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# Value-Based Decision-Making in Daily Tobacco Smokers Following Experimental Manipulation of Mood

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Induction of negative mood increases tobacco choice in dependent smokers; however, less is known about the mechanisms behind this. This study addressed this gap by applying a computational model of value-based decision making to tobacco and tobacco-unrelated choices following mood manipulation. Using a preregistered, within-subject design, 49 daily tobacco smokers (>10 daily cigarettes) watched two different videos which primed them to experience negative and positive mood (tobacco valuation and devaluation, respectively). Participants completed self-report measures of mood and craving to smoke before and after priming, followed by a two-alternative forced-choice task with (separate) blocks of tobacco-related and tobacco-unrelated (animal) images. On each block, participants selected the image that they previously rated higher. A drift-diffusion model was fitted to the reaction time and error data to estimate evidence accumulation processes and response thresholds during the different blocks. After watching videos intended to induce negative mood, happiness scores were lower ($p < .001$, $d = 1.16$), while sadness and craving to smoke scores were higher (both *p*s < .001, *d*s > .60) compared to after watching videos intended to induce positive mood. However, contrary to hypotheses, the experimental manipulation did not robustly affect evidence accumulation rates ($F = 1.15$, $p = .29$, $\eta_p^2 = .02$) or response thresholds ($F = .07$, $p = .79$, $\eta_p^2 = .00$) for either tobacco or tobacco-unrelated decisions. Manipulation of mood in daily smokers did not lead to alterations in the internal processes that precede value-based decisions made about tobacco and tobacco-unrelated cues.

***Public Health Significance***

Contrary to theory, this preregistered study found that being in a negative—relative to a positive—mood state does not correspond to changes in how people value tobacco or tobacco-unrelated alternatives. This result is important because it suggests that negative reinforcement models might not fully explain behavior or that the way mood affects how we value drugs might be more complex than we currently understand.

*Keywords:* computational, experimental, mood, tobacco, valuation

*Supplemental materials:* https://doi.org/10.1037/pha0000781.supp

Tobacco smoking is a leading global cause of preventable disease and death (Forouzanfar et al., 2016). In the United Kingdom, there are around 5.3 million current tobacco smokers (representing 12.7% of the population aged 18 and over; Office for National Statistics, 2023), leading to substantial health and socioeconomic consequences. Behavioral economic *reinforcer pathology* models posit that addiction (tobacco use disorder) develops and is maintained via distortions in valuation processes, such that tobacco is overvalued relative to other available reinforcers (Acuff et al., 2023; Bickel & Athamneh, 2020; Bickel et al., 2011, 2014; García-Pérez et al., 2022). Consistent with behavioral economic models, experimental research has shown that people ascribe higher value to

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tobacco relative to tobacco-unrelated alternative reward following the induction of negative mood (for a review, see Hogarth & Field, 2020). However, less is known about the underlying cognitive mechanisms through which this effect occurs. The present study applied computational advances in the measurement of value-based choice to decisions made about tobacco and tobacco-unrelated cues after experimental manipulation of mood.

Hypothetical purchase tasks are often used to experimentally measure "demand"—a behavioral economic construct that represents the reinforcing value of a commodity (MacKillop, 2016). During the cigarette purchase task (CPT; MacKillop et al., 2008), a person (hypothetically) estimates the number of cigarettes they would purchase to consume across steadily increasing prices. From this, a tobacco demand curve (i.e., a plot of the level of consumption and tobacco-related expenditure as a function of cigarette price) can be generated that enables indices of tobacco value to be extracted (Aston & Cassidy, 2019). An alternative, but also commonly used method of quantifying drug value is with concurrent choice tasks (e.g., Hogarth et al., 2015) whereby a person chooses between tobacco and tobacco-unrelated images for a reward (e.g., image enlargement) over repeated trials. On these tasks, the percentage choice of tobacco (relative to tobacco-unrelated) reward is taken to index the value ascribed to tobacco.

A robust body of evidence using these tools has demonstrated positive associations between nicotine dependence and tobacco value (González-Roz et al., 2019; Hardy et al., 2018; Miele et al., 2018; Zvorsky et al., 2019). Experimentally, studies have also uncovered important statelike fluctuations in drug value (Acuff et al., 2020; Amlung et al., 2015; Aston et al., 2021; Hogarth & Field, 2020). For example, Hogarth et al. (2015) found that when nicotine-deprived smokers smoked to satiety (tobacco devaluation), tobacco choice on the concurrent choice task decreased in participants where positive mood was induced, but this was not observed in participants assigned to negative mood induction. This demonstrates the induction of negative mood augmented tobacco value to the extent that it outweighed the previous devaluation effect. Similar mood induction procedures have been used in alcohol-related studies, findings from which support the notion that negative mood is a powerful driver of elevated drug value (Hardy & Hogarth, 2017; Hogarth et al., 2018). This aligns with *negative reinforcement* models (Baker et al., 2004; Blevins et al., 2016; Cooper et al., 1995): Substances may increase in value because they assist with the avoidance or regulation of negative internal states (Hogarth, 2022). However, existing studies are methodologically limited by concurrent choice tasks which do not provide insights into cognitive processes underlying decisions and which focus solely on drug value. This may be a key oversight considering the emphasis on drug-free reinforcement in contemporary behavioral economic models of addiction (Acuff et al., 2023).

