Article:

Dora, J., Copeland, A., Field, M. orcid.org/0000-0002-7790-5559 et al. (1 more author) (2023) Modeling the value-based decision to consume alcohol in response to emotional experiences. Experimental and Clinical Psychopharmacology. ISSN 1064-1297

https://doi.org/10.1037/pha0000647

Modeling the value-based decision to consume alcohol in response to negative emotional experiences

Jonas Dora[1], Amber Copeland[2], Matt Field[2], & Kevin M. King[1]

[1] University of Washington
[2] The University of Sheffield

Evidence for negative reinforcement of alcohol use is mixed; one possible explanation for this is that people make value-based decisions whether to regulate their emotions via alcohol or an alternative, and only drink-to-cope when alcohol's reinforcing value is larger than that of available alternatives. If this is the case, immediately following a negative emotional event the value for alcohol should increase primarily in heavy drinkers, whereas in light drinkers, alternative ways of coping should be valued. We conducted a preregistered online experiment (N = 200) with a mixed design (between: heavy vs light drinker; within: negative/neutral/positive mood induction). In each of three experimental sessions, participants first provided value ratings for a set of alcohol and food stimuli. Second, they were subjected to a mood induction. Third, they made forced choices between either two alcohol or food stimuli. We then applied a drift diffusion model to these data and tested whether alcohol- and food-related decision-making parameters are differentially affected following the mood inductions in heavy and light drinkers. In preregistered analyses we found that heavy drinkers did not value alcohol more but valued food less after the negative mood induction. Exploratory analyses uncovered that both heavy- and light-drinking participants valued alcohol more following the negative mood induction if they reported high alcohol craving at the start of the session. Collectively, these results provide some evidence for the idea that drinking-to-cope might be a value-based decision-making process.

Preregistration, data, analysis code, supplementary material: https://osf,io/atb4e/

Keywords: Negative reinforcement, alcohol use, decision-making, drift diffusion model, mood induction

For more than half a century, psychologists have studied whether alcohol use is reinforcing via its mood-enhancing effects (Conger, 1956). Since then, many theoretical models have incorporated this idea in some form in their predictions (e.g., Baker et al., 2004; Cloninger, 1987; Cox & Klinger, 1988; Koob & Le Moal, 2008). Very generally, these models hypothesize that drinking alcohol momentarily increases feelings of positive affect and decreases feelings of negative affect, and that in turn people become motivated to drink alcohol when they experience negative affect as they learn this stimulus-response association (Skinner, 1969). One form of support for this idea comes from research on *drinking motives*, which has shown consistently that many people self-report enhancing positive moods and coping with negative moods as major motivation for their alcohol use (Bresin & Mekawi, 2021; Cooper, 1994, 2016). In a similar vein, people seem to often hold *expectancies* that drinking alcohol will improve their mood (Brown et al., 1987; Leigh, 1989). Additionally, a recent meta-analysis found a robust effect of *negative mood inductions* on alcohol use in experimental research performed in the laboratory (d = 0.31; Bresin et al., 2018), which is in line with motivational models of alcohol use (Cox & Klinger, 1988). Similarly, *alcohol administration* studies performed in the laboratory have shown that experiences of negative affect decrease (Donohue et al., 2007) and experiences of positive affect increase (Smith, 2013; Wilkie & Stewart, 2005) following the consumption of alcohol compared to a placebo drink. Collectively, people's self-reports and experimental studies seem to provide robust evidence for affect reinforcement of alcohol use.

However, we recently showed convincingly in a meta-analysis of individual participant data from over 12,000 participants observed on over 350,000 days that negative affect is not associated with same-day alcohol use in everyday life (Dora et al., 2022a). Instead, participants were more likely to drink on days they reported higher positive affect. This finding clearly highlights the disconnect between experimental studies performed in the laboratory and ecological momentary assessment studies in people's natural environment. Importantly, studies employing negative mood inductions in the laboratory can only demonstrate that negative affect motivates alcohol use when alcohol is free and immediately available, and when drinking does not interfere with subsequent plans and responsibilities (participants are typically not allowed to leave the laboratory before their BAC has fallen below .04 dl/L; Bacon et al., 2015; de Wit et al., 2003). Additionally, it is well-known that people regularly use a wide variety of strategies and behaviors to regulate their emotions (Gross, 2015; Smith et al., 2022). Thus, it may be that negative affect motivates alcohol use, but only in a subset of situations where alcohol is available *and* alternative ways of regulation are not available, judged to be inefficient, or simply not valued (Wills & Filer, 1996). This would potentially explain why evidence for negative affect motivating other dysregulated behaviors, such as smoking (Akbari et al., 2020) and binge eating (Haedt-Matt & Keel, 2011) is relatively robust, given that cigarettes and foods are more readily available throughout the day.

One promising avenue to improve our understanding of negative reinforcement and to understand the disconnect between experimental and ecological momentary assessment findings is to apply behavioral economic theories of addiction to the study of negative reinforcement of alcohol use (Field et al., 2020; Hogarth & Field, 2020). Behavioral economic theory conceptualizes substance use as a choice that is made based on the reinforcement value of the substance (e.g., alcohol) relative to the reinforcement value of available substance-free alternatives (Murphy & Mackillop, 2006). It is a possibility that the relative reinforcement value of alcohol increases immediately following the experience of negative affect, which would explain why people consume more alcohol immediately following a negative mood induction in the laboratory (in that moment, alcohol is available and presented as the only available emotion regulation strategy) but this association is not reliably observed in everyday life (alcohol is often not immediately available and other emotion regulation strategies can be chosen).

Previous behavioral economic research has provided some support for negative reinforcement of alcohol use. A meta-analysis across three studies (Acuff et al., 2020) found a small-but-significant effect of negative mood inductions on the behavioral economic demand for alcohol (an indicator of the reinforcement value of alcohol and an idea we are currently attempting to replicate in people's everyday life; Dora et al., 2022b). This would imply that the momentary reinforcement value of alcohol increases when people are faced with negative affect, which may translate to increased consumption at a later point in time. At the same time, however, the momentary reinforcement value of substance-free reinforcers might increase in parallel. To account for this possibility, participants can be presented with a choice between a drug and a substance-free reinforcer. A recent review of experimental studies reported that people reliably are more likely to choose a drug compared to a substance-free reinforcer following negative mood inductions (Hogarth & Field, 2020). Some studies found that this effect is stronger for people reporting more severe substance dependence (e.g., Hardy & Hogarth, 2017), but others did not (e.g., Hogarth et al., 2018). The evidence was somewhat stronger for coping motives to moderate this effect, with eight out of ten studies finding that the effect of negative mood inductions on drug choice was stronger for people reporting the motivation to use substances to cope with negative affect (e.g., Hogarth et al., 2018, 2019; Hogarth & Hardy, 2018b).

The studies reviewed by Hogarth and Field (2020) exploring the effect of negative mood inductions on the choice between a drug versus substance-free reinforcers have been insightful. However, studies relying on concurrent choice models do not provide any insight into the internal mechanisms that drives choice, because they do not enable us to understand whether the value of alcohol increases or the value of substance-free reinforcers decreases. Thus, concurrent choice models cannot explain for whom, when, and how alcohol use is negatively reinforcing in people's everyday life. They show that it is likely that in a moment of distress people will choose from a range of regulatory options based on their *relative* subjective value, which incorporates availability as well as anticipated positive and negative consequences (Berkman, 2018; Berkman et al., 2017). This process is called value-based decision-making (VBDM). A recent proposal laid out how recovery from addictive substances, similar to health behaviors involving self-control, can be studied as a value-based decision-making process (Field et al., 2020) with the help of computational modeling that parameterizes the accumulation of evidence that precedes the choice for alcohol or a substance-free reinforcers. It hypothesizes that as people recover from addiction, we should observe a general shift in people's preferences for alcohol reinforcers to alternative reinforcers. Given that people often have the option to regulate their emotions in multiple ways, we argue that the same approach could be used to study whether alcohol's reinforcing value relative to an alternative coping strategy increases in moments high in emotionality.

As theoretical models assume that reinforcement is learned over time (Dayan & Daw, 2008; Herrnstein, 1974; Niv, 2009), this should be true for individuals who drink frequently, but not necessarily for individuals who rarely drink. For example, people with substance use disorders often show steeper discounting of delayed rewards (Madden & Bickel, 2010), which makes immediate reinforcers such as drugs more appealing. People who use substances more often also have been shown to be less receptive to rewards other than substance use (Lubman et al., 2009) and a review of a total of 27 studies has shown that dependence severity is associated with an increased likelihood to choose a drug compared to a substance-free reinforcer in concurrent choice tasks (Hogarth & Field, 2020). Together, these findings highlight the (uncontroversial) conclusion that people who drink more value alcohol highly relative to alcohol-free alternatives. Thus, we reason that the relative value of alcohol in moments high in negative affect should increase primarily in heavy drinkers, whereas the relative value of alternative ways to cope should primarily increase in light drinkers.

