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Value-based decision-making in regular alcohol consumers following experimental manipulation of alcohol value

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ABSTRACT

Background: Devaluation of alcohol leads to reductions in alcohol choice and consumption; however, the cognitive mechanisms that underpin this relationship are not well-understood. In this study we applied a computational model of value-based decision-making (VBDM) to decisions made about alcohol and alcohol-unrelated cues following experimental manipulation of alcohol value. **Method:** Using a pre-registered within-subject design, thirty-six regular alcohol consumers (≥14 UK units per week) completed a two-alternative forced choice task where they chose between two alcohol images (in one block) or two soft drink images (in a different block) after watching videos that emphasised the positive (alcohol value), and separately, the negative (alcohol devalue) consequences of alcohol. On each block, participants pressed a key to select the image depicting the drink they would rather consume. A drift–diffusion model (DDM) was fitted to reaction time and choice data to estimate evidence accumulation (EA) processes and response thresholds during the different blocks in each experimental condition. **Findings:** In the alcohol devalue condition, soft drink EA rates were significantly higher compared to alcohol EA rates ($p = 0.04$, $d = 0.31$), and compared to soft drink EA rates in the alcohol value condition ($p = 0.01$, $d = 0.38$). However, EA rates for alcoholic drinks and response thresholds (for either drink type) were unaffected by the experimental manipulation. **Conclusions:** In line with behavioural economic models of addiction that emphasise the important role of alternative reinforcement, experimentally manipulating alcohol value is associated with changes in the internal cognitive processes that precede soft drink choice.

1. Introduction

Alcohol consumption increases the risk of premature death and ill health (Degenhardt et al., 2018). In England, over 10 million people consume alcohol at levels above the United Kingdom (UK) Chief Medical Officers "low risk" drinking guidelines (≤14 UK units per week; Office for Health Improvement & Disparities, 2022). Experimental research has shown that devaluation of alcohol leads to reductions in alcohol choice and consumption (Rose et al., 2018); however, less is currently known about the underlying cognitive mechanisms by which valuation processes exert these effects (Rose et al., 2013).

The central tenet of *molar*[1] behavioural economic accounts is that the progression to addiction is characterised by persistently high valuation of substance use compared to alternative substance-free reinforcers, and devaluation of outcomes that are only available after a delay (Bickel et al., 2014; Murphy et al., 2012). Hypothetical purchase (Murphy & MacKillop, 2006) and concurrent choice (Hogarth & Hardy, 2018) tasks are commonly used to capture "demand"—a behavioural economic construct that represents the reinforcing value of a substance (MacKillop, 2016). The alcohol purchase task (Murphy & MacKillop, 2006) assesses hypothetical alcohol consumption across a range of escalating prices. In concurrent choice tasks (Hogarth & Hardy, 2018) people make repeated choices between alcohol and non-alcohol (e.g., food) reinforcers for a reward (e.g., image enlargement); the percentage choice of alcohol reward is used to index alcohol value.

Alcohol value is robustly correlated with alcohol use and dependence severity (Hogarth & Field, 2020; Martínez-Loredo et al., 2021), and is sensitive to experimental manipulation (Acuff et al., 2020). For example, when participants are primed to experience negative mood, this increases alcohol value (Hardy & Hogarth, 2017; Hogarth et al., 2018) compared to baseline and when positive mood is induced. Another study found that when participants consume alcohol that has been manipulated to taste aversive, this decreases alcohol value and actual alcohol consumption (Rose et al., 2018). These findings illustrate

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[1] *Molar* perspectives are primarily concerned with understanding patterns of behaviour over time (Tucker & Vuchinich, 2015).

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that alcohol choice is goal-directed; it is governed by the current motivational value of alcohol (see Hogarth, 2020, for a review). However, despite a robust body of theoretical and empirical evidence demonstrating the importance of valuation processes in determining alcohol-related choice, the cognitive mechanisms that underpin this relationship are currently less well-understood. Furthermore, in both hypothetical purchase and concurrent choice tasks, the role of the alternative reward is rarely considered. This is an important oversight in the context of behavioural economic models which posit that addiction is characterised by changes in *relative* valuation of substance (increased) and alternative (decreased) reward (see Acuff et al., 2023).

Value-based decision-making (VBDM) provides a framework that can model the internal cognitive processes that determine overt choice behaviour. According to VBDM, when a person is faced with a decision, they firstly identify possible response options. The overall value of each response option is determined via a dynamic integration of choice-relevant attributes, which include things such as the anticipated positive and negative consequences (Berkman, 2018; Berkman et al., 2017). Subsequently, response options are compared and the option with the highest value is acted upon through a value-to-action evidence accumulation (EA) process (Berkman, 2018) which can be understood using the drift–diffusion model (DDM; Forstmann et al., 2016; Ratcliff & McKoon, 2008). The DDM assumes that value signals from the brain are tracked in a noisy and probabilistic manner[2], accumulating until the response threshold for committing to a decision is crossed (see Fig. 1.1). By fitting the DDM to behavioural data, this enables elucidation of the underlying cognitive mechanisms that determine value-based choice. Indeed, there is enthusiasm for interdisciplinary extensions to traditional behavioural economic approaches, including the application of computational modelling (Acuff et al., 2022; Amlung et al., 2015; Bickel & Athamneh, 2020).