Value-based decision making (VBDM) provides a framework that can be used to model the internal cognitive processes that determine momentary decisions (Berkman et al., 2017). According to VBDM, choice options (e.g., whether to smoke a cigarette, or to go for a run) are identified and assigned an overall value. The value of each option is determined via an integration of context-sensitive choice-relevant attributes (Berkman, 2018), and the response option with the highest value is acted upon. This process can be understood with the drift-diffusion model (DDM; Ratcliff & McKoon, 2008), which assumes people accumulate noisy evidence in favor of a response option until a response threshold is reached, at which point the decision is made (for a review, see Ratcliff et al., 2016). By fitting the DDM to behavioral data from VBDM tasks (Polanía et al., 2014), parameters with well-established psychological interpretation can be estimated. Two important parameters are rate of evidence accumulation (EA; the average rate at which value evidence is accumulated) and response threshold (decision conservativeness represented by speed–accuracy trade-offs).

Guided by conceptual accounts (Copeland et al., 2021; Field et al., 2020), several studies have extended VBDM to addiction research (Copeland, Stafford, Acuff, et al., 2023; Copeland, Stafford, & Field, 2023; Copeland et al., 2024; Dora, Copeland, et al., 2023). One online experimental study (Dora, Copeland, et al., 2023) found that in heavy drinkers, inducing a negative mood altered the cognitive processes underlying value-based food decisions, but had no effect on alcohol valuation. However, to date, VBDM has not been directly explored in tobacco smokers following the experimental manipulation of mood. It is important to note that in these studies (and the present study), participants make decisions about substance-related and substance-free stimuli separately. Although this methodology deviates from concurrent choice tasks because reinforcer value is not quantified *relatively*, it is essential for obtaining interpretable decision parameters and is common practice within the broader VBDM field (e.g., Polanía et al., 2014).

The present study is inspired by conceptual accounts of VBDM (Copeland et al., 2021; Field et al., 2020) and prior findings indicating that negative mood increases choice for tobacco over nontobacco rewards (Hogarth et al., 2015). We predict that mood manipulation will alter computational parameters of value-based choice (EA rates and response thresholds) in decisions involving tobacco and non tobacco cues. Our hypotheses are as follows:

1. When participants are primed to experience negative mood, they will have increased EA rates and lower response thresholds when choosing between tobacco images compared with when choosing between tobacco-unrelated (animal) images.

2. When participants are primed to experience positive mood, they will have increased EA rates and lower response thresholds when choosing between tobacco-unrelated (animal) images compared with when choosing between tobacco images.

3. When choosing between tobacco images, participants will have increased EA rates and lower response thresholds when primed to experience negative mood compared with when primed to experience positive mood.

4. When choosing between tobacco-unrelated (animal) images, participants will have increased EA rates and lower response thresholds when primed to experience positive mood compared to when primed to experience negative mood.

## Method

We report how we determined our sample size, all data exclusions, all manipulations, and all measures used throughout this section. The design, hypothesis, and analysis strategy were preregistered before data collection commenced (https://aspredicted.org/XR7_6CY). Data preparation and statistical analyses were conducted in RStudio Version 4.0.2 (R Core Team, 2023), and all anonymized data and analysis scripts are available at https://researchbox.org/3481.

## Participants

An a priori power analysis conducted on G*power (Faul et al., 2007) revealed that to detect a difference between two dependent groups with a medium effect size ($d = .50$, or $\eta_p^2 = .06$; Cohen, 1988) at 90% power with an $\alpha$ of .05, 36 participants were required. We recruited 50 daily tobacco smokers via Prolific (https://www.prolific.co/), an online platform designed for recruiting participants for research studies; however, data from one participant was removed prior to analysis.[1] The remaining sample ($n$ = 49; 30 females, 19 males) were aged between 26 and 69 years old ($M_{age} = 46.96$, $SD$ = 12.33). Inclusion criteria were as follows: ≥18 years old, current residence in the United Kingdom, identification as a current smoker who has smoked for >1 year, smoking >10 cigarettes per day, and only smoking tobacco. Participants were required to have taken part >10 previous studies with >95% approval on Prolific to maximize retention and data quality. The study was approved by the University of Sheffield research ethics committee, and all participants gave informed consent. Recruitment took place between July and August 2021. Participants were reimbursed with 0.38p for completing the prescreen and £12.50 for completing the study (in Prolific credit).