The present study

Here, we aim to test whether the value-based decisions to regulate affect via alcohol and an alternative reinforcer (food, as similar affect reinforcement theories have been proposed for emotional eating; Macht & Simons, 2011) differ between heavy-drinking and light-drinking individuals. VBDM provides a framework and set of formalized tools to study discrete decisions (e.g., coping with negative affect via alcohol or food). First, one obtains absolute, momentary value ratings by participants for a range of reinforcing stimuli (half alcohol, half food). Second, participants make repeated forced choices between two of these stimuli, choosing their preferred choice as quickly as possible. Choice reversals (in which an option that was initially assigned lower value is chosen) are considered 'errors' in this context. Behavioral data (response times and errors) are then used to model the decision process, which is assumed to involve the sequential accumulation of evidence until an evidence threshold is reached and a decision is made (Berkman et al., 2017; Ratcliff & McKoon, 2008; Shinn et al., 2020; Wagenmakers et al., 2007). Evidence is assumed to consist of some true underlying signal of value in addition to noise (i.e., the process is assumed to be stochastic). This modeling approach allows us to extract latent parameters that underlie the VBDM process.

By fitting the drift diffusion model (DDM; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998) to observed behavioral data, two important decision parameters can be quantified (Figure 1): First, the drift rate (v) quantifies the average rate of evidence accumulation for an option; a steeper drift rate should make it more likely that this option crosses the decision threshold and be acted upon. Second, the boundary separation (a) quantifies how cautiously a response is made; a lower boundary separation indicates that less evidence needs to be accumulated to trigger a response. Both an increased drift rate and a decreased boundary separation make it more likely that an option is selected. The DDM estimates a third parameter, non-decision time (T_{er}), which quantifies encoding processes and the time it takes to make a motor response once the decision is made. No strong theoretical hypotheses have been formulated for this parameter in addiction-related conceptual VBDM work (Field et al., 2020). In summary, the parameters derived from the DDM allow us to explore the VBDM process underlying alcohol use by quantifying the value or signal or speed with which people accumulate evidence for/against consuming alcohol (drift rate) as well as the general cautiousness with which people make decisions involving alcohol (boundary separation). Our hypotheses were as follows:

H1a: Drift rate associated with alcohol should increase more steeply following a negative mood induction (compared to a neutral mood induction) in heavy-drinking individuals compared to light-drinking individuals.

H1b: Boundary separation associated with alcohol should decrease more steeply following a negative mood induction (compared to a neutral mood induction) in heavy-drinking individuals compared to light-drinking individuals.

H2a: Drift rate associated with food should increase more steeply following a negative mood induction (compared to a neutral mood induction) in light-drinking individuals compared to heavy-drinking individuals.

H2b: Boundary separation associated with food should decrease more steeply following a negative mood induction (compared to a neutral mood induction) in light-drinking individuals compared to heavy-drinking individuals.

Given that our recent meta-analysis indicated robust evidence for positive affect predicting alcohol use (Dora et al., 2022a), we additionally explored whether drift rate and boundary separation associated with alcohol and food in heavy-drinking and light-drinking individuals respectively are sensitive to a positive mood induction compared to a neutral mood induction.

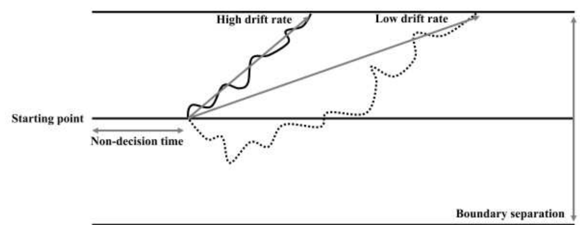

Figure 1. Schematic illustration of the drift diffusion model parameters. Shown are two simulated diffusion processes involving a high and low drift rate. A higher drift rate (via accelerated evidence accumulation) and/or lower boundary separation (via reduced response threshold, not shown) lead to a faster decision.

Methods

Preregistration and data availability

We preregistered design, hypotheses, sample size, and statistical analyses. Our preregistration, anonymized data, power simulation and analysis scripts are available at https://osf.io/atb4e/. The experimental materials are available at https://app.gorilla.sc/openmaterials/446138.

Sample size rationale

We had funds to collect data from 200 participants. We performed a series of simulations to explore how much power we had to detect three different kinds of interactions with this sample size, conservatively assuming small effect sizes. To achieve this, we manipulated the deviations from the overall outcome mean for each of the four cells (light drinkers x neutral induction, light drinkers x negative induction, heavy drinkers x neutral induction, heavy drinkers x negative induction). First, we simulated a "knockout" interaction where drift rate is equivalent following a negative (vs neutral) mood induction in light drinkers and increases by 0.2 points following a negative (vs neutral) mood induction in heavy drinkers. The 95% Bayesian credible interval excluded 0 in 95-100% of the simulations. Second, we simulated a smaller "knockout" interaction where drift rate is equivalent following a negative (vs neutral) mood induction in light drinkers and increases by 0.1 points following a negative (vs neutral) mood induction in heavy drinkers. The 95% Bayesian credible interval excluded 0 in 75-80% of the simulations. Third, we simulated a "50% attenuation" interaction where drift rate increases by 0.1 points following a negative (vs neutral) mood induction in light drinkers and by 0.2 points following a negative (vs neutral) mood induction in heavy drinkers. The 95% Bayesian credible interval excluded 0 in 70-75% of the simulations.

Participants, procedure, and design

We recruited 100 heavy-drinking individuals (M_{age} = 41.81; 25 female sex assigned at birth) and 100 light-drinking individuals (M_{age} = 38.18; 62 female sex assigned at birth) located in the United States via Prolific.co (Palan & Schitter, 2018). For this study, based on Prolific's existing demographics prescreening, we defined heavy-drinking individuals as those who consume ten or more units of alcohol per week (1 unit = 12g alcohol), and light-drinking individuals as those who consume one to four units of alcohol per week. As we compared alcohol and food stimuli, we excluded participants who indicated that they follow a diet of any kind. To ensure data quality and maximize retention, we excluded participants with an approval rate lower than 95% on Prolific and those who had fewer than 20 previous submissions. Participants received $4 per completed experimental session and a bonus payment of $4 if they completed all three sessions. Participants completed a total of 577 out of 600 experimental sessions (96.17% completion rate). They provided informed consent and reported demographics at the beginning of each experimental session. Our experimental paradigm used a mixed (between-within subjects) design.

We recruited two subsamples (*between*-subject): A sample of heavy-drinking individuals, and a sample of light-drinking individuals. All participants in both subsamples completed three experimental sessions on three separate days[1] (*within*-subject): in each session, participants first provided value ratings for a set of alcohol and food images. Second, participants were subjected to a mood induction (positive/negative/neutral), so that each mood was induced once in each participant (order pseudorandomized). Third, across trials on the two-alternative forced-choice (2AFC) task (see below) participants were presented with combinations of two previously rated alcohol or food images and were asked to select the one they would rather consume as quickly as possible (Figure 2). Whether participants completed the alcohol or the food trials first was randomized in each session. Each session took approximately 20 minutes to complete. The study was programmed and administered in Gorilla.sc (Anwyl-Irvine et al., 2020) and was approved by the University of Washington's IRB.

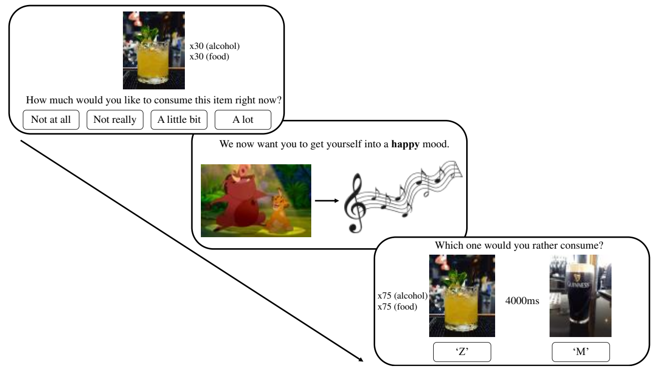

Figure 2. Sequence of events in one experimental session. Shown is an example session in which a positive mood was induced.

