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Copeland, A., Stafford, T. and Field, M. (2023) Recovery from nicotine addiction: a diffusion model decomposition of value-based decision-making in current smokers and ex-smokers. Nicotine & Tobacco Research, 25 (7). pp. 1269-1276. ISSN 1462-2203

https://doi.org/10.1093/ntr/ntad040

Nicotine & Tobacco Research, in press, accepted for publication on 12th March 2023

Recovery from nicotine addiction: A diffusion model decomposition of value-based decision-making in current smokers and ex-smokers

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Implications: The number of people dependent on nicotine has decreased steadily during the past decade; however, the mechanisms that underlie recovery are currently less well understood. The present study applied advances in the measurement of value-based choice. The aim was to explore whether the internal processes that underpin value-based decision-making (VBDM) discriminate current daily tobacco smokers from ex-tobacco smokers who used to smoke daily. Findings revealed that recovery from nicotine addiction was characterised by higher response thresholds when making value-based decisions about tobacco-related cues; this may serve as a novel target for treatment interventions that focus on helping people to stop smoking.

Abstract

Introduction: A considerable number of people successfully give up tobacco smoking. In nicotine-dependent individuals, tobacco choice is determined by greater expected drug value; however, less is known about the underlying mechanisms through which people quit smoking. This study aimed to explore whether computational parameters of value-based decision-making characterise recovery from nicotine addiction. **Methods:** Using a pre-registered, between-subject design, current daily smokers (n = 51) and ex-smokers who used to smoke daily (n = 51) were recruited from the local community. Participants completed a two-alternative forced choice task in which they chose between either two tobacco-related images (in one block) or tobacco-unrelated images (in a different block). During each trial, participants pressed a computer key to select the image they rated most positively during a previous task block. To estimate evidence accumulation (EA) processes and response thresholds during the different blocks, a drift-diffusion model was fitted to the reaction time and error data. **Results:** Ex-smokers had significantly higher response thresholds when making tobacco-related decisions (p = .01, d = .45) compared to current smokers, although there were no significant group differences during tobacco-unrelated decisions. Furthermore, there were no significant group differences in EA rates when making tobacco or tobacco-unrelated decisions. **Conclusions:** Greater cautiousness when making value-based decisions about tobacco-related cues characterised recovery from nicotine addiction.

INTRODUCTION

Tobacco smoking is a leading causal factor of preventable disease and death[1]. However, the number of people who smoke tobacco has declined considerably during the past decade. In England, 12.1% of adults are estimated to be current tobacco smokers—a substantial reduction from the 19.8% of adult smokers in 2011[2]. Behavioural economic accounts posit that the development and maintenance of addiction (substance use disorder) results from excessive valuation ascribed to substances relative to substance-free alternative reinforcers[3]; for recovery to occur, this must be rebalanced such that substances are not disproportionately valued[4]. Behavioural economic accounts are molar in nature; they are primarily concerned with the exploration of *final* causes, that is, the placing of behaviour within broader patterns of behaviour over time[5]. Consequently, less is known about the underlying mechanisms through which valuation processes influence discrete decisions concerning substances and substance-free alternatives. The present study addressed this research gap by applying computational advances in the measurement of value-based choice to the study of recovery from nicotine addiction.

The reinforcing value of—or behavioural economic "demand" for—tobacco is typically measured with the cigarette purchase task (CPT;[6]). In the CPT, respondents estimate the number of cigarettes they would hypothetically consume across prices that gradually increase. Most people exhibit an inverse relationship: as price increases, consumption decreases. However, there are important individual differences in the extent to which price affects responses on the CPT which can be quantified by plotting demand curves[7]. In doing so, separable indices of demand that capture the reinforcing value of tobacco are estimated[8]: intensity (consumption when the price is at zero), O_{max} (maximum expenditure), P_{max} (the price at which demand becomes elastic), breakpoint (first price that suppresses consumption to zero), and elasticity (the rate at which consumption becomes dependent upon price). An

alternative, but also commonly used approach is to use concurrent choice tasks[9] whereby people are instructed to repeatedly choose between pictorial cues that depict tobacco-related (e.g., a cigarette) and tobacco-unrelated (e.g., a chocolate bar) reinforcers. On these tasks, the percentage choice of the tobacco versus tobacco-unrelated alternative reward is used to infer the relative value of tobacco.

A meta-analytic investigation of cross-sectional research that administered the CPT demonstrated that tobacco value is robustly positively associated with individual differences in cigarette consumption and nicotine dependence[10]. More recently, over a 12-month follow-up of people who received smoking cessation treatment, higher tobacco value (indexed by intensity) was significantly associated with a greater risk of relapse[11].

A crucial contributor to the heightened valuation of tobacco may be the undervaluation of tobacco-unrelated alternative reinforcers. Indeed, anhedonia (i.e., diminished interest, pleasure, and enjoyment) is a common consequence of nicotine dependence, and this has been found to predict elevated tobacco value[12]. Further evidence stems from neuroscientific research; nicotine-dependent smokers had blunted value signals in the posterior cingulate cortex when making decisions about tobacco-unrelated rewards (shopping vouchers) compared to people without nicotine dependence[13]. Overall, then, these findings illustrate the importance of distortions in valuation processes within both the development and maintenance of addiction.

Behavioural economic accounts have also been fruitfully applied to the study of recovery from addiction. From this perspective, a person must overcome the distortions in valuation processes that leave them vulnerable to addiction, such that substances are not disproportionately valued relative to substance-free alternatives[3,4]. In line with behavioural economic accounts, a study conducted within a treatment setting[14] found that people who have quit smoking ascribe a lower value to tobacco compared to people currently smoking.

Furthermore, engagement with tobacco-unrelated alternative reinforcers is an important predictor of abstinence from smoking, including in the long-term[15]. Accordingly, many effective treatment interventions for smoking cessation are based upon behavioural economic principles[16]. For example, during contingency management (CM), people receive substance-free incentives (e.g., cash) for a desired behaviour (e.g., verified abstinence from smoking) which may in turn heighten the value of tobacco-unrelated incentives[17]. Although behavioural economic approaches have contributed substantially to the understanding of behavioural patterns over time (i.e., the molar perspective), less is known about the underlying mechanisms through which valuation processes influence discrete instances of decision-making, and how this may change during addiction and recovery from it.

Contemporary neuroscientific accounts of value-based decision-making (VBDM) can be used to model the internal processes that precede decisions made about substances and substance-free alternatives[18]. According to VBDM accounts, the potential response options are firstly identified (e.g., whether to use a substance or engage in an alternative behaviour). Diverse determinants of value for each of the response options (e.g., anticipated positive and negative consequences) are then integrated into a common metric of value which is essential for comparison. Through a value-to-action evidence accumulation (EA) process[19] a response that yields the outcome that is highest in value is enacted, and this can be parameterised using the drift-diffusion model (DDM;[20]). The DDM provides a principled reconciliation of behavioural data from VBDM tasks (e.g., see[21]) to recover parameters that reflect cognitive processes that determine overt behaviour: EA rate (the average rate by which evidence accumulates) and response threshold (response caution indexed by speed-accuracy trade-offs;[22]). Underlying the DDM is the assumption that evidence accumulates in a noisy and probabilistic way in favour of a decision until a response threshold is crossed, at which point

the choice is made[23]. VBDM explores *efficient* causes[24] as the focus is on the identification of cognitive processes that occur immediately prior to a given behaviour.

Conceptual work[18,25] tentatively extended VBDM to recovery from addiction, speculating that the reversal of distortions in valuation processes can be attributed to alterations in the internal processes that occur in the lead up to, and determine, discrete decisions made. More specifically, the following alterations are proposed to underlie recovery, either in combination or isolation: (i) increased response thresholds when making decisions about substances, (ii) suppressed EA rates for substances, and (iii) amplified EA rates for substance-free alternatives. Until recently, empirical exploration of predictions derived from conceptual accounts[18,25] was impeded owing to the absence of a VBDM task appropriate for this purpose. However, recent work[26] identified VBDM task methodology that can be used in addiction-related research, however to date this remains relatively unexplored.

The present study capitalises on recent methodological developments and computational advances in the measurement of value-based choice in an attempt to characterise recovery from nicotine addiction. The design of the study, hypotheses, and analysis strategy were pre-registered prior to the collection of data (http://aspredicted.org/blind.php?x=cc4ir6). Hypotheses were that compared to current smokers, ex-smokers will have: (1) lower EA rates and higher response thresholds when making tobacco-related decisions, and (2) greater EA rates and lower response thresholds when making tobacco-unrelated decisions. Additional hypotheses were made about outputs from a separate mouse-tracking task, however, for conciseness these analyses are placed in the supplementary file.

METHODS

Design

This study used a between-subject design. Dependent variables were EA rates and response thresholds (estimated by fitting the DDM to reaction time (RT) and accuracy data from the VBDM task). Independent variables were group membership (current smoker or ex-smoker), and image type (tobacco images and tobacco-unrelated (animal) images). An *a priori* power analysis revealed that to detect a difference between two independent groups with a medium effect ($d = 0.5$) at 80% power with an alpha of 0.05, a sample size of 51 per group was required.

Participants

We recruited 102 participants (51 current smokers and 51 ex-smokers) who were aged between 18 and 71 years old (mean age = 37.04, SD = 13.92) through social media platforms (e.g., Facebook and Twitter) and advertisements in the local community. Sixty-one participants were female and 41 were male. Inclusion criteria were age ≥18 years old and self-identifying as either a current smoker (defined as daily tobacco smoking) or an ex-smoker (defined as a history of daily tobacco smoking but having quit smoking for at least 6 months). Participants were instructed to only take part in the study if they are not currently using e-cigarettes or vapes. The study was approved by the University of Sheffield's research ethics committee, and all participants gave informed consent. Recruitment took place between February 2019 and August 2019. Participants were reimbursed with a £10 high-street voucher for their time.