## Materials

### *Pictorial Stimuli for the VBDM Task*

The 30 smoking images were selected from the Geneva smoking pictures data set (Khazaal et al., 2012), and the 30 smoking-unrelated (animal) images were selected from the international affective picture system (Lang et al., 2008). Standardized valence ratings that accompany the picture sets were used to guide the selection of images that were likely to be rated as highly positive, highly negative, or intermediate (for more detail, see Supplemental Material).

### *Video Stimuli (Experimental Manipulation)*

Previously validated videos (Marcusson-Clavertz et al., 2019) were used in an attempt to indirectly manipulate tobacco value via mood. The videos (described below) contained film clips and self-referential statements accompanied by music[2] and were selected because they have been found to successfully alter participant mood in an online sample recruited from Prolific (Marcusson-Clavertz et al., 2019). Participants were informed that after watching, they would answer two questions about each video, all of which they answered correctly.

We aimed to induce a positive mood (tobacco devaluation) by instructing participants to watch a 4-min video of Timon and Pumbaa's "Hakuna Matata" scene from The Lion King, followed by another 4-min video, which presented 15 positive Velten statements (e.g., "Most people like me") accompanied by upbeat music (Coppelia, Act I: 1. Prelude et Mazurka by Léo Delibes). Existing positivity ratings (Marcusson-Clavertz et al., 2019) determined the Velten statements' order, ending with the most positive.

We aimed to induce negative mood (tobacco valuation) by instructing participants to watch a 4-min video of Mufasa's death scene from The Lion King, followed by another 4-min video that presented 15 negative Velten statements (e.g., "When I talk no one really listens") accompanied by downbeat music (Adagio for Strings, Op. 11 by Samuel Barber). Existing negativity ratings (Marcusson-Clavertz et al., 2019) determined the Velten statements' order, ending with mostly negative. This experimental condition contained a "mood repair" so that participants would not end their participation in a heightened negative mood.[3]

### *Questionnaires*

We administered the six-item Fagerström Test for Cigarette Dependence (Fagerström, 2012, McDonald's $\omega$ = .60, McDonald, 1970) to measure cigarette dependence, the 13-item Brief Self-Control Scale (Tangney et al., 2004, $\omega$ = .80) to measure self-control, the 22-item CPT (Aston et al., 2021; MacKillop et al., 2008) to estimate indices of cigarette demand (intensity, $O_{max}$, $P_{max}$, breakpoint, elasticity),[4] the Contemplation Ladder (Biener & Abrams, 1991) to capture motivation to quit smoking (ladder ranging from 0 = *no thought about quitting* to 10 = *taking action to quit*), the Positive and Negative Affect Schedule–Expanded (Watson & Clark, 1999, all $\omega$s > .77) to measure participant joviality (eight items) and sadness (five items) pre- and postmanipulation, and a single item of craving (West & Ussher, 2010) to measure craving to smoke (visual analogue scale ranging from 0 = *no urge to smoke* to 100 = *extreme urge to smoke*) pre- and postmanipulation. Finally, we measured participant demographics, age, gender, smoking quit attempts (if any), typical cigarette consumption per day, years smoked, and age of initiation of smoking.

## Procedure

Participants completed the study online. In line with Marcusson-Clavertz et al.'s (2019) study, a short (3-min) prescreen including the Patient Health Questionnaire–2 (Kroenke et al., 2003) was administered to safeguard participants who might be vulnerable to distress induced by the negative mood induction. Participants were not eligible if they scored >1 on both questions of the Patient Health Questionnaire–2.

Eligible participants were invited to two testing sessions (Figure 1), with counterbalanced mood induction order (positive first for half, negative first for the other half; see Supplemental Material for analyses of order effects). After Session 1, participants completed Session 2 within 10 days ($M$ = 2.65, $SD$ = 1.69). In each condition, participants rated images, completed questionnaires (only in Session 1), reported mood and craving before and after mood manipulation, and then completed the VBDM task. The study lasted 88.30 min on

[1] This is because it was not possible to recover DDM parameters for this participant in one of the conditions due to an accuracy score of 0.

[2] The videos are maintained in a library that is owned by Marcusson-Clavertz et al. (2019). Please contact the author(s) for permission to access or use these materials.

[3] This included eight highly rated amusing video clips (Samson et al., 2016), each lasting ∼30 s, distinct from the mood manipulation, which is important for the counterbalanced order of conditions.

[4] See Supplemental Material for the exact scenario wording and price points.

average ($SD$ = 19.07). The VBDM task was programmed in PsychoPy and hosted on Pavlovia (Peirce et al., 2019).

### *Image-Rating Phase*

Participants viewed two sets of 30 images, a tobacco-related set, and a tobacco-unrelated (animal) set and made preferential judgments about them using a computer mouse to indicate how positive they rated the image: "most positive," "somewhat positive," "somewhat negative," and "most negative." For each picture set, participants were instructed to rate all 30 images while assigning at least five images to each category.