Materials

Self-reports. At the beginning of the session, participants reported age, sex assigned at birth, and gender identity. They also reported their current craving for alcohol and current level of hunger using a 100-point visual analogue scale (0 = "not at all" – 100 = "very much"). Finally, participants answered four items from the Drinking Motives Questionnaire (DMQ; Cooper, 1994) that were adapted to reflect daily motives ("To what extent do you agree with these statements if you were to drink alcohol later today?"; Stevenson et al., 2019) on a 100-point visual analogue scale (0 = "strongly disagree" – 100 = "strongly agree"). The chosen items were "Because it makes social gatherings more fun" (social motive), "Because it helps me when I feel depressed or nervous" (coping motive), "Because I like the feeling" (enhancement motive), and "To fit in with a group I like" (conformity motive). In our exploratory analyses, we focused on the coping and enhancement motive as these are thought to reflect the motivation to regulate one's emotions via alcohol (Cooper, 2016).

Stimuli. 30 alcohol images were chosen from the WFAIS alcohol image dataset, whose valence (*"How unhappy-happy does this item make you feel?"*) was rated at least 50 points on a 100-point scale (Peterson et al., 2019). We chose a varied mix of beer, wine, and liquor images so that participants would provide varied ratings during the image rating task, which was important for the VBDM task. 30 food images were chosen from the CROCUFID food image database, whose desirability (*"How much would you like to*

[1] Participants had 10 days to complete all three experimental sessions on three separate days.

eat this item right now if it was in front of you?") was rated at least 50 points on a 100-point scale (Toet et al., 2019). We chose a mix of sweet and savory food images. We chose stimuli from these two databases as they were validated in comparable online samples of US adults, mirroring our sampling strategy for this project.

Image rating task. Participants viewed each of 30 alcohol and food stimuli and indicated for each item how much they would like to consume them 'right now' (1 = "not at all", 2 = "not really", 3 = "a little bit", 4 = "a lot"). Participants had unlimited time to provide these value ratings. We presented these stimuli to participants in random order.

Mood inductions. The mood inductions were mirrored from a recent preregistered validation study of combined mood induction procedures in a large sample of participants recruited online, mirroring our sampling strategy for this project (Marcusson-Clavertz et al., 2019). In the *negative mood induction*, participants were first instructed to get into a sad mood, then watched a depressing four-minute-long video clip ('Death of Mufasa' from the animated motion picture The Lion King; 1994), and finally listened to the first four minutes of the instrumental piece 'Adagio for Strings, Op. 11' composed by Samuel Barber with their eyes closed. In the *neutral mood induction*, participants were first instructed to get into a neutral mood, then watched a four-minute-long clip about magnets (from the documentary program Modern Marvels; 2002), and finally listened to the first four minutes of the instrumental 'Variations for Winds, Strings, and Keyboards' composed by Steve Reich with their eyes closed. In the *positive mood induction*, participants were first instructed to get into a happy mood, then watched an uplifting four-minute-long video clip ('Hakuna Matata' from the animated motion picture The Lion King; 1994), and finally listened to the first four minutes of the instrumental piece 'Coppélia, Act I: 1. Prélude et Mazurka' composed by Léo Delibes with their eyes closed. These combined manipulations have been shown to successfully induce the desired moods of sadness (Hedges $G_{negative} = 0.81$) and joviality (Hedges $G_{positive} = 0.70$) in a sample recruited via Prolific.co (Palan & Schitter, 2018). Participants self-reported their mood with a single item ("Please indicate how you feel right now.") rated on a 100-point visual analogue scale (0 = "very unhappy" – 100 = "very happy") immediately prior to and following each mood induction.

2AFC task. In the 2AFC task (Copeland et al., 2022a; Copeland et al., 2022b), on each trial participants were presented either with two previously rated alcohol images (50% of trials), or with two previously rated food images (50% of trials). The stimuli were randomly selected on each trial, except participants never chose between two stimuli they assigned equal value during the image rating task. This ensured that on each trial there was a 'correct' option to choose. We randomized whether participants first completed the alcohol or the food trials. Participants had four seconds to decide which one they would rather like to consume 'right now' by pressing a corresponding button on their keyboard ('Z' for left and 'M' for right option; appearance of correct option randomized). All decisions were hypothetical. Participants completed a total of 150 trials, 75 alcohol decisions and 75 food decisions, with a short break after 75 trials. Trials were separated by the display of a fixation cross for 250ms.

Analysis plan

Data from trials on which no response was made within four seconds as well as response times under 300 milliseconds were removed as is common in research involving reaction times (e.g., Johannes et al., 2019). This resulted in 0.02% of the trials being removed prior to model fitting. We then fitted the EZ-Drift Diffusion Model (Wagenmakers et al., 2007, 2008) to the accuracy[2] and response time data from the 2AFC task for each experimental session from each participant, in that way extracting six drift rates and six boundary separations for each participant (2 [alcohol, food] x 3[negative, neutral, positive][3]). The EZ DDM has been shown to yield comparably accurate inferences to those recovered from other types of diffusion models that entail more complex parameter fitting procedures (van Ravenzwaaij et al., 2017), may outperform those more complex models when data are sparse (Voss et al., 2015), and has been applied previously to study psychological decision processes (Lin et al., 2020). Additionally, we fit the EZ DDM successfully to comparable VBDM data in the past (Copeland et al., 2022a; Copeland et al., 2022b). We then analyzed our hypotheses with Bayesian mixed ANOVAs, which we fitted with the brm() command (*brms* version 2.17.0; Bürkner, 2017) in R (version 4.2.1; R Core Team, 2021). Based on open DDM data, we expected drift rate and boundary separation to be approximately normally distributed, and thus we specified models with gaussian outcome distributions.

We completed four analyses, one for each preregistered hypothesis. We fitted a random intercept nested in participants to account for the nested data structure in each model. We preregistered weakly informative priors (Gelman et al., 2017) on the fixed effects and random standard deviations of our models; a normally distributed prior with mean 0 and standard deviation 0.25 for our fixed parameters and a half-normally distributed prior with mean 0 and standard deviation 0.125 on the random standard deviations of the model. In each model, we predicted the outcome (drift rate or boundary separation) from induction (negative vs neutral mood), sample (light vs heavy drinking), and the induction x sample interaction, which resulted in the following brms syntaxes:

$$\text{Drift rate}_{alc} \sim 1 + \text{induction} * \text{sample} + (1 \mid \text{subject})$$

[2] Choices for stimuli that were previously rated lower than their counterpart were considered errors.

[3] A minor difference to previous research (Copeland et al., 2022a) is that we did not fit the DDM separately per difficulty level (i.e., the value difference between the two stimuli presented on each trial).

Boundary $\text{sep}_{\text{alc}} \sim 1 + \text{induction} * \text{sample} + (1 \mid \text{subject})$
Drift $\text{rate}_{\text{food}} \sim 1 + \text{induction} * \text{sample} + (1 \mid \text{subject})$
Boundary $\text{sep}_{\text{food}} \sim 1 + \text{induction} * \text{sample} + (1 \mid \text{subject})$

We then computed Bayes factors for each of the interactions by comparing each of these models to a null model excluding the interaction between induction and sample. We preregistered interpreting Bayes factors smaller than 3 as inconclusive, Bayes factors between 3 and 10 as moderate evidence in favor of or against our hypotheses, and Bayes factors larger than 10 as strong evidence. We assessed model convergence and fit by inspecting Rhat values, effective sample sizes, trace plots, and posterior predictive checks.

Results

Descriptive statistics

During the image rating task, participants used each value rating roughly equally often (“Not at all” = 25.8%; “Not really” = 24.9%; “A little bit” = 26.7%; “A lot” = 22.6%). Participants chose the ‘correct’ (i.e., the stimuli they had assigned higher value during the image rating task) option in 86.5% of VBDM trials. The median reaction time after removing reaction times faster than 300 milliseconds was 1032 milliseconds. At the start of the experimental sessions, heavy-drinking participants indicated on average moderately higher alcohol craving (d = 0.59), comparable hunger (d < 0.01), slightly higher coping motivation (d = 0.27), and moderately higher enhancement motivation (d = 0.64) relative to light drinking participants. The distribution of these four self-reports in both subsamples is visualized in Figure 3.

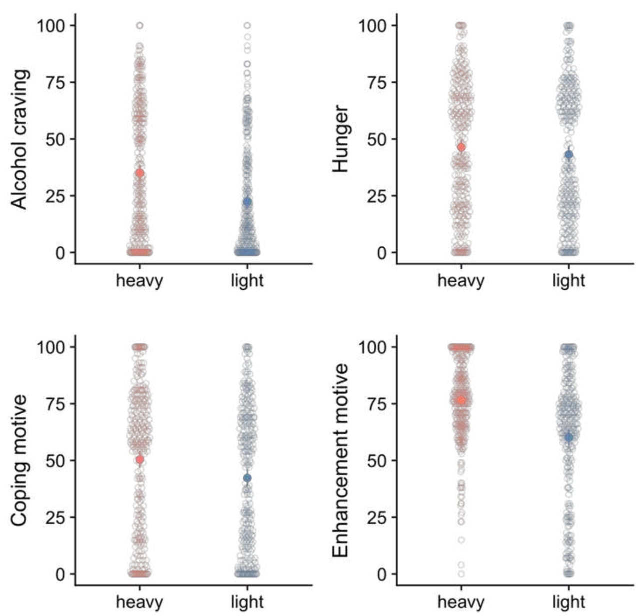

Figure 3. Distribution of self-reports at the start of experimental sessions in heavy-drinking and light-drinking subsample.