Materials

Pictorial stimuli for the VBDM task

The 20 tobacco-related images were selected from the Geneva smoking pictures data set[27], whilst the 20 tobacco-unrelated (animal) images were selected from the international affective picture system (IAPS) data set[28]. We used the standardised valence ratings that accompany both picture sets to include images that were likely to be evaluated as highly

positive, others that were likely to be evaluated as highly negative, and others that are in-between (for more detail, see supplementary file). Stimuli were displayed on a Dell computer screen, with a spatial resolution of 1920 x 1080 pixels and a temporal resolution of 60Hz.

Questionnaire measures

Brief self-control scale (BSCS;[29]): This 13-item scale was used to capture the extent to which people feel that they can resist external influences and control their behaviour, for example, "I am good at resisting temptation". Participants responded on a 1 (not at all like me) to 5 (very much like me) scale. In the current sample, the BSCS had good internal reliability, McDonald's ω = .80.

Fagerström Test for Cigarette Dependence (FTCD;[30]): This scale consisted of six items, such as "Do you smoke even if you are sick in bed most of the day?". Total scores ranged from 0 to 10, with the category labels of low dependence (1-2), low to moderate dependence (3-4), moderate dependence (5-7), and high dependence (8+). Due to a researcher error, the first question ("How soon after waking do you smoke your first cigarette?") did not include the response option "after 60 minutes" meaning that total FTCD scores could potentially have been lower than the values that we obtained. We note that in this sample total FTCD scores indicated low dependence (mean = 3.55, SD = 2.18). The scale had acceptable internal reliability, ω = .78.

Contemplation Ladder[31]: Participants completed the contemplation ladder as an index of motivation (readiness) to quit smoking. The ladder was presented on a scale that ranged from 0 ("no thought about quitting") to 10 ("taking action to quit").

One question from the cigarette purchase task (CPT;[6]): There is not a current validated brief version of the CPT. Nevertheless, the single item "breakpoint" has been advocated to be a viable brief method of measuring tobacco demand[32]. We assessed tobacco demand by presenting participants with a smoking scenario and asking "What is the

maximum price that you would pay for a single cigarette" (scores ranged from £0-£15; see supplementary file for exact scenario wording and price increments).

Demographic and smoking questions: Finally, we obtained demographic information such as participants' age and gender. We asked additional questions regarding cigarette use (see supplementary file for detail), including smoking status, quit attempts (if any), typical cigarette consumption per day, years smoked, age of initiation of smoking, and time since quitting smoking (for ex-smokers).

Procedure

Participants attended a testing session at the University of Sheffield's Psychology Department, which lasted between 60–80 minutes. They provided informed consent and then completed the questionnaire measures listed above. Subsequently, participants completed an image-rating phase and the VBDM task.

Image-rating phase

We asked participants to view two sets of 20 images (a tobacco-unrelated (animal) set and then a tobacco-related set) and make value judgements about them by placing them into categories labelled 'Most positive', 'Somewhat positive', 'Somewhat negative', and 'Most negative'. For both image sets, participants assigned five images to each category by dragging and dropping them using a computer mouse. After rating the images, participants were reminded which images they had assigned to each value category: images from each value category were displayed separately in the centre of the screen for 3 seconds each. Images were presented in the following sequential order to reflect the ratings of individual participants: The five 'Most positive' images, then the five 'Somewhat positive' images, then the five 'Somewhat negative' images, and finally the five 'Most negative' images. Each image was followed by a 500ms fixation cross.

Value-based decision-making (VBDM) task

In line with existing VBDM task procedures[26], on each trial of the task, two images appeared in the centre of the screen (one on the left and one on the right), and participants were instructed to use one of two keys to choose the image that they had previously rated higher by pressing one of two keys ('Z' for left and 'M' for right) as quickly as possible (see Figure 1). Before starting the VBDM task, to familiarise participants, they completed a practice block consisting of 12 trials (50% tobacco-unrelated (animal) trials and 50% tobacco-related trials). Next, they completed the task which consisted of two blocks (a tobacco-unrelated (animal) block and a tobacco-related block; order randomized) of 150 trials each (300 trials in total) with optional short breaks embedded after every 50 trials. Difficulty levels across trials varied, which was determined by the difference in value ratings between the two images which could be 1, 2, or 3 (hard, medium, and easy choices, respectively). When the difference between the images was 1 (e.g., 'Somewhat positive' vs. 'Somewhat negative') these were difficult trials because it was harder to immediately distinguish which image was rated higher. Conversely, when the difference between the two images was 3 ('e.g., 'Most positive' vs. 'Most negative'), these were easier trials because it was likely to be more apparent which image was rated higher. Within each trial block, there were 75 "difficult" trials, 50 "medium" difficulty trials, and 25 "easy" trials". On each trial there was an image that had been rated higher; whether this appeared on the left or the right of the screen was randomised so the 'correct' answer was a left or right keypress with equal frequency. Participants were given a maximum of four seconds to respond on each trial, responses outside of this response window were classed as "miss trials" as commonly used in VBDM tasks[21].

Data preparation and analysis

On the VBDM task, "miss trials" (responses exceeding 4 seconds) were removed (0.47%) in addition to trials that were under 300ms (0.14%) as these are likely to be fast

guesses[33], which resulted in the overall removal of 0.61% of trials. We then fitted the DDM[20] using the EZ method[34] to estimate the DDM parameters. The EZ-DDM takes the mean correct response time, variance of the correct response, and response accuracy as input and produces three key parameters which are: EA rate (v), response threshold (a), and non-decision time (T_{er}). We estimated parameters (EA rates and response thresholds) for each participant, for each difficulty level, and for each image type separately (see supplementary file for analyses on difficulty levels in isolation).

Independent samples *t*-tests (one-tailed) were used to analyse the data for the pre-registered hypotheses, supplemented by exploratory mixed-design ANOVAs to establish the robustness of any group differences. Non-parametric tests were used for data that were not approximately normally distributed. Statistical analyses were conducted in RStudio version 4.0.2[35]. All data and analysis scripts are available: https://researchbox.org/814&PEER_REVIEW_passcode=JTWLTX.

RESULTS

See Table 1 for descriptive statistics of questionnaire measures.

Hypothesis 1: Compared to current smokers, ex-smokers will have lower EA rates and higher response thresholds when making tobacco-related decisions.

When making tobacco decisions, ex-smokers (M = 1.56, SD = .42) did not have significantly lower EA rates compared to current smokers (M = 1.54, SD = .42); $t(100) = -.24$, $p = .60$, $d = .05$. However, ex-smokers did have significantly higher response thresholds (M = 2.06, SD = .34) compared to current smokers (M = 1.91, SD = .30); $t(100) = -2.29$, $p = .01$, $d = .45$.

Hypothesis 2: Compared to current smokers, ex-smokers will have higher EA rates and lower response thresholds when making tobacco-unrelated (animal) decisions.

When making tobacco-unrelated (animal) decisions, ex-smokers (M = 1.88, SD = .38) did not have significantly higher EA rates compared to current smokers (M = 1.84, SD = .38); $t(100) = -.49$, $p = .31$, $d = .10$. Furthermore, ex-smokers (M = 2.00, SD = .31) did not have significantly lower response thresholds compared to current smokers (M = 1.96, SD = .29); $t(100) = -.72$, $p = .76$, $d = .14$.

To aid interpretation of the VBDM results presented above (Figures 2 and 3), we conducted exploratory mixed ANOVAs on EA rates and response thresholds with a within-subject factor of image type (2: tobacco; tobacco-unrelated) and a between-subject factor of smoker status (2: current smoker; ex-smoker). There was a significant main effect of image type on EA rates ($F(1, 100) = 68.20$, $p < .001$, $\eta_p^2 = .41$), but there was no significant main effect of smoking status ($F(1, 100) = .17$, $p = .68$, $\eta_p^2 = .00$), and no interaction ($F(1, 100) = .05$, $p = .83$, $\eta_p^2 = .00$). Post-hoc tests for the significant main effect of image type revealed that, collapsed across smoker status, EA rates were higher for tobacco-unrelated (animal) choices (M = 1.86, SD = .37) compared to tobacco choices (M = 1.55, SD = .42; $p < .001$). This analysis demonstrates that there was a main effect of image type that was not robustly moderated by smoker status. For response thresholds, there was no significant main effect of image type ($F(1, 100) = .00$, $p = .95$, $\eta_p^2 = .00$) or smoker status ($F(1, 100) = 2.95$, $p = .09$, $\eta_p^2 = .03$), although the interaction approached statistical significance ($F(1, 100) = 3.37$, $p = .07$, $\eta_p^2 = .03$). This analysis demonstrates that although ex-smokers have lowered tobacco-related response thresholds compared to current smokers, this is perhaps not robust. However, it is important to acknowledge that the present study was powered to detect differences in means between two independent groups rather than an interaction effect, in line with our pre-registration.

DISCUSSION

This study applied computational advances in the measurement of value-based choice to the study of recovery from nicotine addiction. The primary novel finding is that ex-smokers have significantly higher response thresholds when making tobacco-related decisions compared to current smokers. In other words, ex-smokers require significantly more evidence to be accumulated before they reach a threshold for committing to a decision that concerns value judgments about smoking-related images. Higher substance-related response thresholds in ex-smokers suggest that recovery is characterised by greater caution because the DDM adjusts response thresholds based on the participants' speed-accuracy trade-off—higher response thresholds reflect slower and more accurate decisions[22].

Self-control is an important predictor of recovery from addiction[36] which may enable people to manipulate their environment in a way that promotes behaviour that aligns with a person's *goal-oriented*, as opposed to *temptation-oriented*, valuation system[37]. Indeed, qualitative research has shown that people in stable recovery from addiction cite several situational strategies that they use which minimise their temptation to use substances, many of which involve environmental adjustments[38]. Therefore, it may be that as a person quits smoking, they implement situational strategies (e.g., avoiding walking behind people who are smoking, or avoiding their local shop that sells cigarettes) that potentially minimise exposure to tobacco-related cues and tobacco craving[39,40]. Through the recurrent implementation of situational strategies, greater tobacco-related response thresholds may correspond to a person being able to step back and carefully consider their options when faced with the decision to smoke versus to do something else.