### *VBDM Task*

In the VBDM task, five images were randomly selected from each category ("most positive," "somewhat positive," "somewhat negative," and "most negative"). Each image was displayed in the center of the screen for 3 s, followed by a 500-ms fixation cross, to familiarize participants with the selected images and their evaluations. Following this, participants completed the task. On each trial, two images appeared on the center of the screen, and participants were instructed to use one of two keys to choose the image that they rated higher by pressing one of two keys ("Z" for left and "M" for right) as quickly as possible. They started with some practice trials followed by the main task of 300 trials divided into two 150-trial blocks (tobacco-unrelated and tobacco-related; order randomized) with breaks every 50 trials. Difficulty levels varied: The rating difference between images could be 1 (hard), 2 (medium), or 3 (easy). The higher rated image's position (left or right) was randomized. Participants had up to 4 s to respond; responses outside of this response window were classed as "miss trials" (Polanía et al., 2014).

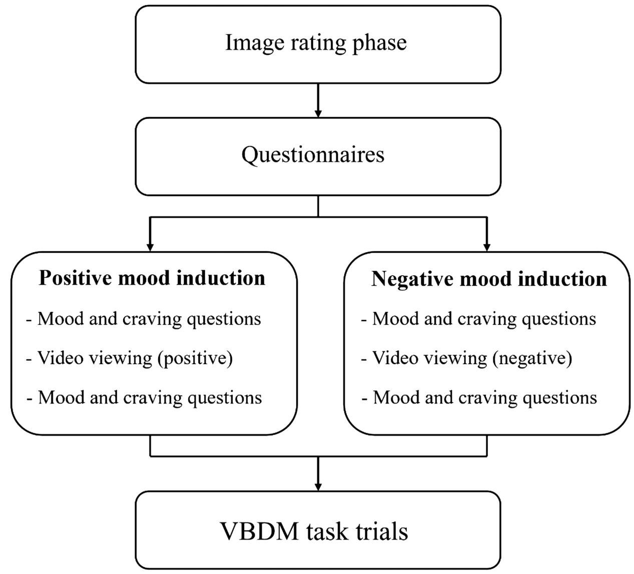
## Data Preparation and Analysis

On the VBDM task, "miss trials" (responses exceeding 4 s) were removed (0.15%) and trials that were under 300 ms (0.21%) as these are likely to be fast guesses (Ratcliff et al., 2006) resulting in the removal of 0.36% of trials. We then fitted the DDM (Ratcliff & McKoon, 2008) using the EZ method (Wagenmakers et al., 2007), which takes response accuracy, mean correct reaction time, and variance of correct reaction time as input to estimate three key parameters: EA rate, also referred to as "drift rate" ($v$); response threshold, also referred to as "boundary separation" ($a$); and non-decision time ($T_{er}$). Parameters were estimated for each of the experimental conditions, difficulty level, and image type (see Supplemental Material for analyses on difficulty levels in isolation).

For the CPT, the consistency of the demand data was checked using a standardized three-point algorithm (Stein et al., 2015) as cases that violate any of the following criteria: *trend* (detection limit for $\Delta Q <$ 0.025), *bounce* (detection limit for $B = 0.10$), and *reversals from zero* (detection limit number for reversals = 2 or more). Data from all participants passed these criteria. Four observed (intensity, breakpoint, $O_{\max}$, $P_{\max}$) indices were generated from raw consumption and expenditure data, while elasticity was derived using the exponentiated demand equation (Koffarnus et al., 2015) in the R package "beezdemand" (Kaplan et al., 2019).[5] Outliers >3.29 standard deviations from the mean (index level) were winsorized to one unit above the greatest nonoutlying value (Tabachnick & Fidell, 2013). The exponentiated equation provided an excellent fit for both participant-level and aggregated data ($R^2$ = 0.92 and $R^2$ = 0.98, respectively).

Paired-samples (one-tailed) $t$ tests were used to analyze the data for the primary preregistered hypotheses, supplemented by exploratory repeated-measure analyses of variance (ANOVAs) to interpret any group differences in VBDM parameters. Nonparametric tests were used for data that were not approximately normally distributed. All participants passed >75% of the attention checks, which was our preregistered criterion.

**Figure 1**
*Schematic Overview of the Study Procedure*




*Note*. Questionnaires include demographic questions (age and gender), questions about cigarette use such as quit attempts (if any), typical cigarette consumption per day, years smoked, and age of initiation of smoking, the Fagerström Test for Cigarette Dependence, the Brief Self-Control Scale, the Cigarette Purchase Task, and a Contemplation Ladder. The order of mood induction was counterbalanced, and participants only completed the self-report questionnaires in the first experimental condition that they completed. VBDM = value-based decision-making.