Manipulation check

On average, participants’ mood (pre vs. post) decreased by 25 points following the negative mood induction, decreased by 5 points following the neutral mood induction, and increased by 5 points following the positive mood induction ($d_{\text{negative vs neutral}} = 0.74$; $d_{\text{positive vs neutral}} = 0.60$; $d_{\text{negative vs positive}} = 1.81$). These differences in self-reported mood are visualized in Figure 4.

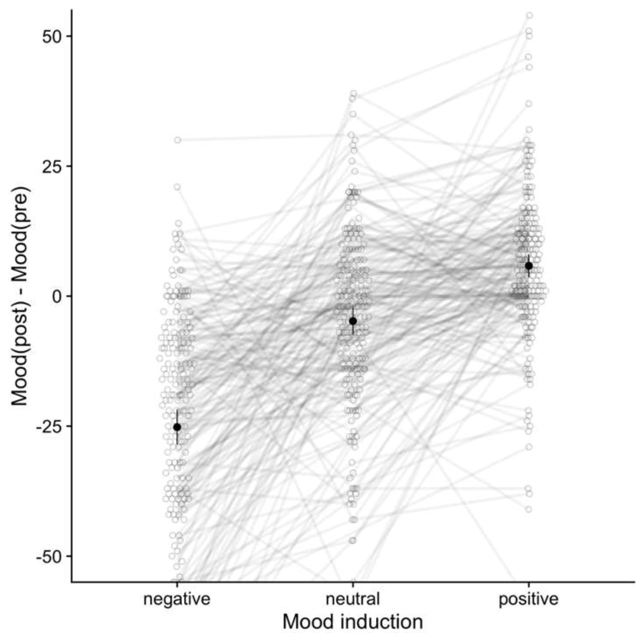

Figure 4. Change in mood following the negative, neutral, and positive mood induction. Displayed is the 95% confidence interval surrounding the aggregated mean as well as the data from the individual participants.

Preregistered confirmatory analyses

All models converged as indicated by Rhat values of 1.00 and sufficient effective sample sizes. Posterior predictive checks confirmed that our models fit the drift rate and boundary separation data well (Figure 5). First, we predicted drift rate associated with alcohol from the mood induction (negative vs neutral), sample (heavy- vs light-drinking), and the interaction between the two. Our data indicated strong evidence against our prediction ($BF_{01} = 12.56$). The effect of the mood induction on drift rate associated with alcohol did not differ between heavy-drinking and light-drinking participants (95% CI = -0.03, 0.04), and there was strong evidence against a mood induction x sample interaction on boundary separation associated with alcohol ($BF_{01} = 17.00$, 95% CI = -0.03, 0.02). Second, we predicted drift rate associated with food from the same interaction. Our data indicated strong evidence for the hypothesized interaction (BF_{10} = 173.02, 95% CI = -0.12, -0.04). For heavy-drinking participants, drift rate (food) was estimated to decrease by 0.06 points following the negative mood induction, whereas for light-drinking participants it was estimated to increase by 0.10 points. Finally, our data indicated strong evidence for the hypothesized interaction on boundary separation associated with food (BF_{10} = 2907.20, 95% CI = 0.03, 0.08). For heavy-drinking individuals, boundary separation (food) was estimated to increase by 0.05 points following the negative mood induction, whereas for light-drinking participants it was estimated to decrease by 0.06 points. The results from our preregistered models are summarized in Table 1 and visualized in Figure 6.[4]

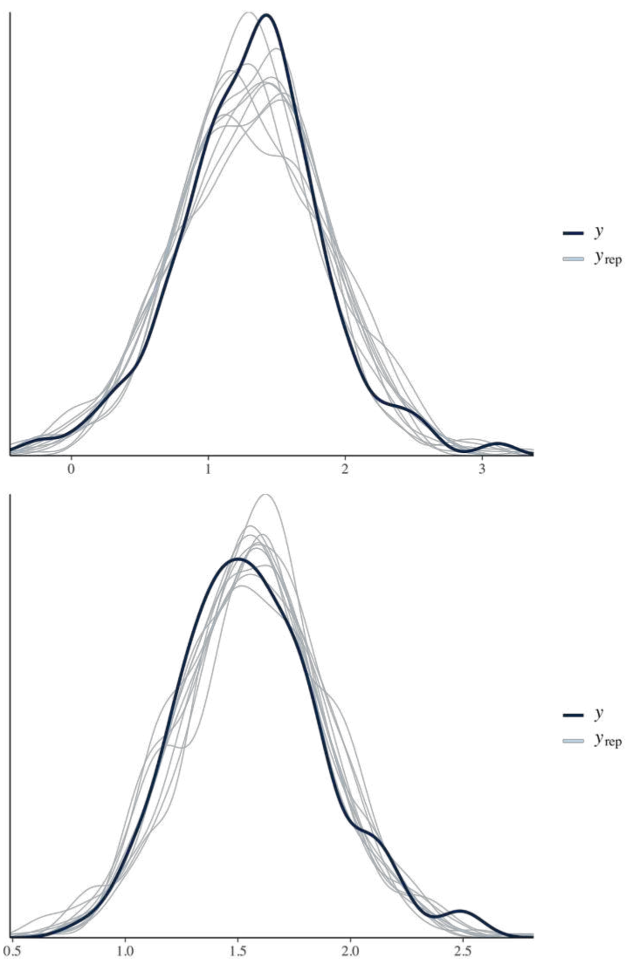

Figure 5. Posterior predictive checks for drift rate (top) and boundary separation (bottom).

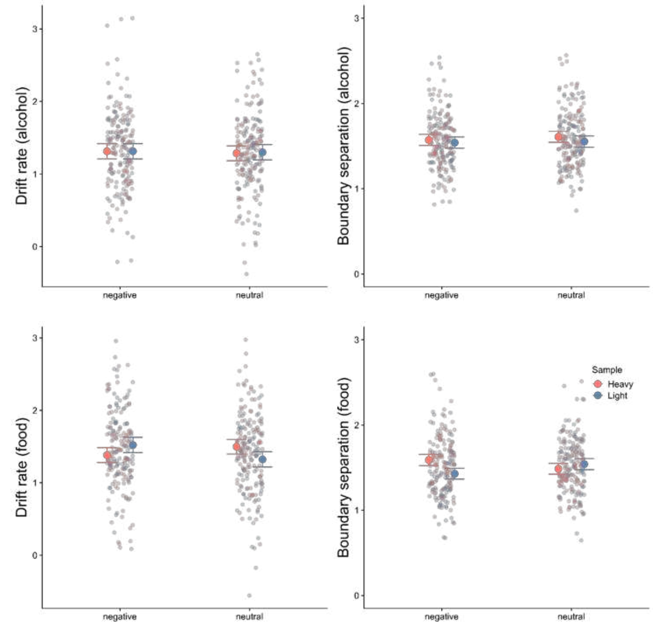

Figure 6. Effect of negative (vs neutral) mood induction on VBDM parameters (top left: drift rate alcohol; top right: boundary separation alcohol; bottom left: drift rate food; bottom right: boundary separation food) in heavy- and light-drinking participants. Displayed is the 95% credible interval as well as the data from the individual participants.

[4] In line with our preregistration, we repeated our analyses after imputing missing data with the mice package (van Buuren & Groothuis-Oudshoorn, 2011). Posterior distributions averaged over 50 imputed datasets did not differ meaningfully from the results presented here.

Table 1. Summary of preregistered model results.

Hypothesis	Parameter	Estimate	95% CI
H1a (alcohol drift rate)			
	Intercept	1.30	1.24, 1.37
	Mood induction	0.01	-0.03, 0.05
	Sample	0.00	-0.07, 0.06
	Mood induction × sample	0.00	-0.03, 0.04
H1b (alcohol boundary separation)			
	Intercept	1.43	1.37, 1.49
	Mood induction	0.02	-0.02, 0.06
	Sample	0.01	-0.05, 0.07
	Mood induction × sample	-0.08	-0.12, -0.04
H2a (food drift rate)			
	Intercept	1.57	1.53, 1.61
	Mood induction	-0.01	-0.04, 0.01
	Sample	0.02	-0.02, 0.06
	Mood induction × sample	-0.01	-0.03, 0.02
H2b (food boundary separation)			
	Intercept	1.51	1.47, 1.55
	Mood induction	0.00	-0.02, 0.02
	Sample	0.03	-0.01, 0.07
	Mood induction × sample	0.05	0.03, 0.08

Preregistered exploratory analyses

Next, given that recent research indicates that drinking in everyday life often seems to follow high positive affect (Dora et al., 2022a; Dora et al., 2022c), we repeated our analyses comparing the positive to the neutral mood induction. Unsurprisingly (given the small effect of the positive induction on mood), these models provided no evidence for an induction x sample interaction on drift rate and boundary separation associated with alcohol (BF_{01} [drift rate] = 5.63, BF_{01} [boundary separation] = 19.55) and food (BF_{01} [drift rate] = 1.49, BF_{10} [boundary separation] = 2.12), with Bayes Factors ranging from strong evidence against our hypothesis to inconclusive.

