- No Meaningful Difference in Attentional Bias Between Daily and Non-Daily Smokers
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Abstract

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Both daily and non-daily smokers find it difficult to quit smoking long-term. One factor associated with addictive behaviour is attentional bias, but previous research in daily and 10 non-daily smokers found inconsistent results and did not report the reliability of their 11 cognitive tasks. Using an online sample, we compared daily (n = 106) and non-daily (n = 106)12 60) smokers in their attentional bias towards smoking pictures. Participants completed a 13 visual probe task with two picture presentation times: 200ms and 500ms. In confirmatory 14 analyses, there were no significant effects of interest, and in exploratory analyses, equivalence 15 testing showed the effects were statistically equivalent to zero. The reliability of the visual 16 probe task was poor, meaning it should not be used for repeated testing or investigating 17 individual differences. The results can be interpreted in line with contemporary theories of attentional bias where there are unlikely to be stable trait-like differences between smoking 19 groups. Future research in attentional bias should focus on state-level differences using more reliable measures than the visual probe task. 21

22 Keywords: Non-daily smokers, Daily smokers, Visual probe task, Attentional bias,
23 Equivalence testing

24 Word count: 4854

No Meaningful Difference in Attentional Bias Between Daily and Non-Daily Smokers

Take-home message

Previous research reported greater attentional bias in daily or non-daily smokers using
the visual probe task. We found no meaningful difference using the traditional approach of
analysing differences in response times. Our visual probe task also showed poor reliability,
meaning response time outcomes from the task should not be used in individual differences
research or measuring changes in attentional bias across repeated measurements.

Purpose Purpose

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Daily and non-daily smokers have different habits and motives but both groups find it
difficult to quit smoking long-term. As attentional bias may be associated with addictive
behaviour, we used the visual probe task to compare daily and non-daily smokers. We
predicted that non-daily smokers would show greater attentional bias towards smoking
images than daily smokers. If non-daily smokers showed greater attentional bias, it would
help to explain why they find it difficult to quit smoking while showing fewer signs of
nicotine dependence.

Introduction

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Historically, smokers have been treated as a single homogeneous group (Shiffman, 2009), but there are fundamental differences in the smoking habits and motives of daily and non-daily smokers (Shiffman, Dunbar, et al., 2012; Shiffman, Tindle, et al., 2012). 13-36% of smokers are defined as non-daily smokers across Europe and the United States (Bogdanovica et al., 2011; Kotz et al., 2012; Tindle & Shiffman, 2011) and non-daily smoking has typically been the most prevalent pattern in ethnic minority groups (Fagan & Rigotti, 2009; Tong et al., 2006). Whereas daily smokers cite negative reinforcers such as avoiding nicotine withdrawal as the key motivators, non-daily smokers cite positive reinforcers such as smoking around friends and alcohol (Shiffman et al., 2014; Shiffman, Dunbar, et al., 2012). Despite these differences, 77-92% of daily smokers and 74-83% of non-daily smokers relapse within 90 days of a quit attempt (Bogdanovica et al., 2011; Kotz et al., 2012; Tindle & Shiffman, 2011), showing both groups find it difficult to quit smoking long-term. This means it is important to investigate potential factors associated with smoking behaviour.

One factor is attentional bias, which is the tendency to fixate attention on cues
associated with smoking. Attentional bias is the product of a classical conditioning process
where smokers develop conditioned responses to substance-related cues through repeated
exposure (Field & Cox, 2008). Theoretical models of attentional bias suggest it has a
reciprocal relationship with craving, supported by a meta-analysis showing there is a small
positive relationship (Field et al., 2009). In situations where cigarettes are available, cues
associated with smoking grab attention, induce craving, which further drives attentional bias.
Updated theories of attentional bias (Field et al., 2016) emphasise the role of momentary
evaluations of smoking cues, meaning attentional bias and craving fluctuates over time, and
describe attempts to extinguish the conditioned response through attentional bias
modification. Due to its predicted role in smoking behaviour, studies have investigated
whether attentional bias is higher in certain groups or conditions.

Consistent with theoretical models, smokers consistently show greater attentional bias 66 towards smoking cues than non-smokers (Baschnagel, 2013; Ehrman et al., 2002; Kang et al., 67 2012; Mogg et al., 2003). However, there are contrasting expectations and findings around how lighter and heavier smokers¹ differ in attentional bias. One view is lighter smokers should show greater attentional bias than heavier smokers since they rarely show signs of nicotine dependence, so smoking-related cues are required to induce craving and motivate 71 substance use. In support, some studies found lighter smokers exhibit greater attentional bias than heavier smokers (Bradley et al., 2003; Hogarth et al., 2003; Mogg et al., 2005). Another view is heavier smokers should show greater attentional bias than lighter smokers since the conditioned response to smoking-related cues should be stronger from repeated exposure. There is also evidence for this view as heavier smokers showed greater attentional bias than lighter smokers (Chanon et al., 2010; Vollstädt-Klein et al., 2011; Zack et al., 2001). Collectively, these studies show smokers consistently display greater attentional bias towards smoking cues than non-smokers, but it is not clear whether lighter or heavier smokers show greater attentional bias. 80

To address this inconsistency, the current study focused on comparing attentional bias towards smoking cues in daily and non-daily smokers. Despite most studies using the visual probe task to measure attentional bias, relatively small sample sizes and inconsistent design features complicate making conclusions about the mixed findings. Therefore, we used a much larger sample size than previous studies and manipulated different features of the visual probe task.