VBDM has been extended to the study of addiction and recovery from it (Copeland et al., 2021; Copeland et al., 2023; Copeland, Stafford, & Field, 2023; Dora et al., 2023; Field et al., 2020). Standard VBDM methodology presents choices derived from a single category (e.g., food; Polanía et al., 2014), and therefore as applied to addiction research, VBDM parameters for different types of decisions (e.g., alcohol and soft drink) are recovered separately. These accounts offer a *molecular*[3] perspective that can serve to be a complementary extension to traditional behavioural economics, broadly speculating that alterations in valuation processes for substances and substance-free alternatives can be mapped onto changes in EA rates and/or response thresholds. However, to date, VBDM has not been explored following the direct manipulation of alcohol value.

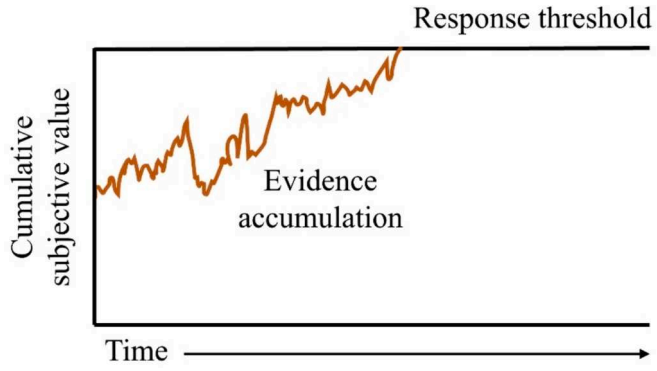

Fig. 1.1. Graphic depiction of the drift–diffusion model (DDM). Noisy evidence accumulates over time until a response threshold is reached, at which point the decision is made.

The present study capitalised on methodological advances in the measurement of value-based choice with the aim to explore whether experimentally manipulating the value of alcohol is associated with changes in the internal cognitive processes that precede decisions made about alcohol and soft drink cues. Design, hypothesis, and analysis strategy were pre-registered before data collection commenced (https://aspredicted.org/yx5yk.pdf). It was hypothesised that:

1. In the alcohol value condition, participants will have increased EA rates and lower response thresholds when choosing between alcohol images compared to when choosing between soft drink images.
2. In the alcohol devalue condition, participants will have increased EA rates and lower response thresholds when choosing between soft drink images compared to when choosing between alcohol images.
3. When choosing between alcohol images, participants will have increased EA rates and lower response thresholds in the alcohol value condition compared to in the alcohol devalue condition.
4. When choosing between soft drink images, participants will have increased EA rates and lower response thresholds in the alcohol devalue condition compared to in the alcohol value condition.

2. Method

2.1. Participants

Based upon an *a priori* power analysis[4], thirty-six regular alcohol consumers (30 female; mean age = 26.11, SD = 10.84) were recruited from the local community through poster advertisements, social media, and an online research participation system (ORPS) hosted by the University of Sheffield. The inclusion criterion was consumption of at least 14 weekly UK units (1 UK unit = 8 g alcohol) whilst the exclusion criterion was a history of treatment for alcohol use disorder. The 14-unit threshold was chosen because it represents alcohol consumption levels that exceed the UK "low-risk" guidelines (Department of Health, 2016). The University of Sheffield's research ethics committee approved the study, and all participants gave informed consent. Recruitment took place between January 2020 and February 2020. Participants were reimbursed with course credits via the ORPS (if they are a student) or a £10 Love2shop voucher that could be spent in retail outlets.

2.2. Materials

2.2.1. Pictorial stimuli

The 35 alcohol and 35 soft drink images were taken from the Amsterdam Beverage Picture Set (ABPS; Pronk et al., 2015) and Google. A subsection of ABPS images were selected that depicted common brands in the UK with a white background. These images were accompanied by images from Google to increase the variability of recognisable alcohol and soft drink options and to ensure there were images that would elicit differential value ratings.

2.2.2. Video stimuli (experimental manipulation)

Previously validated videos (Di Lemma et al., 2015) were used to prime participants to value and devalue alcohol. The alcohol-positive video was intended to increase alcohol value by depicting positive images relating to alcohol consumption (e.g., partying) accompanied by an upbeat soundtrack. The alcohol-negative video was intended to decrease

[2] This is because of the presence of random variability and stochasticity in the decision-making process modelled as Gaussian noise. Due to the stochastic nature of the evidence accumulation process, decisions are probabilistic rather than deterministic.