Non-preregistered exploratory analyses

Given that the self-reports did not differentiate the two subsamples very well (e.g., heavy-drinking individuals regularly reported low alcohol craving, and light-drinking individuals regularly reported high alcohol craving), we explored whether craving, coping motive, and enhancement motive interacted with the mood induction to predict the VBDM parameters associated with alcohol. Although we planned a priori to explore main effects of the self-reports on the VBDM parameters (which are not present in the data), we decided to explore this interaction instead due to the relatively large spread of reported craving and drinking motives in both subsamples. These exploratory analyses suggested that, irrelevant of subsample, the VBDM parameters might be influenced by the negative mood induction as predicted when participants reported high alcohol craving at the start of the experimental session (drift rate: 95% CI = 0.01, 0.10); boundary separation: 95% CI = -0.06, -0.01; Figure 7)[5]. When participants reported craving at baseline one standard deviation above the mean, drift rate was estimated to increase by 0.06 points following the negative mood induction whereas it was estimated to decrease by 0.04 points when participants reported craving at baseline one standard deviation below the mean. Similarly, boundary separation was estimated to decrease by 0.05 points following the negative mood induction when baseline craving was high and to increase by 0.02 points when baseline craving was low. However, we are cautious to conclude that the mood induction affects VBDM parameters as predicted when craving is high due to the exploratory nature of these analyses and the small effects observed. We will expand on this in the discussion. Individual differences in coping motive did not influence the alcohol VBDM parameters (drift rate: 95% CI = -0.07, 0.05; boundary separation: 95% CI = -0.05, 0.02) nor did they moderate the effect of the negative (vs neutral) mood induction on the alcohol VBDM parameters (drift rate: 95% CI = -0.05, 0.03; boundary separation: 95% CI = -0.04, 0.01). Similarly, individual differences in enhancement motive exhibited no main effect (drift rate: 95% CI = -0.06, 0.06; boundary separation: 95% CI = -0.01, 0.06) nor interaction effect (drift rate: 95% CI = -0.05, 0.03; boundary separation: 95% CI = -0.03, 0.03) on the alcohol VBDM parameters following the positive (vs neutral) mood induction.

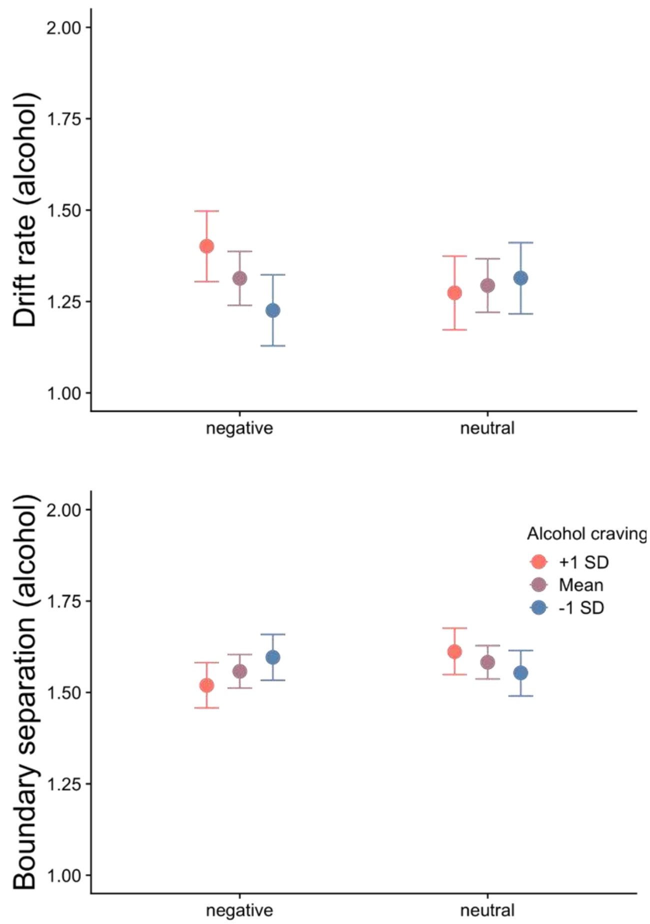

Figure 7. 95% Credible Intervals for drift rate (top) and boundary separation (bottom) associated with alcohol following the negative and neutral mood induction in sessions participants report high, average, and low alcohol craving.

Discussion

Given the contradiction between experimental findings (Bresin et al., 2018) and findings from EMA research (Dora et al., 2022a) regarding the effect of negative affect on alcohol use, one way to improve our understanding of negative

[5] We do not report Bayes factors for non-preregistered analyses as these analyses are fully exploratory and confirmatory tests need to be performed in future research.

reinforcement is to improve our understanding of the decision to drink alcohol. The VBDM perspective posits that this decision is preceded by an evaluation of the momentary reinforcement value of alcohol compared to available substance-free alternatives (Berkman et al., 2017; Field et al., 2020). If this is true, we reasoned that we should see the value-based decision to drink-to-cope affected by a negative emotional experience especially in heavy drinkers, and the value-based decision to cope via an alternative (e.g., eating comforting food) affected especially in light drinkers. Here, we applied an established computational model (Ratcliff & McKoon, 2008; Shinn et al., 2020; Wagenmakers et al., 2007) to experimental data to explore whether heavy drinkers value alcohol more following a negative emotional experience while light drinkers value an alternative (food) more. Our modeling results simultaneously provided some evidence for and against this idea and helped us to identify several directions for future research.

In our preregistered analyses, we found evidence that the cognitive process underlying food-related decisions was more affected following a negative mood induction in light drinkers, but alcohol-related decision-making was not more affected in heavy drinkers. One interpretation of these results is that heavy drinkers (compared to light drinkers) might not value alcohol more when in a negative emotional state but for them the value of alternative ways of coping might not increase in parallel. Given that the VBDM perspective posits that people should integrate the subjective value of competing options when making decisions, this effect should make it more likely that heavy drinkers choose to cope via alcohol. However, this immediately highlights one of the main limitations of our study design – as participants did not make decisions between alcohol and food stimuli directly, it is unclear whether the decision parameters compared here would translate into a higher probability of coping via alcohol in heavy drinkers and coping via food in light drinkers. Similar to previous research (Copeland, Stafford, Acuff, et al., 2022; Copeland, Stafford, & Field, 2022; Tusche & Hutcherson, 2018), we chose this indirect approach because it makes the interpretation of the parameters derived from the model easier to interpret and because it might capture deliberations about alternatives without depicting them side-by-side. Had participants chosen between alcohol and food on each trial, the drift rate and boundary separation could not be clearly linked to each distinct reinforcer. Hence, our results suggest a stronger alcohol reinforcement history might not be reflected in increased valuation of alcohol following a negative emotional experience, but instead in decreased valuation of alternative reinforcers following negative emotional experiences. This is in line with research showing more generally that frequent substance users value substance-free reinforcers less (Hogarth & Hardy, 2018a; Lubman et al., 2009; Rachlin, 2000). The present data suggest that this effect might be amplified in emotional situations. In the context of the study of negative reinforcement of alcohol (Baker et al., 2004; Cox & Klinger, 1988; Koob & Le Moal, 2008), we believe this is a novel finding that warrants further research to understand whether such an effect is likely to lead to a higher probability of deciding to cope via alcohol (versus food) in heavy drinkers.

Interestingly, an earlier study found that students drinking at least monthly (a more lenient inclusion criterion compared to our operationalization of light drinkers) chose alcohol more frequently over food in a 2AFC task following a negative mood induction (compared to prior to the mood induction; Hogarth et al., 2018). However, the study did not involve an experimental manipulation of mood (it used a pre-post design), and thus we cannot be certain that this effect would replicate if choices following a negative mood induction were compared to those following a neutral mood induction. An experimental study by the same authors found no differences in choices for alcohol following a negative (vs positive) mood induction (Hardy & Hogarth, 2017). Additionally, as these studies did not establish the absolute value of each stimulus prior to the 2AFC task, it is uncertain whether choice reversals took place as a function of changes in mood. Ideally, future research should find a way to combine drift diffusion modeling with forced choices between alcohol and alternative reinforcers following experimental mood manipulations to gain insight into this decision.