Another potential explanation for higher response thresholds in ex-smokers may stem from engagement with treatment. For example, mindfulness training has been found to increase self-efficacy—that is, a person's belief in their ability to achieve a desired outcome[41] and this is an important predictor of tobacco smoking cessation[42]. It may be that when a

thought arises (e.g., about substance use), greater tobacco-related response thresholds correspond to a person being present in the moment and allowing the thought to pass, in doing so providing an opportunity to develop and exploit self-efficacy.

Contrary to hypotheses, response-thresholds during tobacco-unrelated decisions did not discriminate current and ex-smokers, nor did EA rates during either tobacco-related or tobacco-unrelated decision-making. The present study therefore did not identify the distinction in EA rates anticipated based upon overt preferences captured in previous studies[9,13,14] and conceptual accounts[18,25]. However, there are important methodological differences that impede the extent to which findings from the present study can be directly reconciled with existing research. In previous studies, for example, participants chose between a tobacco (e.g., cigarette) and tobacco-unrelated (e.g., chocolate) image, whereas this was not the case for the present study. The rationale for this is that to recover VBDM decision parameters using the EZ-DDM[34] with interpretations that can be attributed to decisions made about a specific reinforcer (e.g., tobacco), this requires behavioural data from trials in which both outcomes depict the same reinforcer. Consequently, it would have been impossible to test our hypotheses if choice trials had depicted tobacco and tobacco-unrelated images in competition with each other. Secondly, our tobacco-unrelated category of images was animal-related, and therefore not something that is *appetitive* (e.g., food), which makes it difficult to tease apart processes that are related to appetitive and non-appetitive stimuli[43]. Animal-related images were used rather than food-related images in part because nicotine is a metabolic stimulant that suppresses appetite, and research has shown appetite changes when people stop smoking[44] which may inadvertently influence VBDM parameters for food-related decisions. Furthermore, although high-quality food image sets exist (e.g.,[45]), these were not available at the time the present research was conducted.

Nevertheless, the application of the DDM is accompanied by considerable statistical power gains when comparing two groups[22]. However, there are some important study limitations. Firstly, given the cross-sectional nature of the data, it is not possible to establish causal relationships between VBDM parameters, addiction, and recovery from it. Secondly, smoking status was not biochemically verified, and no information was collected about the recency of nicotine use in current smokers or consumption of other substances (e.g., alcohol or cannabis) which may have influenced reaction time, error rates and VBDM parameters. Furthermore, although the recruitment criterion of smoking at least daily has been used in previous research (e.g.,[46]), this may have inadvertently resulted in a sample that is relatively low in dependence compared to more a strict criterion (e.g., >10 cigarettes per day;[13]). As a result, the strength of the contrast between current smokers and ex-smokers may have been weak. Finally, the breakpoint measure in the present study entails price points directly translated from the brief assessment of alcohol demand[47], despite differences in the typical cost of a single alcoholic beverage versus a single cigarette (see supplementary file). Furthermore, recent research has contested the validity of the single-item breakpoint measure[48] thereby contrasting conclusions from prior research that informed the present study protocol[32]. Self-report tobacco demand should therefore be interpreted cautiously in the present study.

To address these limitations, future studies could set a minimum threshold for smoking (e.g., >10 cigarettes per day) in order to recruit a more heavily dependent sample to contrast with ex-smokers who are abstinent. Furthermore, longitudinal designs (e.g., following a person from early recovery and forward in time) will provide insight into casual relationships between variables captured in the present study. Capturing both molecular "in-the-moment" decisions and molar temporally extended patterns of behaviour would enable the exploration of *efficient* and *final* causes[24], respectively, an approach advocated to enrich

theoretical understanding of addictive behaviours over time and in dynamic environmental contexts[49]. Future studies could also incorporate more robust and valid measures of self-report tobacco demand. Indeed, numerous works cite intensity to be the most important predictor of nicotine dependence[8] and relapse after smoking cessation treatment[11], therefore, this could be captured in future studies. Finally, mixed-method approaches that integrate qualitative techniques alongside computational modelling may be useful to progress understanding of what decision parameters reflect from an individual perspective (e.g., substance-related response thresholds). Interestingly, a recent study raised a similar question by speculating on whether response thresholds in general (i.e., response caution) correlate with self-report impulsivity, finding no evidence that the two are correlated[50]. Continued research in this area will contribute towards characterising decision-making processes that underlie recovery from addiction and help identify novel targets for treatment.

To conclude, these findings contribute a unique insight into recovery from nicotine addiction: recovery was accompanied by increased cautiousness when making tobacco-related decisions. Alterations in substance-related response thresholds may therefore be a core mechanism that underlies recovery, and a novel target for treatment interventions.

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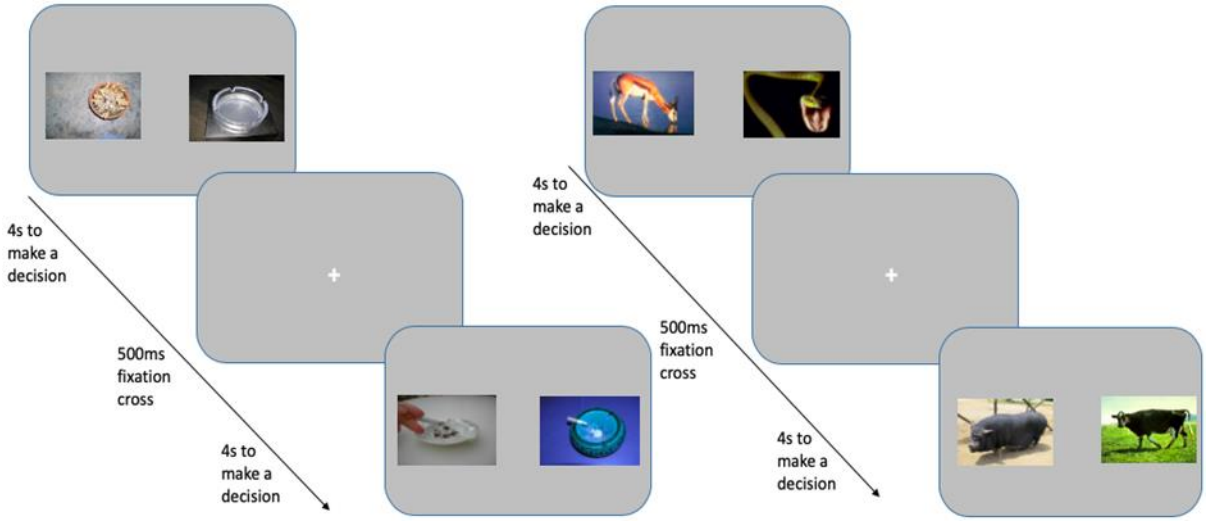
Funding: This research was funded by a PhD studentship awarded to AC from the Department of Psychology at the University of Sheffield.

Declaration of Interests: The authors have no interests to declare.

Data Availability: All data and R analysis scripts are available and can be found on researchbox: https://researchbox.org/814&PEER_REVIEW_passcode=JTWLTX

Figure 1

Schematic depiction of typical tobacco block (left) and typical animal block (right) trials



Note. The question asked was "Which did you rate higher? Press 'Z' for the left image or 'M' for the right image" [26]. Participants had 4 seconds to make a decision per trial, and each trial was followed by a 500ms fixation cross located in the centre of the screen. Images are taken from the Geneva smoking pictures data set [27] and the international affective picture system (IAPS) data set [28].

Table 1

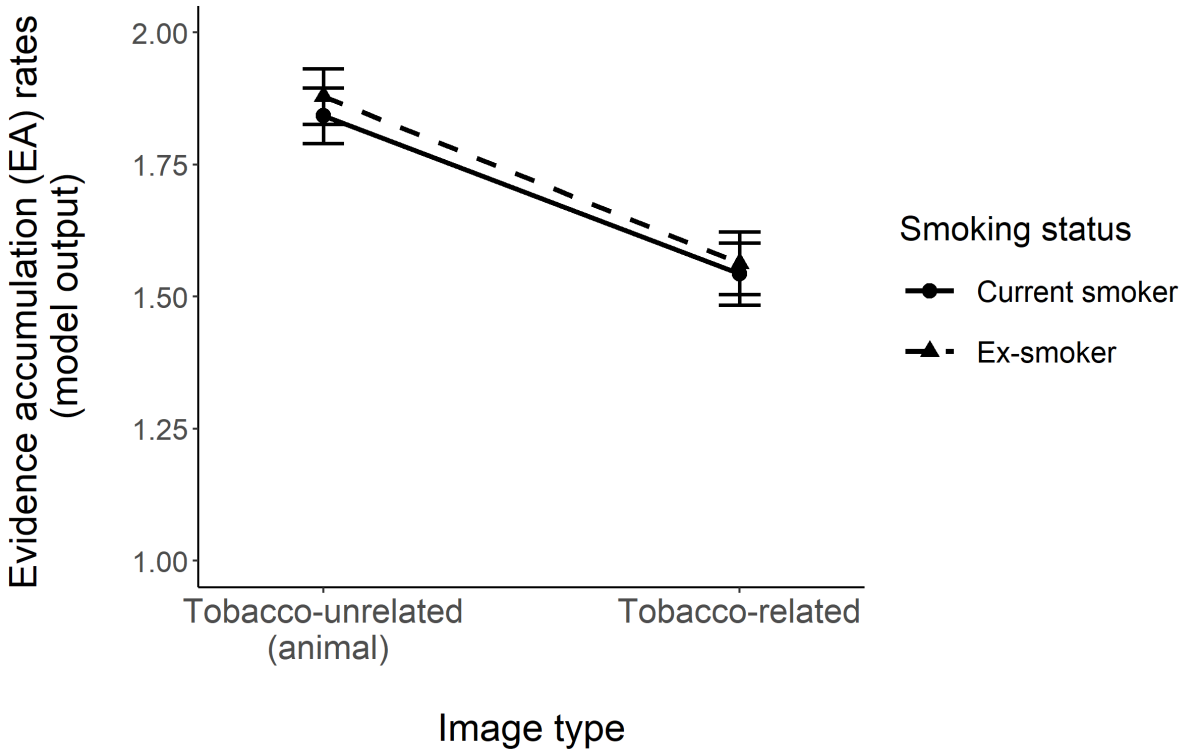
Descriptive statistics split by smoking status (values represent the mean and standard deviation). On the FTCD, almost half (47.06%) of current smokers scored as moderately or highly dependent (FTCD ⩾ 4).