[3] *Molecular* perspectives are primarily concerned with understanding "in-the-moment" decisions.

[4] This was conducted on G*Power (Faul et al., 2007) to detect a difference between two dependent groups with a medium effect ($d = 0.5$; Cohen, 1988) at 90% power with an alpha of 0.05.

alcohol value by depicting negative images relating to alcohol consumption (e.g., vomiting) accompanied by a downbeat soundtrack. As in Hogarth et al. (2015), we did not include a neutral group because the contrast between two more extreme groups offered the best strategy to detect an effect.

2.2.3. Questionnaires

Approach and Avoidance of Alcohol Questionnaire, Right Now Version (AAAQ; McEvoy et al., 2004): This 14-item questionnaire was used to assess motivational tendencies to approach or avoid drinking at that moment in time. The three subscales are: Inclined-indulgent (mild inclinations to drink), obsessed-compelled (strong inclinations to drink), and resolved-regulated (inclinations to avoid alcohol). The three subscales had acceptable internal reliability in each of the four times that the questionnaire was administered (all ω's $\geq$ 0.72; McDonald, 1970, 1999).

Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993): The full 10-item AUDIT was used to detect patterns of alcohol consumption that are hazardous to health. Total scores range between 0 and 40, with scores $>$ 7 indicating hazardous alcohol use. The AUDIT had just under acceptable internal reliability, $\omega = 0.64$.

Brief self-control scale (BSCS; Tangney et al., 2004): This 13-item scale was used to capture the extent to which people feel that they can resist external influences and exert control over their behaviour. Participants responded on a 1 (not at all like me) to 5 (very much like me) scale. In the current sample, the BSCS had acceptable internal reliability, $\omega = 0.81$.

Brief Assessment of Alcohol Demand (BAAD; Owens et al., 2015): This 3-item scale was used to measure alcohol demand by presenting participants with a hypothetical scenario and asking about their alcohol consumption across a range of escalating price points. Intensity refers to alcohol consumption independent of price (responses ranged from 0 to 10 drinks). O_{max} refers to the maximum expenditure on alcohol (responses ranged from £0-£30 or more). Breakpoint refers to the first price that suppresses consumption to zero (responses ranged from £0-£15 or more). See supplementary file for scenario wording and exact price increments.

2.3. Procedure

Volunteers attended the laboratory at University of Sheffield's Department of Psychology, which lasted between 60–80 min (see Fig. 1.2 for a schematic overview of the study procedure).

The order of experimental manipulation was randomised. In the alcohol devalue condition participants watched the alcohol-negative video, while in the alcohol value condition participants watched the alcohol-positive video. In each condition, participants self-reported their inclinations to approach and avoid alcohol, both before and after watching the video; this was followed by the completion of the VBDM task. In between the experimental conditions there was a "washout" phase to minimise carry-over effects from the previously viewed video. This involved presenting participants with facts about the local region and testing their memory of those. Analysis of order effects revealed that the first time that participants completed the alcohol blocks, EA rates were lower and response thresholds were higher. This was irrespective of which experimental condition they completed first and therefore may represent practice effects. Importantly, the effect of the experimental manipulation on soft drink EA rates was unaffected by the order of experimental conditions, and there was some evidence of lower soft drink thresholds after alcohol devaluation (as hypothesised), but this was confounded by order effects. Further information can be found in the supplementary file.

2.3.1. Image-rating phase

We asked participants to make value judgements about two sets of 35 images (a soft drink set and an alcohol set) by placing each image into one of four boxes depending on how much they would like to consume the drink depicted at the end of the experiment ('A lot', 'A little bit, 'Not really', and 'Not at all'). Participants were instructed to rate all images whilst assigning at least five to each category. Five images were randomly selected from each of the categories, and these were each displayed on the centre of the screen for 3 s, followed by a 500 ms fixation cross.

