It seems that individuals who use substances based on approach motivations calculate the risk of their options to minimize costs or maximize rewards (Stuppy-Sullivan et al., 2020). In the context of a loss-only task, this calculated risk taking appears to be a strength. That is, they are effective at minimizing costs when the only options are costs. However, in contexts where losses are balanced with positive outcomes, individuals whose motivation is to enhance positive affect may show difficulty engaging in controlled decision making. Future research should test this hypothesis by manipulating levels of both reward and loss in choice paradigms, especially since in the real world, individuals need to balance both benefits and costs.

Before concluding, we note limitations. First, because probability levels were fully randomized rather than pseudorandomized (balanced probability levels in the original EEfRT task; Treadway et al., 2009), the proportion of each probability level presented in the task differed across participants. For example, 88% probability loss trials ranged from 17.5% of all trials to 62.5% trials across participants. Given that experiencing multiple losses biases decision making (i.e., gambler's fallacy; Dong et al., 2014), it is possible that experiencing more high probability loss trials—which would likely result in losses—impacted choice behavior. However, the contribution of loss magnitude and probability to effort allocation remained even when controlling for the outcome of a previous trial, suggesting that consideration of loss information remained consistent.

Second, the recency and frequency of motivations for substance use were not assessed. Research shows that motivations are often assessed as stable traits, but can also be studied as states that fluctuate quickly (e.g., hourly or daily), which could lead to different relationships with outcomes depending on how and when motivations are sampled (Votaw & Witkiewitz, 2021). While the temporal contribution of motivations for substance use was not the focus of this study, better characterizing motivation itself may be helpful for clarifying how and when it guides decision making.

Finally, other factors not measured here could have impacted the relationship between affective motivations for substance use and cost comparisons. For example, psychological factors such as distress intolerance and impulsivity have been linked to less effective choices (Juarascio et al., 2020; McHugh et al., 2013). Measuring and manipulating these psychological factors that can shape choices could better clarify relationships with substance use motivations. Other factors, such as experiences with affect (e.g., sensitivity, frequency) and cognitive abilities (Barch et al., 2014; J. A. Cooper et al., 2019) also could contribute to affective motivations and cost considerations. In terms of affective experiences, mixed-method designs could allow researchers to both characterize affect in daily life (e.g., using ecological momentary assessment to describe contextual factors surrounding affect) and clarify the relationship between momentary affect and subsequent choice (e.g., experimentally manipulating affect). The effects we report capture just one component of the choice process—the comparison of cost variables. Future work that disentangles relationships among experiences of affect, motivation, and choice will be needed to refine our understanding of how these factors influence decision making.

The present study showed that affective motivations for substance use differentially related to the consideration of cost information to guide effort-based decision making. Individuals who used substances to avoid negative affect had difficulty distinguishing between loss probabilities and systematically using cost information to guide choices. Conversely, individuals who used substances to enhance positive affect effectively distinguished among loss magnitudes. Though choices to continue using substances despite facing consequences inherently involve cost comparisons, the effectiveness of those comparisons relates differently to the motivation for use. There is extensive research examining sensitivity to various aspects of rewards, however, the present study suggests that understanding sensitivities to costs also is important for conceptualizing the cognitive factors related to substance use. Ultimately, characterizing how and when individuals effectively make cost comparisons can inform the application of strategies tailored to their specific motivations.

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