Variable	Current smokers	Ex-smokers	*p*-value and effect size
Age (years)	31.37 (11.81)	42.71 (13.65)	$p < .001$, $d = .89$
BSCS	36.16 (6.65)	39.57 (8.82)	$p = .03$, $d = .44$
Quit attempts	1.98 (1.57)	3.23 (2.64)	$p = .01$, $r_{rb} = .28$
Cigarettes per day	12.01 (8.67)	16.99 (9.83)	$p < .01$, $r_{rb} = .33$
Duration of time smoked (years)	14.92 (12.42)	16.79 (11.43)	$p = .43$, $d = .16$
Age of smoking initiation	16.31 (3.29)	16.44 (3.14)	$p = .84$, $d = .04$
Duration since quitting	-	8.37 (8.93)	-
FTCD	3.55 (2.18)	-	-
Contemplation ladder	5.18 (2.84)	-	-
Breakpoint (demand)	2.12 (2.13)	-	-

Note. Effect sizes are Cohen's *d* (for data that are approximately normally distributed) or rank-biserial correlations (r_{rb}; for data that are not approximately normally distributed). BSCS = brief self-control scale (possible range of values: 13 to 65). FTCD = Fagerström test for cigarette dependence (possible range of values: 0 to 10). The contemplation ladder provides an index of motivation to quit smoking (possible range of values: 0 to 10). Breakpoint = first price that suppresses consumption to zero (possible range of values: £0 to £15). Estimated cigarettes per day ranged from 1 to 50 in smokers and 3 to 45 in ex-smokers.

Figure 2

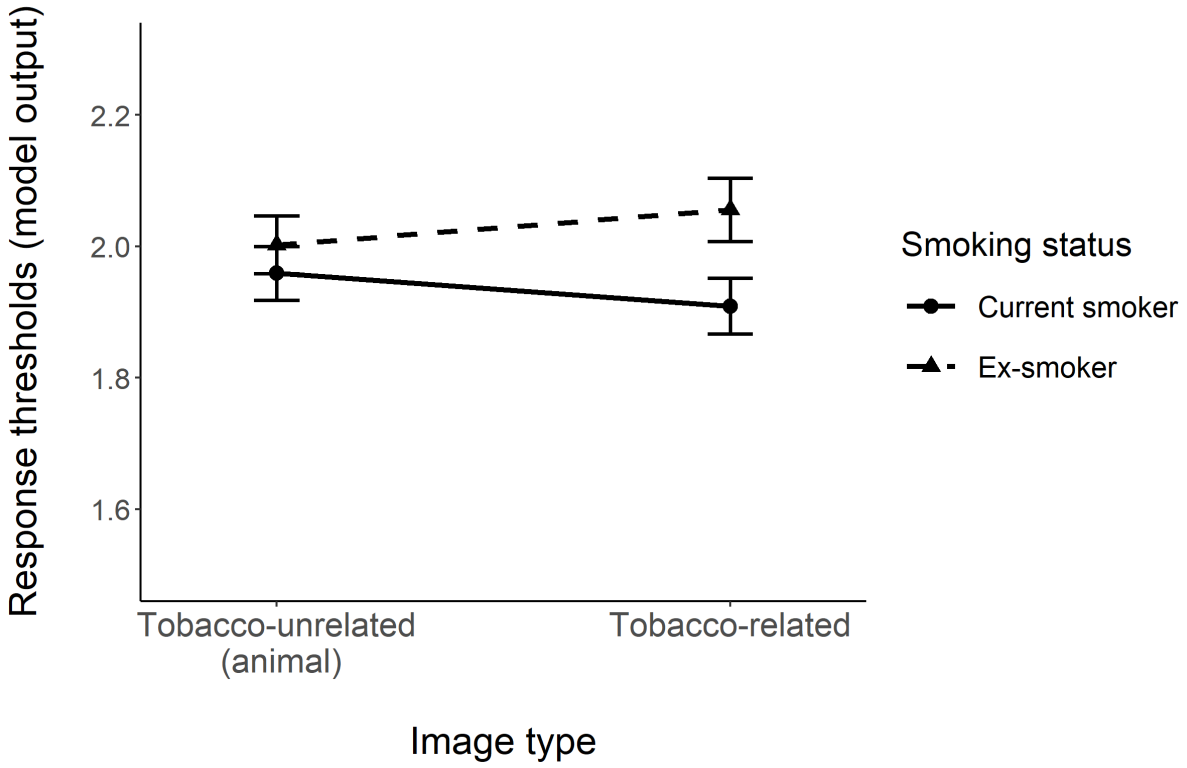
Mean overall EA rates for tobacco-unrelated (animal) and tobacco-related choices split by current smokers (solid black line; circle) and ex-smokers (dashed black line; triangle)



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

Figure 3

Mean overall response thresholds for tobacco-unrelated (animal) and tobacco-related choices split by current smokers (solid black line; circle) and ex-smokers (dashed black line; triangle)



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

Supplementary materials for:

"Recovery from nicotine addiction: A diffusion model decomposition of value-based decision-making in current smokers and ex-smokers"

Contents

1. MouseTracker: pre-registered hypotheses and analyses

It was hypothesised that compared to current smokers, ex-smokers will have: (i) greater conflict when tobacco images are the 'correct' answer, and (ii) lower conflict when tobacco-unrelated (animals) are the 'correct' answer.

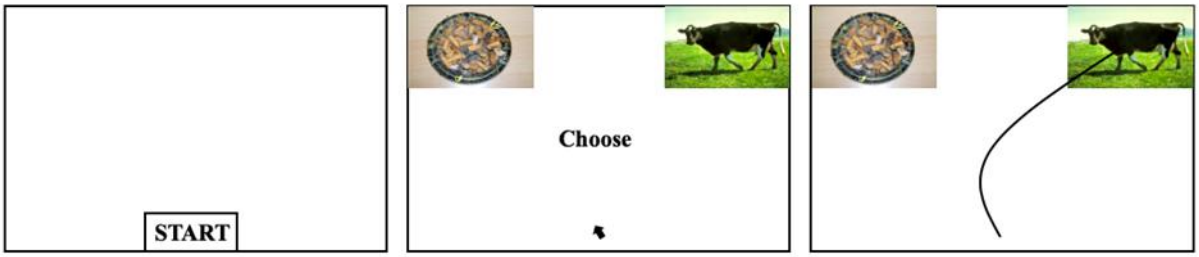
In the MouseTracker task, two images (one tobacco-related and one tobacco-unrelated (animal)) were displayed in the top left-hand and the top right-hand corner of the computer screen and participants were instructed to drag a mouse cursor to click on the image they rated higher[1]. Each trial began with a "START" button at the bottom centre of the screen; once participants clicked on this the two images appeared, along with a caption that said "Choose" (see Figure S1). The decision in this task was between smoking and animal stimuli. Participants firstly completed a practice block, consisting of 12 trials (50% tobacco-unrelated (animal) trials and 50% tobacco-related). Next, they completed the task which consisted of 300 trials (with embedded breaks after every 50 trials). In 150 of the trials the smoking image was the 'correct' answer, whilst in the other 150 trials the animal image was the 'correct' answer; whether this was on the left or the right side was random so that the 'correct' answer should have been a left and right mouse click with equal frequency. In line with previous research (Stillman et al., 2017), participants were asked to select the image as quickly as possible, and if they took longer than 1000ms to initiate mouse movement, a message asking them to respond quicker appeared (e.g., "Please start moving earlier on even if you are not fully certain of a response yet!"). Encouraging participants to initiate mouse movements early within the trial is important to capture varying components of cognitive, including initial response tendency and momentary changes of mind within mouse trajectories (Kieslich et al.,

[1] The "correct" image was determined based on preferences that participants had previously expressed during the testing session.

2020). For example, if a person were to make a decision before mouse movement is initiated, their mouse trajectory would appear straight indicating minimal conflict. However, this would not necessarily mean that the person did not experience conflict, but rather, because they made their choice before moving their mouse, the conflict is not reflected in the mouse trajectory (Kieslich et al., 2020).

Figure S1

Schematic depiction of a typical MouseTracker trial



Note. On each trial, participants clicked on the "START" button, and then were asked to choose between two images by dragging the mouse to click on the image that they rated as more positive. Participants were asked to respond as quickly as possible. A warning message appeared saying "Please start moving earlier on even if you are not fully certain of a response yet!" if participants took over 1000ms to initiate mouse movement. Schematics are adapted with permission from those in (Stillman et al., 2017).