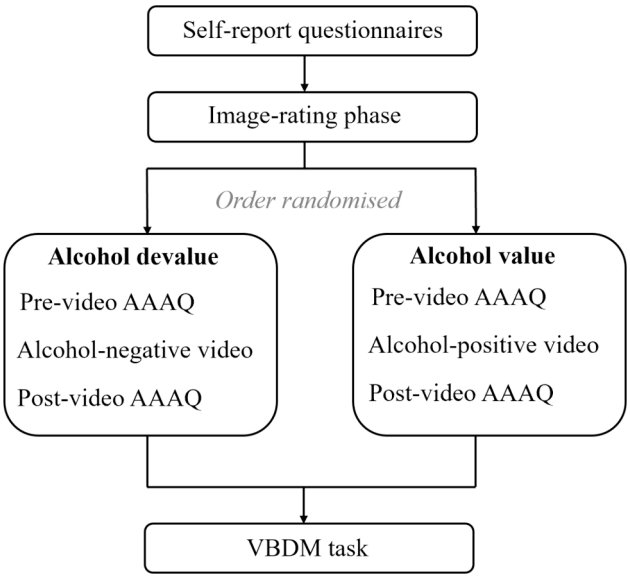

Fig. 1.2. Schematic overview of the study procedure. *Note.* Self-report questionnaires comprise demographic questions (age and gender), the Brief Self-Control Scale (BSCS), the Alcohol Use Disorders Identification Test (AUDIT), and the Brief Assessment of Alcohol Demand (BAAD). The order of experimental manipulation was randomised: For half of the sample the alcohol value condition was first, while for the remaining half the alcohol devalue condition was first.

2.3.2. Value-based decision-making (VBDM) task

The task was programmed in PsychoPy (Peirce et al., 2019). On each trial, two images appeared in the centre of the screen, and participants were instructed to use one of two keys to choose the image that depicts the drink they would rather consume ('Z' for left and 'M' for right) as quickly as possible (see Fig. 1.3). Participants completed some practice trials before completing two blocks (one soft drink block where they choose between two soft drink images and one alcohol block where they choose between two alcohol images; order randomised) of 150 trials (300 trials in total) with embedded breaks after every 50 trials. Difficulty levels across trials were varied, in that the difference in ratings between the two images could be 1, 2, or 3 (hard, medium, and easy choices, respectively). On each trial there was a correct answer; whether this appeared on the left or the right of the screen was random. Responses outside four seconds were classed as "miss trials" as commonly used in VBDM tasks (Polanía et al., 2014).

2.4. Data preparation and analysis

On the VBDM task, "miss trials" (responses exceeding 4 s) were removed (0.13 %) in addition to trials that were under 300 ms (0.06 %) as these are likely fast guesses (Ratcliff et al., 2006). This resulted in the overall removal of 0.19 % of trials. We then fitted the DDM (Ratcliff & McKoon, 2008) to accuracy and speed data from responses on the VBDM task, using the EZ method (Wagenmakers et al., 2007). This simplified version of the DDM takes the mean correct RT, variance of correct RT, and response accuracy as input to estimate three key parameters that capture relevant aspects of the psychological processes that underlie decision-making. These are: drift rate (v; also termed 'EA rate'),

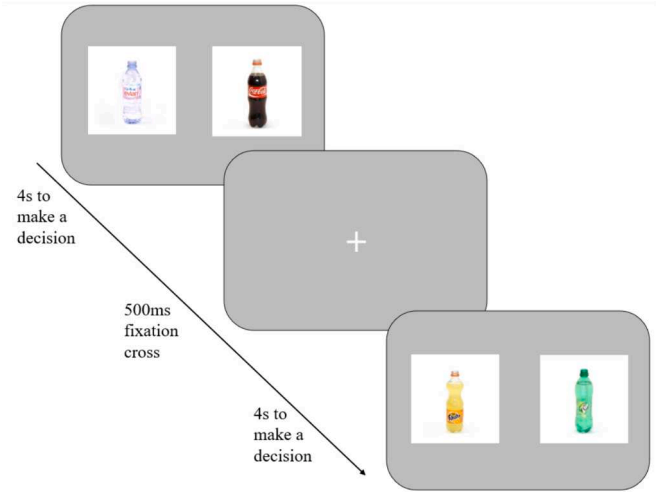

Fig. 1.3. Example of typical trials (in the soft drink block). *Note.* The question asked was "which would you rather consume" and participants were instructed to press a key to select either of the images ('Z' for left, 'M' for right). Participants had 4 s to decide per trial, and each trial was followed by a 500 ms fixation cross located in the centre of the screen. Images are taken from the Amsterdam Beverage Picture Set (Pronk et al., 2015).

boundary separation (*a*; also termed 'response threshold'), and non-decision time (T_{er}). Drift rate reflects the average strength of value evidence accumulation which is interpreted to index subjective value attributed to a particular reinforcer (Field et al., 2020). This parameter can be distinguished from other characteristics of the decision-maker such as their response caution (indexed by response thresholds) or the time taken to encode stimuli and execute a motor response (indexed by non-decision time) when they are making choices about that particular reinforcer. We estimated the parameters (EA rates and response thresholds) for each of the experimental conditions, for each difficulty level, and for each image type (see supplementary file for analyses on difficulty levels in isolation).

Paired samples (one-tailed) *t*-tests were used to analyse the data for the core pre-registered hypotheses, supplemented by exploratory repeated-measure ANOVAs to interpret any group differences in VBDM parameters. Non-parametric tests were used for data that were not approximately normally distributed. Statistical analyses were conducted in RStudio version 4.0.2 (R Core Team, 2023).