# Results

See Table 1 for descriptive statistics.

## Effects of Experimental Manipulation on Mood Scores

Self-report mood ratings were analyzed using a three-way repeated-measures ANOVA with mood (2: happy; sad), time (2: before video; after video), and experimental condition (2: positive; negative) as within-subject variables. There was a significant three-way interaction between mood, time, and condition, $F(1, 48) = 66.96$, $p < .001$, $\eta_p^2 = .58$. To examine this interaction further, subsequent two-way ANOVAs were conducted on each mood separately, followed by post hoc tests (applying the Holm-Bonferroni correction to $p$ values

[5] The $k$ value was approximately 2.48 and was calculated using the *GetK* function in "beezdemand" (Kaplan et al., 2019).

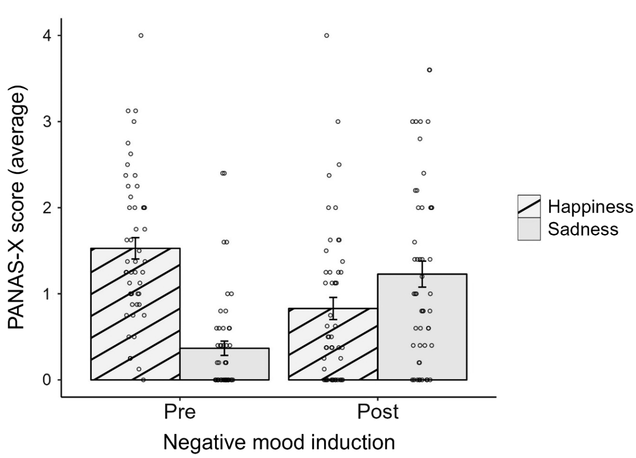
**Table 1**
*Descriptive Statistics of the Sample: Mean (Standard Deviation and Range)*

| Variable | *M* (*SD*, range) |
|---|---|
| BSCS | 37.61 (7.75, 23–52) |
| FTCD | 5.10 (1.79, 1–10) |
| Contemplation Ladder | 5.45 (2.56, 0–10) |
| Cigarettes smoked per day | 17.94 (8.13, 5–60) |
| Years smoked | 30.84 (12.09, 12–53) |
| Age (years) of smoking initiation | 15.49 (2.76, 10–22) |
| Number of previous quit attempts | 1.76 (1.52, 0–6) |
| CPT indices of demand | |
| Intensity | 22.37 (8.02, 10–41) |
| $O_{max}$ | 14.13 (11.68, 2–49) |
| BP1 | 2.89 (2.72, .40–10) |
| $P_{max}$ | 1.79 (1.89, .20–7) |
| Elasticity | .01 (.01, .00–.04) |

*Note.* BSCS = Brief Self-Control Scale; FTCD = Fagerström Test for Cigarette Dependence; CPT = cigarette purchase task; BP1 = breakpoint.

for multiple comparisons). These analyses revealed a significant interaction between time and experimental condition for both moods: happy mood, $F(1, 48) = 67.32$, $p < .001$, $\eta_p^2 = .58$; sad mood, $F(1, 48) = 43.01$, $p < .001$, $\eta_p^2 = .47$. Post hoc tests revealed that after watching the videos intended to induce negative mood, happiness scores decreased ($p < .001$, $d = .78$), while sadness scores increased compared with before viewing the videos ($p < .001$, $d = 1.76$). A different pattern was seen after participants watched the videos intended to induce positive mood: Happiness scores increased compared with before viewing the videos ($p < .001$, $d = .44$), but sadness scores did not significantly differ as a result of viewing the videos ($p = .07$, $d = .36$; Figures 2 and 3).

**Figure 2**
*Average PANAS-X Scores (Happiness and Sadness Subscales) Pre (Before) and Post (After) Watching the Negative Videos in the Negative Mood Experimental Condition*




*Note.* Error bars represent the standard error of the mean. PANAS-X = Positive and Negative Affect Schedule–Expanded.

Looking at contrasts for scores after watching the videos only, sadness scores were significantly higher after the negative videos compared with after the positive videos ($p < .001$, $d = 1.52$), while happiness scores were significantly higher after the positive videos compared with after the negative videos ($p < .001$, $d = 1.16$). Looking at contrasts before watching the videos only, there were no significant differences in sadness ($p = .70$, $d = .07$) or happiness ($p = .73$, $d = .05$) scores.

## Effects of Experimental Manipulation on Craving to Smoke

Craving scores were analyzed using a two-way repeated-measures ANOVA with time (2: before video; after video) and experimental condition (2: positive; negative) as within-subject variables. There was a significant interaction between time and condition, $F(1, 48) = 17.90$, $p < .001$, $\eta_p^2 = .27$. Post hoc tests revealed that in the negative mood condition, craving was higher after watching the videos compared with before watching, but this was not statistically significant ($p = .05$, $d = .28$). Similarly, in the positive mood condition, there were no significant differences in craving before versus after watching the videos ($p = .08$, $d = .23$; Figure 4).