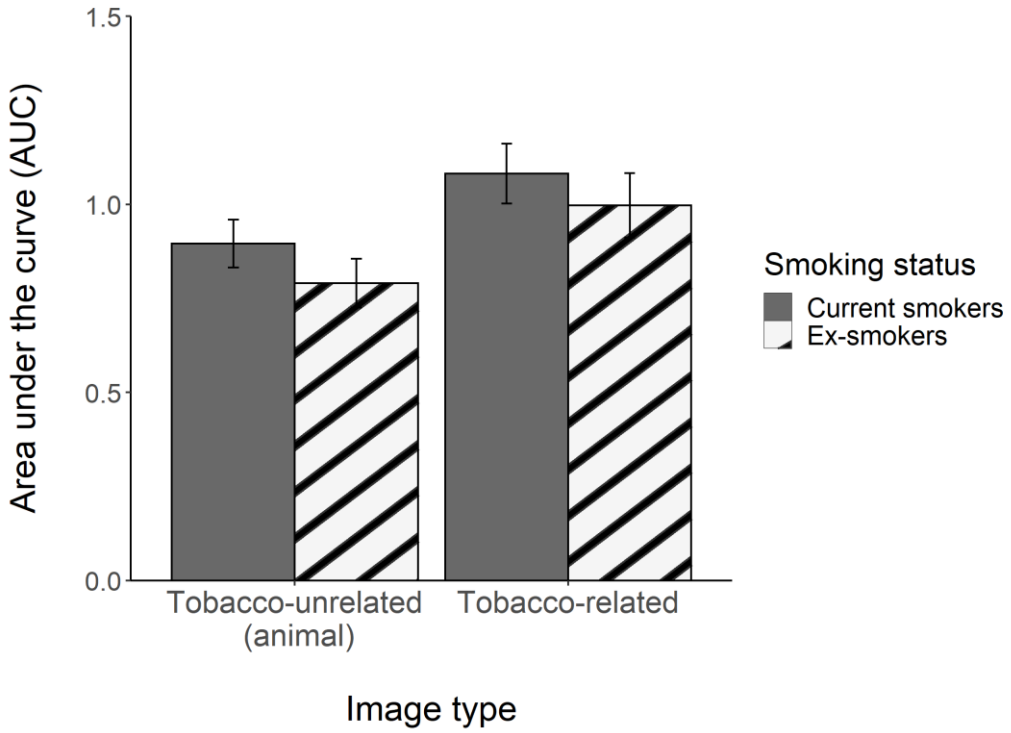
Standard recommended practices were followed in relation to preparation of MouseTracker data (see Freeman & Ambady, 2010). Mouse trajectories were time-normalized into 101-time bins and responses were rescaled such that the trajectory terminated at the top-right response location. Trials whereby participants made the incorrect choice (i.e., they did not choose the image that they had rated higher previously) were removed. Following established procedures (Stillman et al., 2017), outliers that were ±3 standard deviations from individual participant

means on reaction time, AUC, and time until initial mouse movement were then removed, which resulted in the removal of 11.33% of trials. The mean time until initial mouse movement was 228.4ms (SD = 188.42) which demonstrates that participants were moving their mouse from the onset of the choices rather than waiting until relatively late in their processing stream to begin moving the mouse.

When the tobacco image was the correct answer, ex-smokers (M = 1.00, SD = .61) did not have significantly greater conflict compared to current smokers (M = 1.08, SD = .57); $t(100) = .72$, $p = .76$, $d = .14$. Similarly, when the tobacco-unrelated (animal) image was the correct answer, ex-smokers (M = .79, SD = .46) did not have significantly lower conflict compared to current smokers (M = .90, SD = .45); $t(100) = 1.16$, $p = .13$, $d = .23$.

Figure S2

Mean level of conflict represented by area under the curve (AUC scores) when correctly choosing the tobacco-unrelated and tobacco image split by current smoker (grey) and ex-smoker (striped)



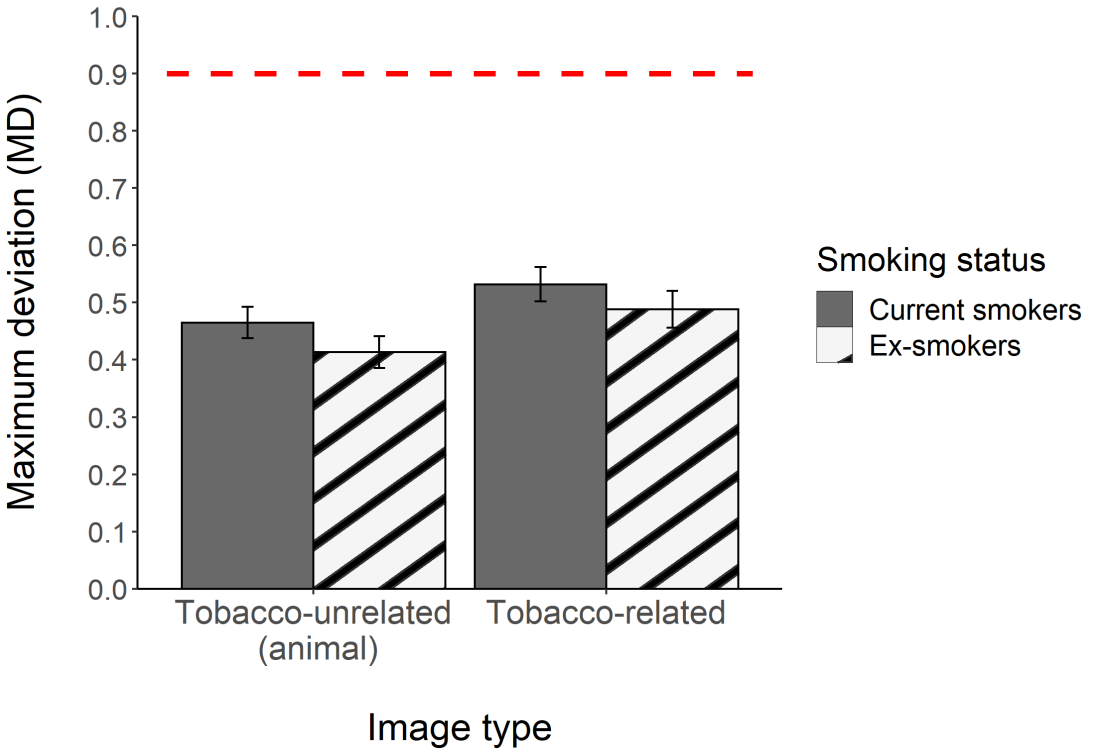
Note. Error bars represent the standard error of the mean.

In our pre-registration, we stated that we were interested in exploring the nature of the mouse trajectories from the MouseTracker task to explore whether they are in line with a dual-systems model or a dynamical systems model. In previous research, it has been demonstrated that trajectories for which the MD exceeds 0.9 demonstrate the abrupt mid-flight corrections that dual-systems accounts predict (Freeman, 2014). Findings from our sample are in line with dynamical systems approach, as the average MD score for both animal and smoking choices were below the .09 cut-off (see Figure S3). Further supporting this, we conducted additional analyses to quantify the nature of mouse trajectories by exploring the modality of the distributions of conflict across MouseTracker trials (Freeman & Dale, 2013). Dual-process accounts posit that during decision-making, 'automatic' processes are either confirmed (resulting in relatively small levels of conflict) or are overridden by 'controlled' processes (resulting in larger amounts of conflict), which results in a bimodal distribution of conflict. Conversely, dynamical VBDM approaches posit that information from different

response options compete against each-other dynamically over time until a final response emerges, which would result in a continuum of conflict that range from small to large and so a unimodal distribution of conflict. Therefore, if distributions are bimodal, that is evidence of abrupt trajectories with mid-flight corrections (in line with dual-process accounts) whereas if they are unimodal, that is evidence of smooth trajectories (in line with a dynamical VBDM account). A statistical method, referred to as Hartigan's dip statistic, is a robust measure of bimodality (Freeman & Dale, 2013; Hartigan & Hartigan, 1985). If the test is significant, this is evidence against the null hypothesis of a unimodal distribution. Using Hartigan's dip statistic we found no evidence for bimodality in either tobacco-unrelated (animal) trials, p = .96, or tobacco trials, p = .20. Therefore, trials were unimodal in nature, and this further supports the notion that making value-based decisions appear to unfold in a smooth and dynamical, rather than abrupt, manner.

Figure S3

Mean maximum deviation (MD) for tobacco and tobacco-unrelated trials split by current smoker (grey) and ex-smoker (striped)



Note. The red dashed line represents the 0.9 cut-off for abrupt trajectories with mid-flight corrections that dual processes theories predict. Error bars represent the standard error of the mean.