3. Results

See Table 1.1 for descriptive statistics[5].

3.1. Effects of video manipulation on AAAQ scores (Figs. 1.4 and 1.5)

AAAQ ratings were analysed using a three-way repeated measures ANOVA with subscale (3: inclined-indulgent; obsessed-compelled; resolved-regulated), time (2: before video; after video), and experimental condition (2: alcohol value; alcohol devalue) as within-subject variables. There was a significant three-way interaction between subscale, time, and condition, $F(1.65, 57.60) = 42.68$, $p < 0.001$, $\eta_p^2 = 0.55$.

[5] The supplementary file contains exploratory correlations between variables measured in the study, for example between VBDM parameters and self-reported alcohol demand. We observed positive correlations between O_{max} and response thresholds in the alcohol value condition, but this was irrespective of drink type. In other words, higher (maximum) amounts spent on alcohol correspond to higher response caution indexed by response thresholds. There were no other significant correlations between BAAD indices and VBDM parameters.

Table 1.1
Descriptive statistics of the sample (values represent the mean, standard deviation, and range). All but two participants (94.44 % of the sample) were hazardous or harmful drinkers (AUDIT > 7).

Variable	Mean (SD, range)
Age	26.11 (10.84, 18–62)
BSCS	39.47 (7.60, 25–53)
AUDIT	13.75 (4.80, 6–23)
Intensity	6.67 (2.18, 3–10)
O_{max}	20.33 (7.53, 3–30)
Breakpoint	6.24 (2.36, 3–15)

Note. BSCS = Brief Self-Control Scale (possible range of values: 13 to 65). AUDIT = Alcohol Use Disorders Identification Test (possible range of values: 0 to 40). Intensity = hypothetical consumption of drinks if they are free (possible range of values: 0–10 or more drinks). O_{max} = hypothetical maximum expenditure on alcohol during a drinking occasion (possible range of values: £0-£30 or more). Breakpoint = hypothetical maximum expenditure on a single drink (possible range of values: £0-£15 or more).

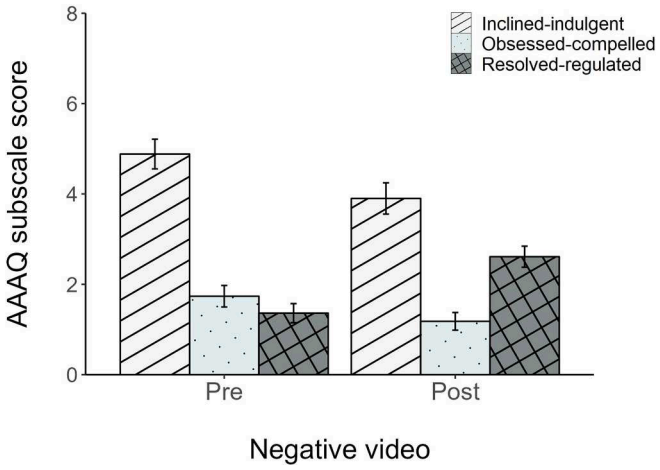

Fig. 1.4. Mean AAAQ scores split by subscale pre (before) and post (after) watching the negative video in the alcohol devalue condition. *Note.* Error bars represent the standard error of the mean (SE).

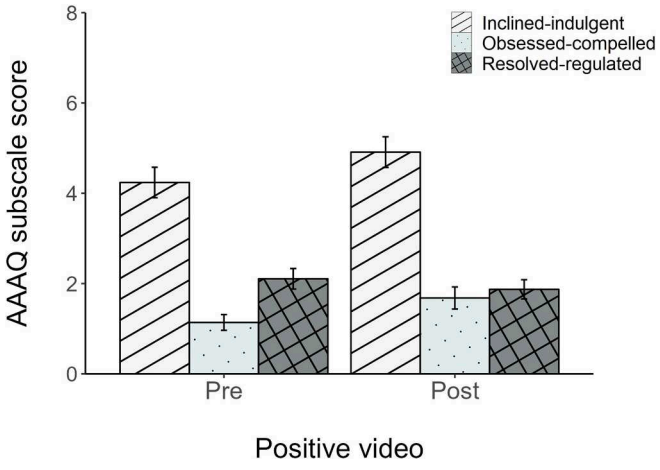

Fig. 1.5. Mean AAAQ scores split by subscale pre (before) and post (after) watching the positive video in the alcohol value condition. *Note.* Error bars represent the standard error of the mean (SE).