Looking only at craving after viewing the videos, craving scores were significantly higher after the negative videos compared with after positive videos ($p < .001$, $d = .60$). Looking at contrasts only before watching the videos, there were no significant differences in craving scores ($p = .39$, $d = .10$).

## Preregistered Analyses

### *Hypothesis 1*

When primed to experience a negative mood, participants did not have significantly higher tobacco EA rates ($M = 1.83$ $SD = 0.49$) compared with tobacco-unrelated (animal) EA rates ($M = 2.13$, $SD = 0.45$), $t(48) = 4.50$, $p = 1.00$, $d = .64$. Furthermore, participants did not have significantly lower tobacco response thresholds ($M = 1.57$, $SD = 0.31$) compared with tobacco-unrelated (animal) thresholds ($M = 1.57$, $SD = 0.31$), $t(48) = .09$, $p = .46$, $d = .01$. Therefore, this hypothesis was not supported.

### *Hypothesis 2*

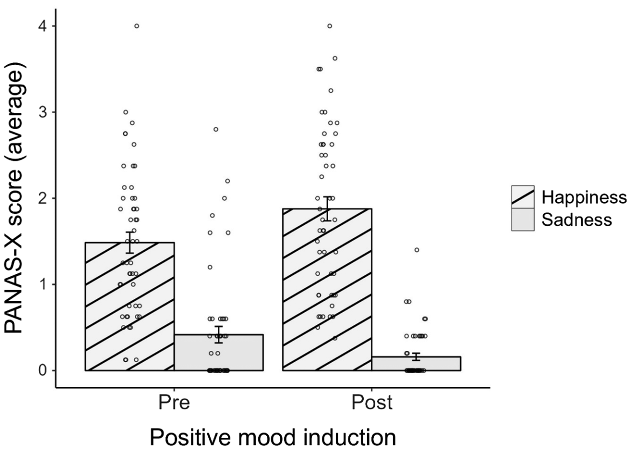
When primed to experience a positive mood, participants had significantly higher tobacco-unrelated (animal) EA rates ($M = 2.14$, $SD = 0.44$) compared with tobacco EA rates ($M = 1.75$, $SD = 0.48$), $t(48) = 6.02$, $p < .001$, $d = .86$. However, they did not have significantly lower tobacco-unrelated (animal) response thresholds ($M = 1.54$, $SD = 0.29$) compared with tobacco response thresholds ($M = 1.52$, $SD = 0.29$), $t(48) = .53$, $p = .70$, $d = .08$. Therefore, this hypothesis was partially supported.

### *Hypothesis 3*

When choosing between tobacco images, EA rates in the negative mood condition ($M = 1.83$, $SD = 0.49$) were not significantly higher compared with in the positive mood condition ($M = 1.75$, $SD = 0.48$), $t(48) = 1.15$, $p = .13$, $d = .16$. Furthermore, response thresholds were not significantly lower in the negative mood condition ($M = 1.57$, $SD = 0.31$) compared with in the positive

**Figure 3**

*Average PANAS-X Scores (Happiness and Sadness Subscales) Pre (Before) and Post (After) Watching the Positive Videos in the Positive Mood Experimental Condition*




*Note.* Error bars represent the standard error of the mean. PANAS-X = Positive and Negative Affect Schedule–Expanded.

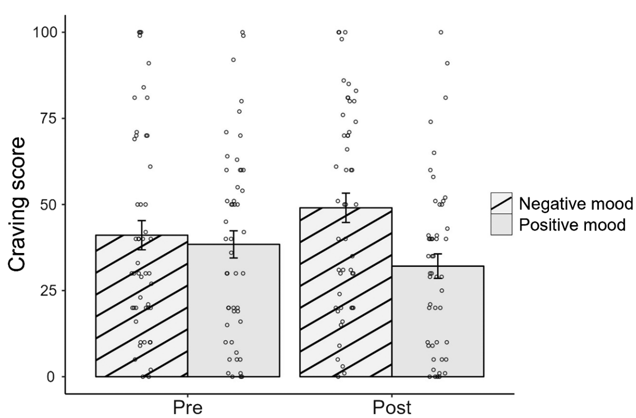
mood condition ($M = 1.52$, $SD = 0.29$), $t(48) = 1.24$, $p = .89$, $d = .18$. Therefore, this hypothesis was not supported.