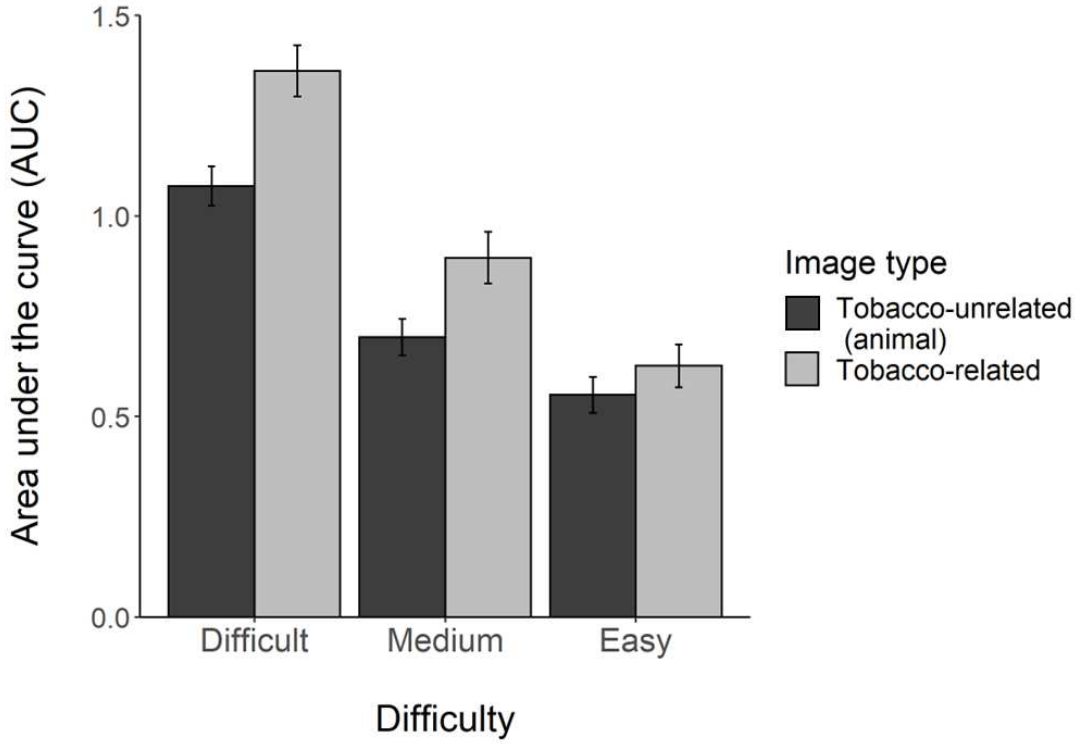
Exploration of the difficulty effect

Magnitude of conflict on the MouseTracker task increased with the level of difficulty in the trials (Figure S4). There was also significant main effect of difficulty on response conflict on trials where the tobacco-unrelated (animal) image was the correct answer, $F(1.78, 180.16) = 220.30$, $p < .001$, $\eta p^2 = .69$. Post-hoc tests revealed that tobacco-unrelated (animal) response conflict in the easier trials (M = .55, SD = .45) was reduced compared to medium trials (M = .70, SD = .46; $p < .001$) and difficult trials (M = 1.07, SD = .50; $p < .001$). Furthermore, tobacco-unrelated (animal) response conflict on medium trials was reduced compared to conflict on difficult trials ($p < .001$). An identical pattern was seen for response conflict on trials where the tobacco image was the correct answer, $F(2, 202) = 233.12$, $p < .001$, $\eta p^2 =$

.70; easier trials (M = .63, SD = .54) vs. medium trials (M = .90, SD = .65; $p < .001$); easier trials vs. difficult trials (M = 1.36, SD = .65; $p < .001$). medium trials vs. difficult trials ($p < .001$).

Figure S4

Mean level of conflict (AUC scores; including all participants) for tobacco-unrelated (animal) and tobacco choices split by trial difficulty level



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

Brief discussion

Findings did not reveal any significant differences in the magnitude of conflict between current smokers and ex-smokers when tobacco was the correct answer and when the tobacco-unrelated (animal) was the correct answer, refuting hypotheses. Self-control is inversely associated with conflict during decision-making (Gillebaart et al., 2016; Stillman et al., 2017), and positively associated with recovery from addiction (Stein & Witkiewitz, 2019).

We therefore anticipated that a difference would exist between current smokers and ex-smokers, but this was not the case for our sample. However, in line with previous findings (Stillman et al., 2017), mouse trajectories during choices whereby participants correctly choose the image that they rated higher in value were unimodal in nature. These findings support the notion that value-based decisions unfold in a smooth and dynamical manner in line with a VBDM approach, rather than a dual-process approach. This demonstrates that when faced with a conflicting decision, resolution of conflict is characterised by the dynamical integration of value inputs, in line with neuroscientific work (Cosme et al., 2019) and recent theoretical advances in the field of self-regulation (Berkman et al., 2017) as opposed to 'controlled' processes inhibiting 'automatic' processes (Veling et al., 2008).

2. Exact wording of the instructions to assess breakpoint (tobacco demand) and price point increments

"Think about a scenario that is typical of your usual smoking behaviour, such as smoking on a night out with friends, or smoking at home. The following question asks you how much you would pay for a single cigarette at various prices. The cigarette would be of the brand that you typically smoke."

"What is the maximum that you would pay for a single cigarette?" (breakpoint)

Response options: £0, £1.50, £3, £4.50, £6, £7.50, £9, £10.50, £12, £13.50, £15 or more

3. Further detail on additional questions regarding cigarette use

This section provides detail about the wording of questions to measure cigarette use, including smoking status, quit attempts (if any), typical cigarette consumption per day, years smoked, age of initiation of smoking, and time since quitting smoking (for ex-smokers).

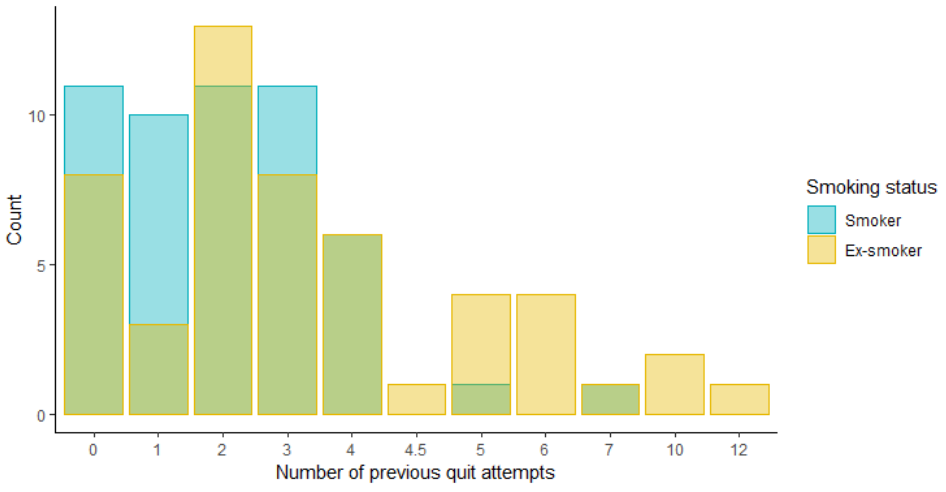
Number of previous quit attempts: "How many (if any) serious previous quit attempts have you had?" for current smokers, and "How many serious quit attempts did you have before successfully giving up smoking?" for ex-smokers.

Cigarettes smoked per day: "On average, how many cigarettes do you smoke per day?" for current smokers, and "On average, how many cigarettes did you USED to smoke per day before quitting smoking?" for ex-smokers.

Age of smoking initiation: "How old were you (in years) when you started smoking?"

Figure S5

A visual depiction of the count of quit attempts split by smoking status



4. Exact images used to depict tobacco and tobacco-unrelated (animal) cues

The 20 smoking images (Table S1) are taken from the Geneva Smoking Images (Khazaal et al., 2012) set. These tobacco-related images comprise the product itself (e.g., a burning cigarette), smoking-related behaviours (e.g., a person smoking), and tobacco-related cues (e.g., an ashtray, a lighter). Images which depicted tobacco brands were not included to reflect the plain packaging legislation in the UK. Below are the filenames of the images and their valence ratings. All images can be found in the supplementary material of the original paper here: https://www.karger.com/Article/Fulltext/335083

Table S1

The 20 smoking images (Table S1) are taken from the Geneva Smoking Images

Image (file) name	**Valence rating**	**Category**	**Number of participants who placed the image in the anticipated category**
GSP1.jpg	3.50	*Highest in value*	10 (9.80%)
GSP29.jpg	3.96	*Highest in value*	88 (86.28%)
GSP25.jpg	4.22	*Highest in value*	35 (34.31%)
GSP30.jpg	4.30	*Highest in value*	86 (84.31%)
GSP20.jpg	4.30	*Highest in value*	32 (31.37%)
GSP32.jpg	5.13	*Second highest in value*	24 (23.53%)
GSP6.jpg	5.15	*Second highest in value*	16 (15.69%)
GSP50.jpg	5.15	*Second highest in value*	43 (42.16%)

GSP31.jpg	5.26	*Second highest in value*	52 (50.98%)
GSP26.jpg	5.33	*Second highest in value*	41 (40.20%)
GSP8.jpg	6.07	*Second lowest in value*	27 (26.47%)
GSP17.jpg	6.09	*Second lowest in value*	48 (47.06%)
GSP22.jpg	6.13	*Second lowest in value*	57 (55.88%)
GSP15.jpg	6.24	*Second lowest in value*	28 (27.50%)
GSP10.jpg	6.62	*Second lowest in value*	38 (37.26%)
GSP24.jpg	7.26	*Lowest in value*	25 (24.51%)
GSP11.jpg	7.59	*Lowest in value*	73 (71.57%)
GSP56.jpg	7.83	*Lowest in value*	42 (41.18%)
GSP9.jpg	7.83	*Lowest in value*	75 (73.53%)
GSP51.jpg	7.96	*Lowest in value*	78 (76.47%)

Note. Lower scores reflect increased valence.

The 20 animal images (Table S2) are taken from the International Affective Picture System (IAPS; Lang et al., 2008). These images comprise a number of different animals (e.g., birds, dogs, insects, snakes). Below are the filenames of these images and their valence ratings. This link has information on how to request access to the images:

https://csea.phhp.ufl.edu/media/iapsmessage.html

Table S2

The 20 animal images are taken from the International Affective Picture System

Image (file) name	**Valence rating**	**Category**	**Number of participants who placed the image in**

			the anticipated category
1710.jpg	8.34	*Highest in value*	67 (65.69%)
1750.jpg	8.28	*Highest in value*	46 (45.10%)
1460.jpg	8.21	*Highest in value*	57 (55.88%)
1440.jpg	8.19	*Highest in value*	66 (64.71%)
1620.jpg	7.37	*Highest in value*	29 (28.43%)
1740.jpg	6.91	*Second highest in value*	36 (35.29%)
1603.jpg	6.90	*Second highest in value*	40 (39.22%)
1812.jpg	6.83	*Second highest in value*	32 (31.37%)
1650.jpg	6.65	*Second highest in value*	34 (33.33%)
1419.jpg	6.54	*Second highest in value*	66 (64.71%)
1670.jpg	5.82	*Second lowest in value*	28 (27.50%)
1903.jpg	5.50	*Second lowest in value*	69 (67.65%)
1350.jpg	5.25	*Second lowest in value*	54 (52.94%)
1726.jpg	4.79	*Second lowest in value*	52 (50.98%)
1390.jpg	4.50	*Second lowest in value*	34 (33.33%)
1930.jpg	3.79	*Lowest in value*	80 (78.43%)
1300.jpg	3.55	*Lowest in value*	80 (78.43%)
1050.jpg	3.46	*Lowest in value*	80 (78.43%)
1202.jpg	3.35	*Lowest in value*	67 (65.69%)
1274.jpg	3.17	*Lowest in value*	81 (79.41%)

Note. Higher scores reflect increased valence.