Intriguingly, exploratory results uncovered a weak effect in our data that all participants both accumulated evidence faster and displayed a reduced decision threshold for alcohol following the negative mood induction *only* when they reported high alcohol craving at the start of the experimental session. Paired with the fact that the difference in craving between the two subsamples was only moderate, one interpretation of this finding is that our inclusion criterion focusing on average drinking quantity per week did not successfully create two separate groups of drinkers. Importantly, craving is thought to be a central feature of addiction (Sayette, 2016). In this context, our results could indicate that drinking history matters less, and instead any regular drinker (heavy or light) might be more likely to drink-to-cope on days they *already* crave alcohol. In other words, it may not be that negative moods cause craving, but that existing alcohol cravings are more likely to cause drinking to cope when people also experience negative moods. From a VBDM perspective (Berkman et al., 2017), this might indicate that either high negative affect or high craving are not sufficient to amplify the value signal for alcohol, but they do when increased simultaneously. However, we are not entirely convinced by the data here as the tests were exploratory, the effects were small, and craving was not experimentally manipulated. Additionally, coping motive, which might be viewed as another proxy of increased momentary valuation of alcohol at the start of the experiment, did not display a similar effect. Thus, it is unclear whether this finding would replicate, and it is unclear whether craving is the variable that explains the response to the mood induction or is merely a correlate. We conclude from this finding that future research should explore further whether intra-individual (as opposed to inter-individual) differences (especially fluctuations in craving) can explain the link between negative affect and the decision to consume alcohol. If this effect replicates, this would indicate that an initial valuation of alcohol (as indicated by high alcohol craving and irrelevant of alcohol reinforcement history) prior to the experience of negative affect makes it more likely that alcohol is chosen as emotion regulation strategy later that day.

A second clear limitation of our study was the small average change in self-reported mood following the positive mood induction. Although positive mood inductions generally are weaker than negative mood inductions (Joseph et al., 2020; Westermann et al., 1996), in our study the positive mood induction was even weaker than in the study it was mirrored from (Marcusson-Clavertz et al., 2019) for unknown reasons (the negative mood induction was comparable in strength). It may be that positive moods are generally more difficult to induce in laboratory settings because the stimuli that induce positive moods are more idiosyncratic than those used to induce negative moods (Ellard et al., 2012). Recent research has indicated repeatedly that positive affect is a stronger predictor of alcohol use in everyday life than negative affect (Dora et al., 2022a; Dora et al., 2022c; Dvorak et al., 2018; Russell et al., 2020; Stevens et al., 2021). Unfortunately, we were not able to provide a strong test whether heavy and light drinkers react to a positive mood induction in different ways due to the limited success of the positive mood induction. Our exploratory finding that more positive mood prior to the 2AFC task (irrelevant of mood induction) did not differentially predict the VBDM parameters in heavy and light drinkers provides some evidence against our hypothesis (and to be balanced, also against the negative affect hypothesis). However, this test is not particularly convincing as it is confounded by the mood induction that took place just prior to the self-report and is entirely correlational. In future research, stronger manipulations of positive mood are needed to thoroughly explore positive reinforcement of alcohol in experimental studies.

Future directions and conclusion

A clear improvement to the research presented here would be an adapted experimental design in which the 2AFC task features choices between alcohol and an alternative reinforcer (Hogarth & Field, 2020). If we could fit the drift diffusion model to the data from such a task (and interpret the parameters), we would be able to more accurately model the real-world decision that involves choosing between alcohol and non-alcohol reinforcers rather than two variations of the same option. One way this could work would be to present heavy drinkers with 2AFC trials between alcohol and food stimuli, and to code trials on which the choice for the alcohol stimulus is 'correct' as trials that reflect the decision for alcohol over food and vice versa. By then biasing the drift rate and boundary separation depending on the type of trial during the model fitting (Shinn et al., 2020), we can recover VBDM parameters that reflect these opposing choices. Alternatively, the 2AFC task described here could be paired with a second task in which forced choices between alcohol and food are made, which would require a separate computational model to analyze in parallel. Additionally, future research could compare alcohol to substance-free reinforcers other than food. For example, a recent study found that people scoring higher on the Alcohol Use Disorder Identification Test (Allen et al., 1997) showed a preference to choose alcoholic over soft drink stimuli (Rose et al., 2013, 2018). Thus, comparing alcoholic to non-alcoholic drinks in a VBDM task would be interesting, especially given that in social situations people often have the choice between alcoholic and non-alcoholic beverages.

Second, future research should consider different inclusion criteria to ensure that the two subsamples differ in their valuation of alcohol. The moderate effect sizes in craving and drinking motives highlight that focusing on differences in weekly frequency of use may not be sufficient. One simple way to start could be to compare heavy drinkers to people who used to drink heavily but now drink in moderation (Copeland et al., 2022b). Alternatively, subsamples could be separated by an inclusion criterion that focuses on a combination of frequency of use and alcohol-related problems, such as scores on the Alcohol Use Disorder Identification Test (AUDIT; Allen et al., 1997), or meeting diagnostic criteria for Alcohol Use Disorder. This might be necessary as some theoretical models predict alcohol to be negatively reinforcing especially in clinical samples (Baker et al., 2004; Koob & Le Moal, 2008).

Third, future research should find a way to induce a positive mood more reliably than we did here. While the mood induction procedure we used had the advantage of being validated in online samples (Marcusson-Clavertz et al., 2019), other procedures may be more effective. For example, one study found that positive mood inductions produce stronger effects if a neutral mood is induced first (Gable & Harmon-Jones, 2008). Another recent study found success using idiographic scripts to induce positive moods (Weiss et al., in prep), suggesting that perceptions of positive emotional events may be less universal than perceptions of negative emotional events. Positive emotions are multifaceted and can include states such as joviality, serenity, and engagement. Although positive emotions have traditionally been treated as a uniform state, it may be easier to induce and focus on specific facets of positive emotions which may be most strongly connected to alcohol use (Desira et al., 2020). Ultimately, we believe that rigorously testing positive reinforcement of alcohol use as value-based decision-making may be even more important than negative reinforcement due to the robust effect of positive affect on alcohol use in everyday life (Dora et al., 2022a).

This was the first study to attempt to computationally model the value-based decision to drink-to-cope (and drink-to-enhance). Although heavy drinkers did not assign higher relative value to alcohol after a negative emotional event (as hypothesized), our data indicate that light drinkers assign higher value to food following a negative emotional event, whereas heavy drinkers do not. Exploratory analyses further indicated that negative mood may increase the value assigned to alcohol in heavy and light drinkers, albeit only in moments people report relatively high craving for alcohol. We identified and discussed several limitations of this first study applying a VBDM perspective to the study of affect regulation of alcohol use. As of now, the value of our VBDM paradigm to understanding negative reinforcement of alcohol use is uncertain. We believe that the mixed results reported here are interesting and that future research should build on these novel findings to explore whether the relative value of alcohol (versus substance-free reinforcers) is or is not elevated in moments high in negative affect. We hope to have reported and discussed our results transparently so that readers can come to their own conclusions.

Data Availability

All anonymized data and code are publicly available on the Open Science Framework project of this article https://osf.io/atb4e/.

Funding

Preparation of this article was supported by a grant from the Institute of Translational Health Sciences to Jonas Dora.

References

Acuff, S., Amlung, M., Dennhardt, A., Mackillop, J., & Murphy, J. (2020). Experimental manipulations of behavioral economic demand for addictive commodities: A meta-analysis. *Addiction*, *115*, 817–831. https://doi.org/10.1111/add.14865

AI Roker Productions (Director). (2002). *Modern Marvels: Magnets*.

Akbari, M., Hasani, J., & Seydavi, M. (2020). Negative affect among daily smokers: A systematic review and meta-analysis. *Journal of Affective Disorders*, *274*, 553–567. https://doi.org/10.1016/j.jad.2020.05.063

Allen, J., Litten, R., Fertig, J., & Babor, T. (1997). A review of research on the Alcohol Use Disorders Identification Test (AUDIT). *Alcoholism: Clinical and Experimental Research*, *21*, 613–619. https://doi.org/10.1111/j.1530-0277.1997.tb03811.x

Allers, R., & Minkoff, R. (Directors). (1994). *The Lion King*. Walt Disney Pictures.