To examine this interaction further, subsequent two-way ANOVAs were conducted on each subscale separately, followed by post-hoc tests[6]. These analyses revealed a significant interaction between time and experimental condition for all three subscales (inclined-indulgent, $F(1, 35) = 35.19$, $p < 0.001$, $\eta_p^2 = 0.50$; obsessed-compelled, $F(1, 35) = 24.80$, $p < 0.001$, $\eta_p^2 = 0.41$; and resolved-regulated, $F(1, 35) = 41.14$, $p < 0.001$, $\eta_p^2 = 0.54$). Post-hoc tests revealed that in the alcohol devalue condition, after watching the alcohol-negative video, scores on the inclined-indulgent and obsessed-compelled subscales decreased compared to before the video (both p's < 0.001). Whereas scores on the resolved-regulated subscale increased after watching the video ($p < 0.001$). A different pattern was seen after participants had watched the alcohol-positive video (positive condition): scores on the inclined-indulgent and obsessed-compelled subscales increased (both p's < 0.001). However, there were no significant changes in scores on the resolved-regulated subscale after watching the positive video ($p = 0.18$).

To explore differences in each of the subscale scores after watching each of the videos (e.g., the positive video versus the negative video), a two-way ANOVA with subscale (3: inclined-indulgent; obsessed-compelled; resolved-regulated) and experimental condition (2: alcohol value; alcohol devalue) using only scores from after video viewing was conducted. There was a significant interaction between subscale and experimental condition, $F(1.46, 50.94) = 25.22$, $p < 0.001$, $\eta_p^2 = 0.42$. Post-hoc tests revealed that scores on the inclined-indulgent and obsessed-compelled subscales were lower after watching the negative video compared to after watching the positive video ($p < 0.001$ and $p = 0.03$, respectively). Scores on the resolved-regulated subscale were increased after watching the negative video compared to the positive video ($p < 0.001$).

3.2. Pre-registered analyses

In the alcohol value condition, there were no significant differences in alcohol EA rates (M = 1.89, SD = 0.55) compared to soft drink EA rates (M = 1.89, SD = 0.34), $t(35) = 0.07$, $p = 0.47$, $d = 0.01$. Furthermore, there were no significant differences in alcohol response thresholds (M = 1.64, SD = 0.39) compared to soft drink response thresholds (M = 1.63, SD = 0.36), $t(35) = 0.26$, $p = 0.60$, $d = 0.04$.

In the alcohol devalue condition, soft drink EA rates (M = 2.02, SD = 0.49) were significantly higher compared to alcohol EA rates (M = 1.88, SD = 0.50), $t(35) = -1.86$, $p = 0.04$, $d = 0.31$. There were no significant differences in soft drink response thresholds (M = 1.54, SD = 0.36) compared to alcohol response thresholds (M = 1.60, SD = 0.30), $t(35) = 1.35$, $p = 0.09$, $d = 0.22$.

When participants made alcohol decisions, there were no significant differences in EA rates in the alcohol value condition (M = 1.89, SD = 0.55) compared to the alcohol devalue condition (M = 1.88, SD = 0.50), $t(35) = 0.18$, $p = 0.43$, $d = 0.03$. Furthermore, there were no significant differences in response thresholds in the alcohol value condition (M = 1.64, SD = 0.39) compared to in the alcohol devalue condition (M = 1.60, SD = 0.30), $t(35) = 1.00$, $p = 0.84$, $d = 0.17$.

When participants made soft drink decisions, EA rates were significantly higher in the alcohol devalue condition (M = 2.02, SD = 0.49) compared to the alcohol value condition (M = 1.89, SD = 0.34, $t(35) = -2.27$, $p = 0.01$, $d = 0.38$. However, there were no significant differences in response thresholds in the alcohol devalue condition (M = 1.54, SD = 0.36) compared to the alcohol value condition (M = 1.63, SD = 0.36), $t(35) = 1.52$, $p = 0.07$, $d = 0.25$.

3.3. Exploratory analyses

To supplement the VBDM analyses presented above (Figs. 1.6 and 1.7), we conducted exploratory repeated-measure ANOVAs on EA rates and response thresholds using within-subject factors of image type (2: alcohol; soft drink) and experimental condition (2: alcohol value; alcohol devalue). When looking at EA rates, there was a significant interaction between image type and experimental condition ($F(1, 35) = 4.37$, $p = 0.04$, $\eta_p^2 = 0.11$), but no main effect of image type ($F(1, 35) = 1.19$, $p = 0.28$, $\eta_p^2 = 0.03$) or experimental condition ($F(1, 35) = 2.20$, $p = 0.15$, $\eta_p^2 = 0.06$). Post-hoc tests for the significant interaction effect revealed that soft drink EA rates were higher in the alcohol devalue condition (M = 2.02, SD = 0.49) compared to in the alcohol value condition (M = 1.89, SD = 0.34) although this fell short of statistical significance ($p = 0.10$). However, it should be noted that in line with our pre-registration, our study was powered to detect differences in means between two dependent groups rather than an interaction effect. When looking at response thresholds, there was no significant main effect of image type ($F(1, 35) = 1.24$, $p = 0.27$, $\eta_p^2 = 0.03$) or experimental condition ($F(1, 35) = 2.13$, $p = 0.15$, $\eta_p^2 = 0.06$), and no interaction between the two ($F(1, 35) = 0.82$, $p = 0.37$, $\eta_p^2 = 0.02$).