### *Hypothesis 4*

When choosing between tobacco-unrelated (animal) images, EA rates were not significantly higher in the positive mood condition ($M = 2.14$, $SD = 0.44$) compared with the negative mood condition ($M = 2.13$, $SD = 0.45$), $t(48) = .10$, $p = .46$, $d = .01$. Furthermore, response thresholds were not significantly lower in the positive mood condition ($M = 1.54$, $SD = 0.29$) compared with the negative

**Figure 4**

*Craving to Smoke Scores Split by Experimental Condition Pre (Before) and Post (After) the Experimental Induction of Negative and Positive Mood*




*Note.* Error bars represent the standard error of the mean.

mood condition ($M = 1.57$, $SD = 0.31$), $t(48) = .89$, $p = .19$, $d = .13$. Therefore, this hypothesis was not supported.

## Exploratory Analyses

To supplement the VBDM analyses presented above (Figures 5 and 6), we conducted exploratory repeated-measure ANOVAs on EA rates and response thresholds using within-subject factors of image type (2: tobacco unrelated [animal], tobacco) and experimental condition (2: positive, negative).[6] When looking at EA rates, there was a significant main effect of image type, $F(1, 48) = 43.37$, $p < .001$, $\eta_p^2 = .47$, but no significant main effect of experimental condition, $F(1, 48) = .33$, $p = .57$, $\eta_p^2 = .01$, and no interaction, $F(1, 48) = 1.15$, $p = .29$, $\eta_p^2 = .02$. Post hoc tests for the significant main effect of image type revealed that, collapsed across experimental condition, EA rates were higher for tobacco-unrelated (animal) choices ($M = 2.14$, $SD = 0.35$) compared with tobacco choices ($M = 1.79$, $SD = 0.43$; $p < .001$). When looking at response thresholds, there was no significant main effect of image type, $F(1, 48) = .20$, $p = .66$, $\eta_p^2 = .00$, or experimental condition, $F(1, 48) = 2.47$, $p = .12$, $\eta_p^2 = .05$, and no interaction between the two, $F(1,48) = .07$, $p = .79$, $\eta_p^2 = .00$.

## Discussion

The present study applied computational advances in the measurement of value-based choice to daily smokers' tobacco and tobacco-unrelated decisions following experimental manipulation of mood.

Inspired by conceptual accounts of VBDM (Copeland et al., 2021; Field et al., 2020) and prior findings (Hogarth & Field, 2020; Hogarth et al., 2015), we hypothesized that negative (relative to positive) mood would increase tobacco value, reflected in EA rates and/or response thresholds. Unexpectedly, we did not observe any robust between or within-condition differences in VBDM parameters following the experimental manipulation of mood, and therefore our findings did not support preregistered hypotheses. Although tobacco-unrelated (animal) EA rates were significantly higher compared with tobacco EA rates when participants were primed to experience positive mood, additional analyses demonstrated that tobacco-unrelated EA rates were consistently higher regardless of the experimental manipulation.

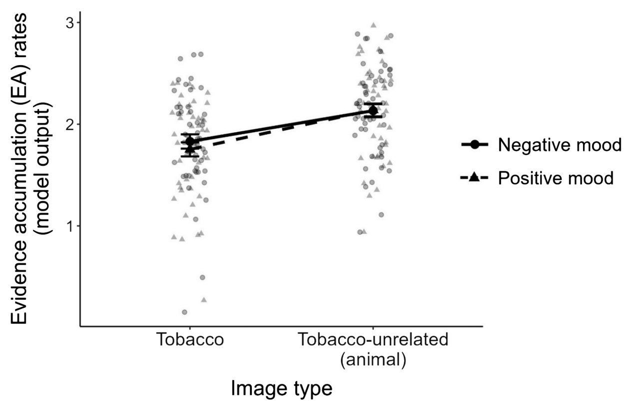
The finding that mood manipulation did not robustly alter VBDM parameters does not align with conclusions derived from existing experimental studies that captured overt choice (Hardy & Hogarth, 2017; Hogarth et al., 2015, 2018). Our findings highlight the need to reassess the robustness of existing assumptions about the relationships between mood and drug value. While we can be reasonably confident that postmanipulation there were statistically significant differences in self-reported mood across groups, the anticipated effects on VBDM parameters were not empirically observed. This null result warrants careful consideration, as it suggests either that negative reinforcement models may be inaccurate or that nuanced effects of mood on drug value remain uncaptured.

However, it is important to acknowledge methodological differences that impede direct comparison between the present study and previous work, including the task used to capture value-based

[6] We note that our study was powered to detect mean differences between dependent groups, not interaction effects.