Anwyl-Irvine, A., Massonnie, J., Flitton, A., & Kirkham, N. (2020). Gorilla in our midst: An online behavioral experiment builder. *Behavior Research Methods*, *52*, 388–407. https://doi.org/10.3758/s13428-019-01237-x

Bacon, A., Cranford, A., & Blumenthal, H. (2015). Effects of Ostracism and Sex on Alcohol Consumption in a Clinical Laboratory Setting. *Psychology of Addictive Behaviors*, *29*, 664–672. https://doi.org/10.1037/adb0000054

Baker, T., Piper, M., McCarthy, D., Majeskie, M., & Fiore, M. (2004). Addiction motivation reformulated: An affective processing model of negative reinforcement. *Psychological Review*, *111*, 33–51. https://doi.org/10.1037/0033-295X.111.1.33

Berkman, E. (2018). Value-based choice: An integrative, neuroscience-informed model of health goals. *Psychological Health*, *33*, 40–57. https://doi.org/10.1080/08870446.2017.1316847

Berkman, E., Hutcherson, C., Livingston, J., Kahn, L., & Inzlicht, M. (2017). Self-control as value-based choice. *Current Directions in Psychological Science*, *26*, 422–428. https://doi.org/10.1177/0963721417704394

Bresin, K., & Mekawi, Y. (2021). The "Why" of Drinking Matters: A Meta-Analysis of the Association Between Drinking Motives and Drinking Outcomes. *Alcoholism: Clinical and Experimental Research*, *45*, 38–50. https://doi.org/10.1111/acer.14518

Bresin, K., Mekawi, Y., & Verona, E. (2018). The effect of laboratory manipulations of negative affect on alcohol craving and use: A meta-analysis. *Psychology of Addictive Behaviors*, *32*, 617–627. https://doi.org/10.1037/adb0000383

Brown, S., Christiansen, B., & Goldman, M. (1987). The Alcohol Expectancy Questionnaire: An instrument for the assessment of adolescent and adult alcohol expectancies. *Journal of Studies on Alcohol*, *48*, 483–491. https://doi.org/10.15288/jsa.1987.48.483

Bürkner, P. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, *80*, 1–28. https://doi.org/10.18637/jss.v080.i01

Cloninger, R. (1987). Neurogenetic adaptive mechanism in alcoholism. *Science*, *236*, 410–416. https://doi.org/10.1126/science.2882604

Conger, J. (1956). Reinforcement Theory and the Dynamics of Alcoholism. *Quarterly Journal of Studies on Alcohol*, *17*, 296–305. https://doi.org/10.15288/qjsa.1956.17.296

Cooper, M. (1994). Motivations for alcohol use among adolescents: Development and validation of a four-factor model. *Psychological Assessment*, *6*, 117–128. https://doi.org/10.1037/1040-3590.6.2.117

Cooper, M. (2016). Motivational Models of Substance Use: A Review of Theory and Research on Motives for Using Alcohol, Marijuana, and Tobacco. In *The Oxford Handbook of Substance Use Disorders* (1st ed., Vol. 1). Oxford University Press.

Copeland, A., Stafford, T., Acuff, S. F., Murphy, J. G., & Field, M. (2022). Behavioral economic and value-based decision-making constructs that discriminate current heavy drinkers versus people who reduced their drinking without treatment. *Psychology of Addictive Behaviors*. https://doi.org/10.1037/adb0000873

Copeland, A., Stafford, T., & Field, M. (2022). Methodological issues with value-based decision-making (VBDM) tasks: The effect of trial wording on evidence accumulation outputs from the EZ drift-diffusion model. *Cogent Psychology*, *9*, 2079801. https://doi.org/10.1080/23311908.2022.2079801

Cox, M., & Klinger, E. (1988). A Motivational Model of Alcohol Use. *Journal of Abnormal Psychology*, *97*, 168–180. https://doi.org/10.1037/0021-843X.97.2.168

Dayan, P., & Daw, N. (2008). Decision theory, reinforcement learning, and the brain. *Cognitive, Affective, & Behavioural Neuroscience*, *8*, 429–453.

de Wit, H., Soderpalm, A., Nikolayev, L., & Young, E. (2003). Effects of Acute Social Stress on Alcohol Consumption in Healthy Subjects. *Alcoholism: Clinical and Experimental Research*, *27*, 1270–1277. https://doi.org/10.1097/01.ALC.0000081617.37539.D6

Desira, B., Watson, S., Van Doorn, G., Timora, J., & Spence, C. (2020). Happy Hour? A Preliminary Study of the Effect of Induced Joviality and Sadness on Beer Perception. *Beverages*, *6*(2), 35. https://doi.org/10.3390/beverages6020035

Donohue, K., Curtin, J., Patrick, C., & Lang, A. (2007). Intoxication Level and Emotional Response. *Emotion*, *7*, 103–112. https://doi.org/10.1037/1528-3542.7.1.103

Dora, J., Piccirillo, M., Foster, K., Arbeau, K., Armeli, S., Auriacombe, M., Bartholow, B., Beltz, A., Blumenstock, S., Bold, K., Bonar, E., Braitman, A., Carpenter, R., Creswell, K., DeHart, T., Dvorak, R., Emery, N., Enkema, M., Fairbairn, C., … King, K. (2022). *The daily association between affect and alcohol use: A meta-analysis of individual participant data*. https://doi.org/10.31234/osf.io/xevct

Dora, J., Schultz, M., Kuczynski, A., Acuff, S., Murphy, J., & King, K. (2022). An experimental investigation into the effect of negative affect on the behavioral economic demand for alcohol. *Psychology of Addictive Behaviors*.

Dora, J., Schultz, M., Shoda, Y., Lee, C., & King, K. (2022). No evidence for trait- and state-level urgency moderating the daily association between negative affect and subsequent alcohol use in two college samples. *Brain and Neuroscience Advances*.

Dvorak, R., Stevenson, B., Kilwein, T., Sargent, E., Dunn, M., Leary, A., & Kramer, M. (2018). Tension Reduction and Affect Regulation: An Examination of Mood Indices on Drinking and Non-Drinking Days among University Student Drinkers. *Experimental Clinical Psychopharmacology*, *26*, 377–390. https://doi.org/10.1037/pha0000210

Ellard, K. K., Farchione, T. J., & Barlow, D. H. (2012). Relative Effectiveness of Emotion Induction Procedures and the Role of Personal Relevance in a Clinical Sample: A Comparison of Film, Images, and Music. *Journal of Psychopathology and Behavioral Assessment*, *34*(2), 232–243. https://doi.org/10.1007/s10862-011-9271-4

Field, M., Heather, N., Murphy, J., Stafford, T., & Witkiewitz, K. (2020). Recovery from addiction: Behavioral economics and value-based decision-making. *Psychology of Addictive Behaviors*, *34*, 182–193. https://doi.org/10.1037/adb0000518

Gable, P., & Harmon-Jones, E. (2008). Approach-Motivated Positive Affect Reduces Breadth of Attention. *Psychological Science*, *19*, 476–482. https://doi.org/10.2307/40064782

Gelman, A., Simpson, D., & Betancourt, M. (2017). The Prior Can Often Only Be Understood in the Context of the Likelihood. *Entropy*, *19*, 555. https://doi.org/10.3390/e19100555

Gross, J. (2015). Emotion Regulation: Current Status and Future Prospects. *Psychological Inquiry*, *26*, 1–26. https://doi.org/10.1080/1047840X.2014.940781

Haedt-Matt, A., & Keel, P. (2011). Revisiting the affect regulation model of binge eating: A meta-analysis of studies using ecological momentary assessment. *Psychological Bulletin*, *137*, 660–681. https://doi.org/10.1037/a0023660

Hardy, L., & Hogarth, L. (2017). A novel concurrent pictorial choice model of mood-induced relapse in hazardous drinkers. *Experimental and Clinical Psychopharmacology*, *25*, 448–455. https://doi.org/10.1037/pha0000155

Herrnstein, R. (1974). Formal properties of the matching law. *Journal of the Experimental Analysis of Behavior*, *21*, 159–164. https://doi.org/10.1901/jeab.1974.21-159

Hogarth, L., & Field, M. (2020). Relative expected value of drugs versus competing rewards underpins vulnerability to and recovery from addiction. *Behavioural Brain Research*, *394*, 112815. https://doi.org/10.1016/j.bbr.2020.112815

Hogarth, L., & Hardy, L. (2018a). Alcohol use disorder symptoms are associated with greater relative value ascribed to alcohol, but not greater discounting of costs imposed on alcohol. *Psychopharmacology*, *235*, 2257–2266. https://doi.org/10.1007/s00213-018-4922-8

Hogarth, L., & Hardy, L. (2018b). Depressive statements prime goal-directed alcohol-seeking in individuals who report drinking to cope with negative affect. *Psychopharmacology*, *235*(1), 269–279. https://doi.org/10.1007/s00213-017-4765-8