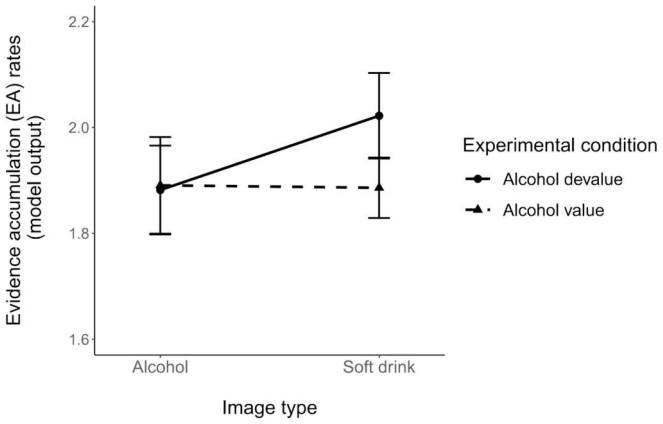

Fig. 1.6. Mean overall EA rates for alcohol and soft drink choices split by alcohol devaluation (solid black line; circle) and alcohol valuation (dashed black line; triangle) experimental conditions. *Note.* Error bars represent the standard error of the mean (SE).

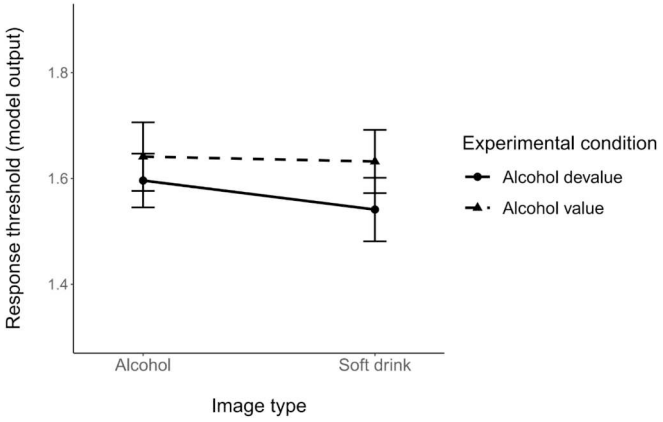

Fig. 1.7. Mean overall response thresholds for alcohol and soft drink choices split by alcohol devaluation (solid black line; circle) and alcohol valuation (dashed black line; triangle) experimental conditions. *Note.* Error bars represent the standard error of the mean (SE).

4. Discussion

The novel finding of this study is that after regular alcohol consumers had been primed to devalue alcohol, their decision-making became characterised by significantly higher EA for soft drinks compared to for

[6] Bonferonni-Holm correction was applied to p-values for multiple comparisons.

alcohol. This finding was corroborated by a within-condition difference: soft drink EA rates were significantly higher when participants were primed to devalue alcohol compared to when they were primed to value alcohol. However, contrary to hypotheses, we did not identify significant differences in alcohol EA rates, or response thresholds for either drink type, across experimental conditions.

Contrary to hypotheses, alcohol EA rates were insensitive to our experimental manipulation of alcohol value. This result was surprising in the context of results from two prior experimental studies (Rose et al., 2013, 2018) that devalued alcohol by making its taste aversive prior to completion of a concurrent choice task. In these studies, alcohol devaluation (compared to a control manipulation) reduced alcohol choice, which is indicative of lowered alcohol value. However, a closer look at these findings reveals some ambiguity: another way to frame decreases in the percentage choice of alcohol is to frame it as increases in the percentage choice of the alternative reward, which in Rose et al. (as in the present study), was soft drinks. It is therefore difficult to disentangle whether the findings reported by Rose et al. can be attributed to reduced value of alcohol, increased value of soft drinks, or both. An important contribution of our study is the demonstration that devaluation of alcohol (or other drugs) may alter the valuation of competing rewards, and this may explain the effects on overt choice for alcohol (or other drugs) versus those competing rewards. Further work is required to determine how our findings might generalise to different choice contexts and to the prediction of overt choice for alcohol. If this finding is confirmed in subsequent research, it would be in line with contemporary behavioural economic models that emphasise the importance of the availability and value attributed to alternative reinforcement as determinants of drug choice (Acuff et al., 2023). However, it is important to keep in mind that our experimental manipulation did not influence VBDM indicators of the value ascribed to alcohol. This limits the clinical implications of the present findings and suggests that, in line with Acuff et al. (2023), other manipulations that have the potential to simultaneously reduce the value ascribed to alcohol and increase the value ascribed to alternative reinforcers, should be investigated.