**Figure 5**

*Evidence Accumulation Rates for Tobacco and Tobacco-Unrelated (Animal) Choices Split by Negative (Solid Black Line; Circle) and Positive (Dashed Black Line; Triangle) Mood Conditions*



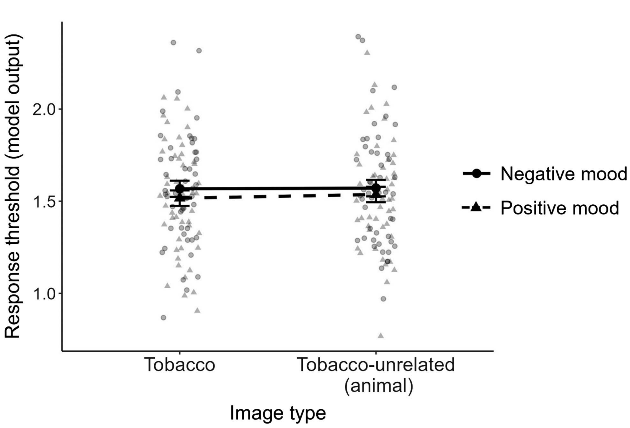

*Note.* Error bars represent the standard error of the mean.

choice. In line with existing VBDM research (e.g., Polanía et al., 2014), we instructed participants to choose between two tobacco or tobacco-unrelated images in separate blocks because this generates the behavioral data required to recover interpretable parameters that represent the internal processes underpinning value-based choice (Field et al., 2020). In addition, Hogarth et al. (2015) used a similar, but briefer manipulation of mood and administered a singular scale to explore the effect of the mood manipulation. Other differences are that the present study used a within-subjects, rather than between-subjects, design, and that it was conducted online rather than in a laboratory setting. Overall, these methodological differences may in part account for why it is difficult to reconcile our findings with previous research.

Another potential explanation for the nonsignificant findings in the present study stems from research uncovering complexity in

**Figure 6**

*Response Thresholds for Tobacco and Tobacco-Unrelated (Animal) Choices Split by Negative (Solid Black Line; Circle) and Positive (Dashed Black Line; Triangle) Mood Conditions*




*Note.* Error bars represent the standard error of the mean.

relationships between mood and drug use. An individual-level meta-analysis (Dora, Piccirillo, et al., 2023) containing daily survey data from >12,000 participants found that people are more likely to drink heavily on days they experience high positive affect, not when they experience high negative affect. These observational findings challenge the general assumption that people consume more alcohol in response to negative mood. Although the aforementioned findings are specific to alcohol, the direct contrast between negative and positive mood in the present study may have obscured any clear distinction in VBDM parameters. Meta-analytic findings (Acuff et al., 2020) have also quantified small and nonsignificant effect sizes for the influence of negative affect on tobacco value as captured by hypothetical purchase tasks; therefore, it may be that our manipulation of tobacco value was relatively weak in comparison to other techniques such as deprivation (Lawn et al., 2015), satiation (Hogarth, 2012; Hogarth & Chase, 2011), and stress induction (Aston et al., 2021). While negative mood induction strongly heightened feelings of sadness, and moderately heightened craving to smoke, it did not lead to alterations in tobacco value.

This study has limitations; unlike previous research (Dahne et al., 2017), we did not measure the time since participants last smoked or the number of cigarettes consumed before participating, meaning baseline differences in nicotine satiety may have added noise to the mood manipulation effect. Future studies of this type should use biochemical verification of smoking status and recent smoking, where possible. Second, participants took part from home, limiting environmental control. However, Prolific is known for generating high-quality data (Peer et al., 2022), likely due to its ID verification requirements, which other crowdsourcing platforms do not have, and participants were instructed to complete the study in a quiet, distraction-free setting. Third, depression is associated with mood-induced tobacco seeking (Hogarth et al., 2017), and our prescreening process (in which we prioritized participant well-being) may have unintentionally excluded participants most susceptible to a mood-driven increase in tobacco craving.

Future VBDM research may recruit larger samples and use different techniques to manipulate tobacco value such as deprivation (Lawn et al., 2015) and satiety (Hogarth, 2012; Hogarth & Chase, 2011), which can be objectively verified by expired carbon monoxide. This would also enable quantification of time since participants last smoked, meaning this can be controlled for. Another interesting avenue would be to recruit a sample with a broader range of depressive symptom scores, alongside the inclusion of self-report measures that may also be important predictors of negative mood-induced tobacco seeking, such as coping motives (Hogarth, 2022). Finally, previous studies have used food/chocolate (Chase et al., 2013; Hogarth et al., 2015) or face (Hardy et al., 2018) images as the tobacco-unrelated category. We used animal stimuli to align with our previous VBDM research on tobacco choice (Copeland, Stafford, & Field, 2023), but future studies could explore tobacco-unrelated stimuli that are perceived as equally rewarding as tobacco cues. Additionally, although our experimental comparison aligns with that of Hogarth et al.'s (2015) study, future research should compare mood-induced effects on VBDM parameters with a neutral manipulation.

To conclude, the experimental manipulation of mood in daily tobacco smokers did not alter EA rates or response thresholds for tobacco and tobacco-unrelated decisions. These findings suggest that in contrast to existing experimental evidence and negative reinforcement models, the induction of negative mood may not consistently lead to elevations in drug value, although future research is this area is warranted.

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