Hogarth, L., Hardy, L., Bakou, A., Mahlberg, J., Weidemann, G., Cashel, S., & Moustafa, A. A. (2019). Negative Mood Induction Increases Choice of Heroin Versus Food Pictures in Opiate-Dependent Individuals: Correlation With Self-Medication Coping Motives and Subjective Reactivity. *Frontiers in Psychiatry*, *10*, 274. https://doi.org/10.3389/fpsyt.2019.00274

Hogarth, L., Hardy, L., Mathew, A. R., & Hitsman, B. (2018). Negative mood-induced alcohol-seeking is greater in young adults who report depression symptoms, drinking to cope, and subjective reactivity. *Experimental and Clinical Psychopharmacology*, *26*(2), 138–146. https://doi.org/10.1037/pha0000177

Johannes, N., Dora, J., & Rusz, D. (2019). Social Smartphone Apps Do Not Capture Attention Despite Their Perceived High Reward Value. *Collabra: Psychology*, *5*(1), 14. https://doi.org/10.1525/collabra.207

Joseph, D. L., Chan, M. Y., Heintzelman, S. J., Tay, L., Diener, E., & Scotney, V. S. (2020). The manipulation of affect: A meta-analysis of affect induction procedures. *Psychological Bulletin*, *146*(4), 355–375. https://doi.org/10.1037/bul0000224

Koob, G., & Le Moal, M. (2008). Addiction and the Brain Antireward System. *Annual Review of Psychology*, *59*, 29–53. https://doi.org/10.1146/annurev.psych.59.103006.093548

Leigh, B. (1989). In search of the seven dwarves: Issues of measurement and meaning in alcohol expectancy research. *Psychological Bulletin*, *105*, 361–373. https://doi.org/10.1037/0033-2909.105.3.361

Lin, H., Saunders, B., Friese, M., Evans, N., & Inzlicht, M. (2020). Strong effort manipulations reduce response caution: A preregistered reinvention of the ego-depletion paradigm. *Psychological Science*, *31*, 531–547. https://doi.org/10.1177/0956797620904990

Lubman, D., Yucel, M., Kettle, J., Scaffidi, A., MacKenzie, T., Simmons, J., & Allen, N. (2009). Responsiveness to drug cues and natural rewards in opiate addiction: Associations with later heroin use. *Archives of General Psychiatry*, *66*, 205–212. https://doi.org/10.1001/archgenpsychiatry.2008.522

Macht, M., & Simons, G. (2011). Emotional eating. In *Emotion regulation and well-being* (pp. 281–295). Springer.

Madden, G., & Bickel, W. (2010). *Impulsivity: The behavioral and neurological science of discounting*. American Psychological Association.

Marcusson-Clavertz, D., Kjell, O., Persson, S., & Cardeña, E. (2019). Online validation of combined mood induction procedures. *Plos One*, *14*, e0217848. https://doi.org/10.1371/journal.pone.0217848

Murphy, J., & Mackillop, J. (2006). Relative Reinforcing Efficacy of Alcohol Among College Student Drinkers. *Experimental and Clinical Psychopharmacology*, *14*, 219–227. https://doi.org/10.1037/1064-1297.14.2.219

Niv, Y. (2009). Reinforcement learning in the brain. *Journal of Mathematical Psychology*, *53*, 139–154. https://doi.org/10.1016/j.jmp.2008.12.005

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27. https://doi.org/10.1016/j.jbef.2017.12.004

Pennington, C. R., Shaw, D. J., Adams, J., Kavanagh, P., Reed, H., Robinson, M., Shave, E., & White, H. (2020). Where's the wine? Heavy social drinkers show attentional bias towards alcohol in a visual conjunction search task. *Addiction*, *115*(9), 1650–1659. https://doi.org/10.1111/add.14997

Peterson, H., Simpson, S., & Laurienti, P. (2019). Wake Forest Alcohol Imagery Set (WFAIS): Development and validation of a large standardized alcohol imagery dataset. *Alcoholism: Clinical and Experimental Research*, *43*, 2559–2567. https://doi.org/10.1111/acer.14214

R Core Team. (2021). *R: A language and environment for statistical computing* (4.0.5). R Foundation for Statistical Computing.

Rachlin, H. (2000). The lonely addict. In *Reframing Health Behavior Change With Behavioral Economics*. Lawrence Erlbaum Associates.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*, 873–922. https://doi.org/10.1162/neco.2008.12-06-420

Ratcliff, R., & Rouder, J. N. (1998). Modeling Response Times for Two-Choice Decisions. *Psychological Science*, *9*(5), 347–356. https://doi.org/10.1111/1467-9280.00067

Russell, M., Linden-Carmichael, A., Lanza, S., Fair, E., Sher, K., & Piasecki, T. (2020). Affect Relative to Day-Level Drinking Initiation: Analyzing Ecological Momentary Assessment Data With Multilevel Spline Modeling. *Psychology of Addictive Behaviors*, *34*, 434–446. https://doi.org/10.1037/adb0000550

Sayette, M. (2016). The Role of Craving in Substance Use Disorders: Theoretical and Methodological Issues. *Annual Review of Clinical Psychology*, *12*, 407–433. https://doi.org/10.1146/annurev-clinpsy-021815-093351

Shinn, M., Lam, N. H., & Murray, J. D. (2020). A flexible framework for simulating and fitting generalized drift-diffusion models. *ELife*, *9*, e56938. https://doi.org/10.7554/eLife.56938

Skinner, B. F. (1969). *Contingencies of reinforcement*. Appleton-Century-Crofts.

Smith, A. (2013). Effects of caffeine and alcohol on mood and performance changes following consumption of lager. *Psychopharmacology*, *227*, 595–604. https://doi.org/10.1007/s00213-013-2991-2

Smith, M., Seldin, K., Galtieri, L., Alawadhi, Y., Lengua, L., & King, K. (2022). Specific emotion and momentary emotion regulation in adolescence and early adulthood. *Emotion*.

Stevens, A., Haikalis, M., & Merrill, J. (2021). Unplanned vs planned drinking: Event-level influences of drinking motives and affect. *Addictive Behaviors*, *112*, 106592. https://doi.org/10.1016/j.addbeh.2020.106592

Stevenson, B., Dvorak, R., Kramer, M., Peterson, R., Dunn, M., Leary, A., & Pinto, D. (2019). Within- and Between-Person Associations From Mood to Alcohol Consequences: The Mediating Role of Enhancement and Coping Drinking Motives. *Journal of Abnormal Psychology*, *128*, 813–822. https://doi.org/10.1037/abn0000472

Toet, A., Kaneko, D., de Kruijf, I., Ushiama, S., van Schaik, M., Brouwer, A., Kallen, V., & van Erp, J. (2019). *CROCUFID: A cross-cultural food image database for research on food elicited affective responses*. *101*, 1–21. https://doi.org/10.3389/fpsyg.2019.00058

Tusche, A., & Hutcherson, C. A. (2018). Cognitive regulation alters social and dietary choice by changing attribute representations in domain-general and domain-specific brain circuits. *ELife*, *7*, e31185. https://doi.org/10.7554/eLife.31185

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*, 1–67. https://doi.org/10.18637/jss.v045.i03

van Ravenzwaaij, D., Donkin, C., & Vandekerckhove, J. (2017). The EZ diffusion model provides a powerful test of simple empirical effects. *Psychonomic Bulletin & Review*, *24*(2), 547–556. https://doi.org/10.3758/s13423-016-1081-y

Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analyses: A tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00336

Wagenmakers, E.-J., van der Maas, H., & Grasman, R. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin & Review*, *14*, 3–22. https://doi.org/10.3758/BF03194023

Wagenmakers, E.-J., van der Maas, H. L. J., Dolan, C. V., & Grasman, R. P. P. P. (2008). EZ does it! Extensions of the EZ-diffusion model. *Psychonomic Bulletin & Review*, *15*(6), 1229–1235. https://doi.org/10.3758/PBR.15.6.1229

Weiss, N., Schick, M., Raudales, A., Forkus, S., Thomas, E., Contractor, A., & Sullivan, T. (in prep). *Experimental Investigation of the Influence of Positive Emotion Dysregulation on Risky Behavior Following Idiographic Emotion Inductions*.

Westermann, R., Spies, K., Stahl, G., & Hesse, F. (1996). Relative effectiveness and validity of mood induction procedures: A meta-analysis. *European Journal of Social Psychology*, *26*, 557–680. https://doi.org/10.1002/(SICI)1099-0992(199607)

Wilkie, H., & Stewart, S. (2005). Reinforcing Mood Effects of Alcohol in Coping and Enhancement Motivated Drinkers. *Alcoholism: Clinical and Experimental Research*, *29*, 829–836. https://doi.org/10.1097/01.ALC.0000163498.21044.CB

Wills, T., & Filer, M. (1996). Stress—Coping Model of Adolescent Substance Use. In *Advances in Clinical Child Psychology* (pp. 91–131). Plenum Press.