Importantly, the VBDM task allows for subjective valuation of images to differ across participants because the task is personalised for each participant to reflect their own ratings. Therefore, the process of ensuring that there was a wide spread of perceived valence by using the standardised valence ratings data that accompanies both picture sets was merely to ensure that there was a wide spread of perceived valence, rather than as a strict guide as to what images *should* be placed in each value category.

5. Within-subject differences

Within-subject contrasts are derived from two-tailed tests as the study pre-registration did not encompass directional hypotheses. In current smokers, EA rates for tobacco-unrelated (animal) decisions were significantly higher than EA rates for tobacco decisions ($t(50) = 5.91$, $p < .001$, $d = .83$). There were no significant differences in tobacco-unrelated (animal) and tobacco-related response thresholds ($t(50) = 1.36$, $p = .18$, $d = .19$).

An identical pattern was seen in ex-smokers, in whom EA rates for tobacco-unrelated (animal) decisions were significantly higher than for tobacco decisions ($t(50) = 5.78$, $p < .001$, $d = .81$). However, there were no significant differences in response thresholds for tobacco compared to for tobacco-unrelated (animal) decisions choices ($t(50) = 1.25$, $p = .22$, $d = .18$).

6. DDM analyses conducted on each individual difficulty level in isolation (Table S1)

Table S3

Core analyses repeated on each difficulty level in isolation

Contrast	Easy trials	Medium trials	Difficult trials
Drift / EA rate			
Tobacco: smokers vs. ex-smokers	p = .62, d = .06	p = .47, d = .02	p = .69, d = .10
Animal: smokers vs. ex-smokers	p = .26, d = .13	p = .62, d = .06	p = .17, d = .19
Smokers: animal vs. tobacco	**p = .001, d = .47**	**p < .001, d = .65**	**p < .001, d = .80**
Ex-smokers: animal vs. tobacco	**p = .002, d = .46**	**p < .001, d = .68**	**p <. 001, d = .86**
Response threshold / boundary			
Tobacco: smokers vs. ex-smokers	p = .12, d = .23	**p = .004, d = .53**	**p = .05, r_{rb} = .19**
Animal: smokers vs. ex-smokers	p = .39, d = .05	p = .53, d = .02	p = .98, d = .43
Smokers: animal vs. tobacco	p = .61, d = .07	p = .17, d = .20	**p = .02, d = .33**
Ex-smokers: animal vs. tobacco	**p = .04, d = .29**	**p = .04, d = .29**	p = .09, d = .24

Note. Effect sizes are Cohen's d (for data that are approximately normally distributed) or rank-biserial correlations (r_{rb}; for data that are not approximately normally distributed). Significance is indicated by bold text. Within-subject contrasts are derived from two-tailed tests as the study pre-registration did encompass directional hypotheses.

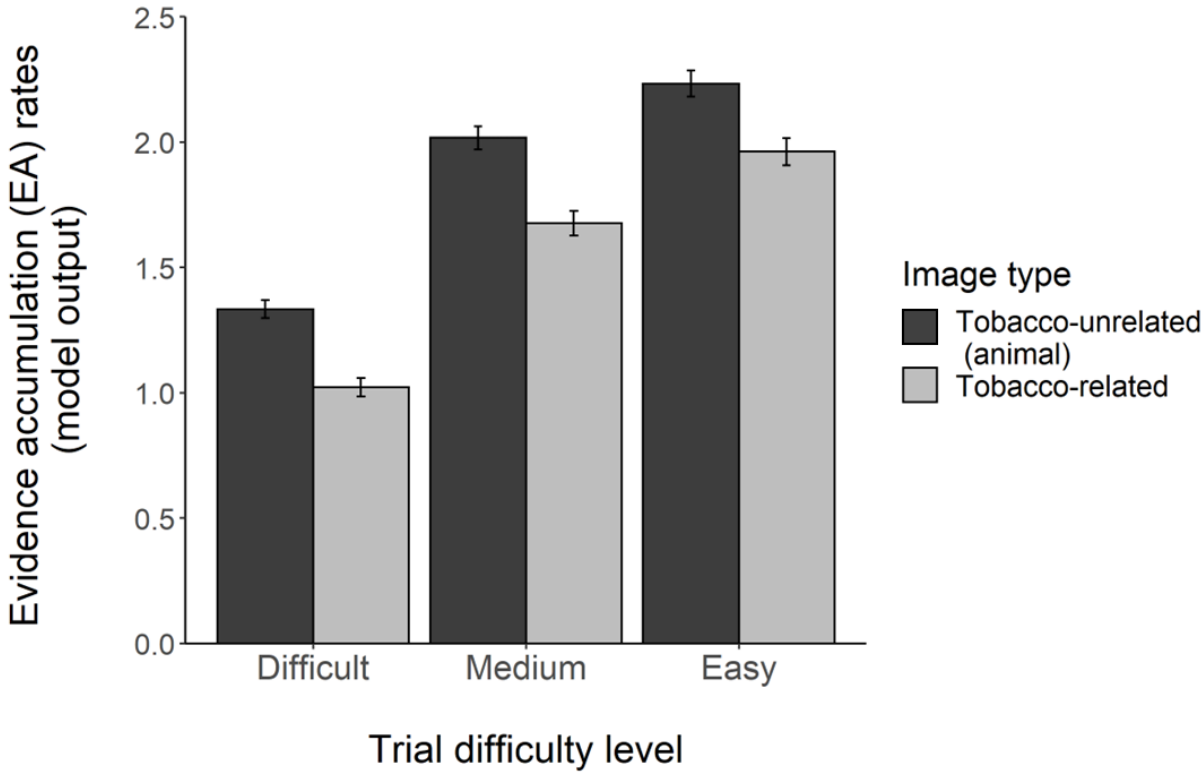
Interestingly, current smokers have significantly lower response thresholds when making tobacco decisions (M = 1.83, SD = .38) compared to tobacco-unrelated (animal) decisions (M = 1.93, SD = .30), but only on trials that are difficult. Furthermore, ex-smokers have significantly higher response thresholds when making tobacco-decisions (M = 2.25, SD = .40) compared to tobacco-unrelated (animal) decisions (M = 2.14, SD = .38) on medium trials. A similar pattern is found on easy trials; ex-smokers have significantly higher response thresholds when making tobacco-decisions (M = 1.95, SD = .45) compared to tobacco-unrelated (animal) decisions (M = 1.79, SD = .48).

7. Establishing a 'difficulty effect' on the VBDM task (Figure S6)

We pre-registered the exploration of a 'difficulty effect' on the VBDM task; EA rates should increase alongside decreasing trial difficulty level. One-way repeated measures ANOVAs explored the effect of difficulty level (easy, medium, and difficult) on EA rates (see Figure S5). There was a significant main effect of difficulty on tobacco-unrelated (animal) EA rates, $F(1.77, 179.07) = 215.16$, $p < .001$, $\eta p^2 = .68$. Subsequent post-hoc contrasts (applying the Holm-Bonferroni correction to p-values for multiple comparison) revealed that tobacco-unrelated (animal) EA rates in the easier trials (M = 2.23, SD = .53) were significantly increased compared to medium trials (M = 2.02, SD = .46; $p < .001$) and difficult trials (M = 1.33, SD = .36; $p < .001$). Furthermore, tobacco-unrelated (animal) EA rates on medium trials were significantly increased compared to EA rates on difficult trials ($p < .001$). An identical pattern was seen for tobacco EA rates, $F(1.69, 170.32) = 295.19$, $p < .001$, $\eta p^2 = .75$; easier trials (M = 1.96, SD = .55) vs. medium trials (M = 1.68, SD = .50; $p < .001$) easier vs. difficult trials (M = 1.02, SD = .37; $p < .001$); medium vs. difficult trials ($p < .001$).

Figure S6

Mean evidence accumulation rates (all participants) for tobacco-unrelated (animal) and tobacco choices split by trial difficulty level



Note. Error bars represent the standard error (SE) of the mean.

8. Order of blocks of trials on the VBDM task: does this matter?

The order of blocks in the decision-making task was randomized, such that for some participants the tobacco-unrelated (animal) trials were completed first, whilst for others the tobacco-related trials were completed first. To explore the importance of order of blocks presented in the decision-making task, we conducted a two-way between-subjects ANOVA with smoking status (2: current smoker; ex-smoker) and order (2: tobacco-unrelated (animal) first; tobacco-related first). In the data, order of blocks is coded as 1 = tobacco-unrelated (animal) first, and 2 = tobacco-related first. Overall, for EA rates and response thresholds for both tobacco-related and tobacco-unrelated (animal) choices, there was no evidence to suggest that the order in which participants completed the blocks altered the decision-parameters (all *p*s ≥ .21, see below).

<u>EA rates</u>

There was no significant main effect of order of blocks ($F(1, 98) = 1.36$, $p = .25$, $\eta p^2 = .01$) or significant interaction between smoking status and order of blocks ($F(1, 98) = .07$, $p = .78$, $\eta p^2 = .00$) on tobacco-related EA rates. There was no significant main effect of order of blocks ($F(1, 98) = 1.01$, $p = .32$, $\eta p^2 = .01$) or significant interaction between smoking status and order of blocks ($F(1, 98) = .73$, $p = .40$, $\eta p^2 = .01$) on tobacco-unrelated (animal) EA rates.