Interestingly, Rose et al. (2018) demonstrated that when participants were primed to devalue alcohol, this reduced eye movements to alcohol cues and increased eye movements to soft drink cues. An extension of the DDM (attentional DDM) incorporates visual attention in the value integration process (Krajbich et al., 2012) and posits that on average a person accumulates more value evidence for an item when it is being attended to. This finding can be reconciled with the speculation that changes in the value ascribed to soft drinks is important.

Methodological differences impede direct comparisons between the present findings and those from previous research that used concurrent choice tasks. Firstly, we instructed participants to choose between two alcohol or two soft drink images in separate blocks because this generates the behavioural data required to model the internal processes that underpin value-based choice for each type of reinforcer. This is standard methodology in the broader VBDM literature (e.g., Polanía et al., 2014). If we had required participants to choose between alcohol and soft-drink images within the same block (as happens during a concurrent choice task), the resulting VBDM parameters would reflect that choice context, but it would be impossible to attribute them to one reinforcer rather than the other. Furthermore, our experimental manipulation of alcohol value differed to that of existing research which targeted either mood (Dora et al., 2023; Hardy & Hogarth, 2017; Hogarth et al., 2018) or taste (Rose et al., 2013, 2018). Moreover, it may be that our manipulation to increase alcohol value was not as effective as our manipulation to decrease the value of alcohol as each of the three AAAQ subscales (alcohol approach and avoid inclinations) altered significantly after watching the negative video that was intended to devalue alcohol. However, after watching the positive video that was intended to increase the value of alcohol, only approach inclinations changed significantly; avoid inclinations were unaffected.

We did not observe significant differences in response thresholds following the experimental manipulation. In a previous study (Copeland, Stafford, & Field, 2023) using a similar experimental task, we demonstrated that recovery from nicotine addiction was characterised by elevated response thresholds when making tobacco-related decisions, but there was no difference in EA rates. A speculative explanation for this lack of consistency is that recovery from addiction may be characterised by cautious decision-making because people are actively making the choice to not consume a substance in their everyday lives. By contrast, in the present study (and in another VBDM study that experimentally manipulated mood; Dora et al., 2023) the participants were regular alcohol consumers who were making a series of rapid (inconsequential) decisions about alcohol and alcohol-unrelated cues.

This study has some strengths. There is increasing awareness of the benefits of applying the DDM to behavioural data, such as enhanced statistical power (Stafford et al., 2020). However, there are some important limitations. Although data were collected in-person, there were no explicit attention checks, and females were overrepresented in our sample which limits the generalizability of findings to the wider population, and to previous studies in which male and female participants were more equally represented (e.g., Rose et al., 2013, 2018; Hardy & Hogarth, 2017; Hogarth et al., 2018). In addition, due to the manipulation in this study, we cannot establish whether the higher EA rates for soft drinks following alcohol devaluation would also be seen in comparison to a more neutral manipulation (rather than a manipulation that increases the value of alcohol). Although our approach aligns with standard methodology in the broader VBDM research literature (e.g., Polanía et al., 2014), a limitation of our implementation of the EZ-DDM (Wagenmakers et al., 2007) is that parameters were recovered for each drink type separately. To fully reconcile these results within the broader behavioural economic research, future research could explore the possibility of using more complex versions of the DDM to recover interpretable parameters from VBDM tasks that present alcohol and alternative reinforcers concurrently. In other domains, individual differences in VBDM parameters have been used to characterise psychological disorders including depression, anxiety, and schizophrenia (e.g., Limongi et al., 2018; Pedersen et al., 2021; White et al., 2010). Future research with a clinical focus might explore how VBDM parameters influence decision-making in the broader context of alcohol versus alcohol-free alternatives, in addition to including images that represent a range of alcohol-free reinforcement (e.g., exercising). For example, whether changes in alcohol-free alternative parameters correspond to changes in alcohol-related behaviour. Future extensions of this work might also employ reversal or ABAB designs in order to fully characterise the causal influence of alcohol (de)valuation on VBDM parameters (Kazdin, 2011).

To conclude, findings demonstrate partial support for predictions derived from conceptual accounts of VBDM (Copeland et al., 2021; Field et al., 2020): when regular alcohol consumers were primed to devalue alcohol, their decision-making was characterised by significantly higher EA for soft drinks, although EA rates for alcoholic drinks, and response thresholds for either drink type, were unaffected by the experimental manipulation.

CRediT authorship contribution statement

Amber Copeland: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Tom Stafford:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Matt Field:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and code for this manuscript can be found here: https://researchbox.org/1898.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2024.108069.

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