<u>Response thresholds</u>

There was no significant main effect of order of blocks ($F(1, 98) = .16$, $p = .69$, $\eta p^2 = .00$) or interaction between smoking status and order of blocks ($F(1, 98) = 1.61$, $p = .21$, $\eta p^2 = .02$) on tobacco-related response thresholds. There was no significant main effect of order of blocks ($F(1, 98) = .05$, $p = .83$, $\eta p^2 = .00$) or interaction between smoking status and order of

blocks ($F(1, 98) = 1.15$, $p = .29$, $\eta p^2 = .01$) on tobacco-unrelated (animal) response thresholds.

9. Exploratory correlations between DDM parameters and self-report variables split by smoker status (Tables S4 and S5)

Table S4

Correlations between DDM parameters and self-report questionnaire variables in current smokers

	1	2	3	4	5	6	7	8
1. Animal EA rates	-							
2. Tobacco EA rates	**.54*** **	-						
3. Animal thresholds	**-.67*** **	-.22	-					
4. Tobacco thresholds	**-.31***	.05	**.61*** **	-				
5. BSCS	.10	.09	-.14	.04	-			
6. Dependence	-.10	-.17	.20	.02	-.27	-		
7. Motivation to quit	-.25	**-.34***	.07	.12	.04	-.05	-	
8. Breakpoint	-.04	.23	.23	.25	-.07	-.14	-.05	-

Note. *p < .05*, **p<.01, ***p<.001

Interestingly, in current smokers, motivation to quit smoking is negatively correlated with tobacco-related EA rates. Put another way, higher motivation to give up smoking is characterised by lower EA rates for tobacco.

Table S3

Correlations between DDM parameters and self-report questionnaire variables in ex-smokers

	1	2	3	4	5
1. Animal EA rates	-				

2. Tobacco EA rates	**.53*** **	-			
3. Animal thresholds	**-.61*** **	-.24	-		
4. Tobacco thresholds	-.26	**-.41** **	**.49*** **	-	
5. BSCS	.03	.05	.05	.12	-
6. Duration since quitting smoking	.23	.08	-.01	-.11	.23

Note. *p < .05*, **p<.01, ***p<.001

10. Exploratory analyses as requested during the peer review process

Below we report several exploratory analyses as requested by a reviewer during the peer review process. These analyses should be interpreted with caution because they were not pre-registered, and our study was only powered for the primary analyses that we report in the manuscript.

Quit attempts were categorised into none (0 attempts), low to medium (between 1 and 3 attempts), and high (between 4 and 12 attempts). Crucially, there was no significant three-way interaction between image type, smoking status, and the number of quit attempts on EA rates ($F(2, 96) = 1.70$, $p = .19$, $\eta_p^2 = .03$) or on response thresholds ($F(2, 96) = .07$, $p = .93$, $\eta_p^2 = .00$). Cigarettes per day were categorised into low-to-medium (between 1-10), medium-to-high (between 11–20), and high (between 21–50). There was no significant three-way interaction between image type, smoking status, and number of cigarettes per day on EA rates ($F(2, 96) = 1.02$, $p = .36$, $\eta_p^2 = .02$) or on response thresholds ($F(2, 96) = 1.50$, $p = .23$, $\eta_p^2 = .03$). These analyses suggest that the number of quit attempts and cigarettes per day did not moderate relationships between smoking status and VBDM parameters.

Using PROCESS (Hayes, 2012), we investigated whether the relationship between smoking status and VBDM parameters was moderated by self-reported self-control (BSCS). We calculated bias-corrected, bootstrapped (5000 samples) confidence intervals. Self-control was not a significant moderator of the relationship between smoking status and tobacco-related response thresholds ($b = .00$, $p = .89$, 95% CI = -.02 to .02; Figure S7), animal response thresholds ($b = .01$, $p = .33$, 95% CI = -.01 to .02; Figure S8), tobacco EA rates ($b = -.00$, $p = .78$, 95% CI = -.03 to .02; Figure S9), or animal EA rates: ($b = -.00$, $p = .68$, 95% CI = -.02 to .02; Figure S10).

Figure S7

A scatterplot to show the relationship between self-control and smoking-related response thresholds split by smoker status.

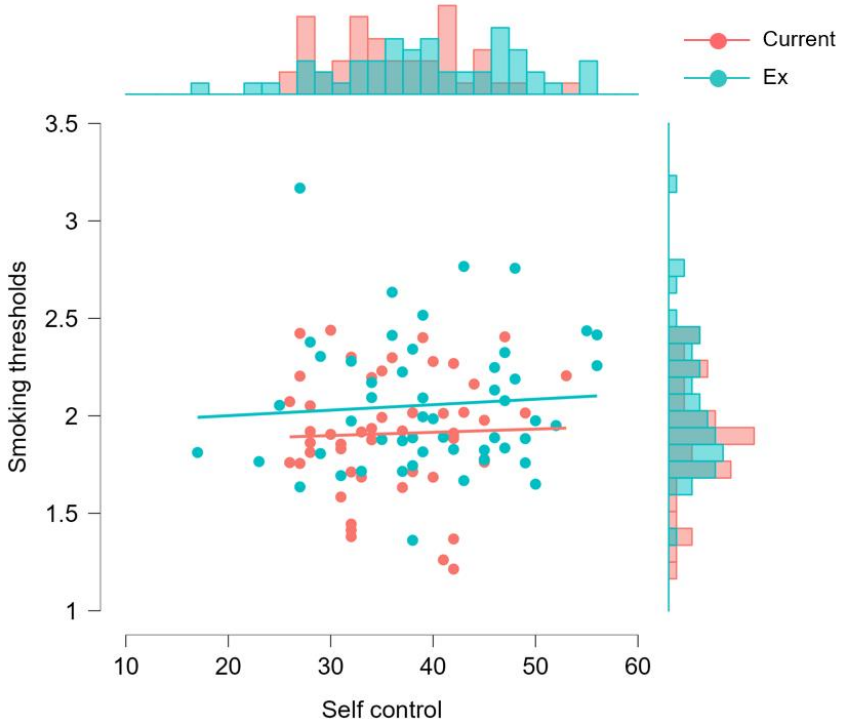


Figure S8

A scatterplot to show the relationship between self-control and animal-related response thresholds split by smoker status.

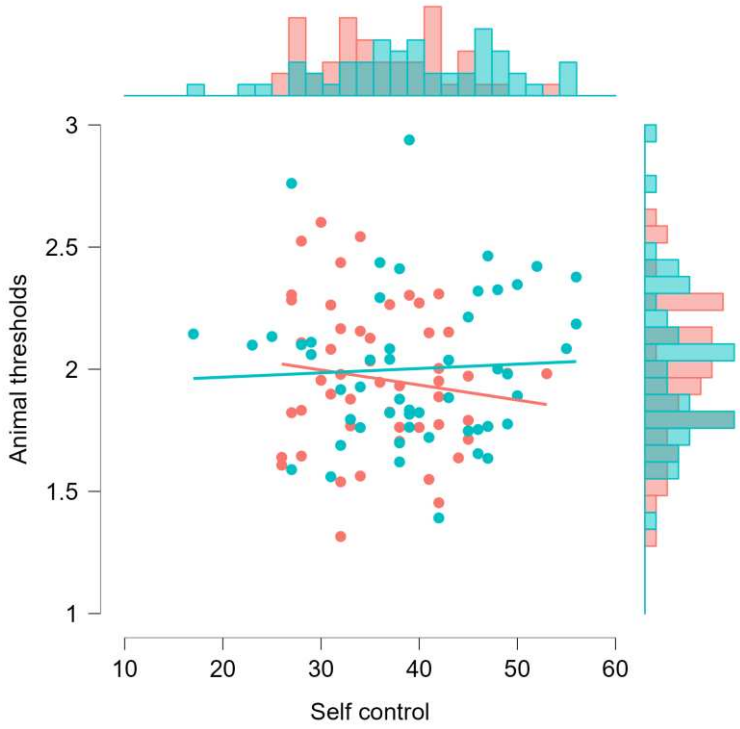


Figure S9

A scatterplot to show the relationship between self-control and tobacco-related EA rates split by smoker status.

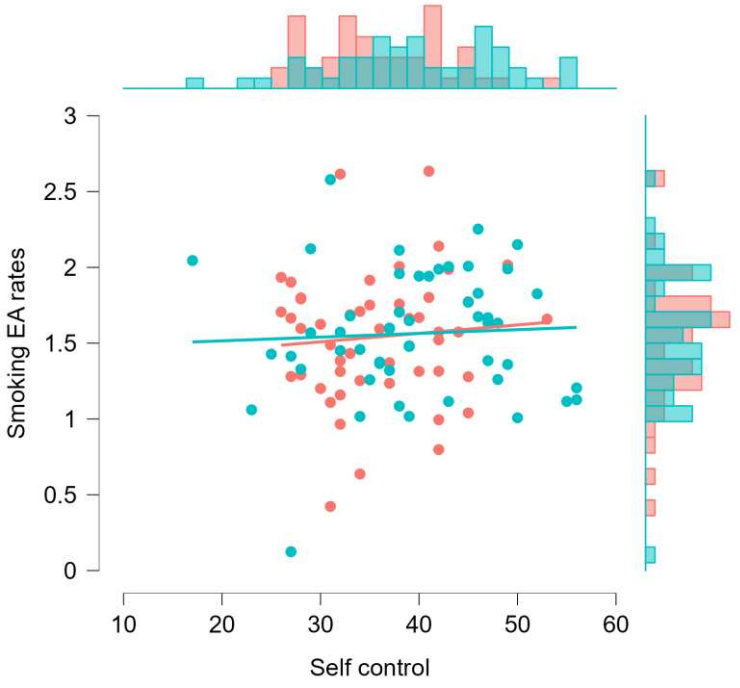


Figure S10

A scatterplot to show the relationship between self-control and animal-related EA rates split by smoker status.