The visual probe task infers attention through differences in response time (RT). Two images are presented and when they disappear, the participant is required to indicate the location of a small probe that replaces one of the images. Faster RTs to particular stimuli

¹ Note, we refer to lighter and heavier smokers here as the studies used different definitions. In our study, we operationalise the groups as daily and non-daily smokers.

reflect selective attention (Field & Cox, 2008), but as the location of attention is inferred through differences in RT after the stimuli disappear, the presentation time can be manipulated. Short Stimulus Onset Asynchronies (SOA) of 200ms or less measure involuntary attentional processes (Field & Cox, 2008). Longer SOAs of 500ms or more target voluntary attention as there is enough time to make multiple fixations. Previous research used single SOAs of 500ms (Vollstädt-Klein et al., 2011) and 2000ms (Hogarth et al., 2003; Mogg et al., 2005). None of the studies used a very short SOA to measure more involuntary attentional processes. Chanon et al. (2010) found that in comparison to non-smokers, attentional bias was greater in smokers under a 200ms conditions than a 550ms condition. To investigate the conflict in results between daily and non-daily smokers, this study used two SOAs of 200ms and 500ms.

A final consideration of our study was to evaluate and report the internal consistency 101 of the visual probe task. There is growing awareness that the reliability of cognitive tasks 102 should be taken seriously (Parsons et al., 2019; Pennington et al., 2021), but reliability has a 103 different meaning depending on the context. For experimental measures to be reliable, we 104 want to consistently observe effects between groups or conditions, but for correlational 105 measures to be reliable, we want to consistently rank individuals (Hedge et al., 2018). This 106 means the attributes of experimental measures may not be compatible with the requirements 107 for reliable correlation research. As researchers often use the visual probe task as a measure 108 in cognitive bias modification procedures, it must be reliable to detect any changes across 109 time. Previous attempts at evaluating the internal consistency of the visual probe task have 110 been disappointing (Ataya et al., 2012; Schmukle, 2005; Waechter et al., 2014). Therefore, 111 we are following recommendations to habitually report the reliability of cognitive tasks 112 (Parsons et al., 2019), even when it is not the main focus of the study. 113

The protocol and hypotheses for this project were pre-registered on the Open Science Framework (OSF; https://osf.io/ju7kv). Given the relevance of smoking cues for non-daily smokers and the results from previously unpublished research, we hypothesised non-daily smokers would show greater attentional bias than daily smokers. There was no *a priori* hypothesis for the effect of SOA condition. This means we expected non-daily smokers to show greater attentional bias than daily smokers, but it was not clear what the difference in magnitude would be under different SOA conditions.

121 Method

122 Design

We used a 2 x 2 mixed design with one between-subjects IV of smoking group with two levels: daily and non-daily smokers. Participants responded to the question "Do you usually smoke cigarettes every day?". Non-daily smokers responded "No" and daily smokers responded "Yes". There was one within-subjects IV of the visual probe task SOA which had two levels: 200ms and 500ms. The dependent variable was the attentional bias index (ms) calculated by subtracting the mean RT to smoking trials from the mean RT to non-smoking trials. This means positive values indicate greater attentional bias towards smoking cues.

Participants and Sample Size Calculation

We collected data online using Prolific where inclusion criteria consisted of participants should have normal or corrected-normal vision, be between the ages of 18 to 60, and smoke at least one cigarette per week or four cigarettes per month.

We simulated a power analysis to justify the sample size. We set the smallest effect size of interest based on a previously unpublished study (Bartlett, 2020) where the mean difference in attentional bias score between smoking groups was 6.13ms (95% CI = [-5.27, 17.53]) for a 200ms SOA and 11.35ms (95% CI = [-4.51, 27.21] for a 500ms SOA. However, we also consulted previous research due to the wide confidence intervals. The smallest known effects for a 200ms SOA was 5ms (Chanon et al., 2010) and 11ms for a 500ms SOA (Bradley et al., 2003). Our smallest effect sizes of interest were 5ms (200ms) and 10ms (500ms), and a

conservative standard deviation of 20ms based on Vollstädt-Klein et al. (2011).

These values were used to conduct a simulated power analysis for a 2 x 2 mixed ANOVA using R (code available on the OSF; https://osf.io/am9hd/). We expected non-daily smokers to display greater attentional bias towards smoking images than daily smokers. We set the conditions of the power analysis as non-daily smokers having a 5ms (200ms) and 10ms (500ms) greater mean difference than daily smokers. For each condition, the values were sampled from a normal distribution with a standard deviation of 20ms. The sample size for each smoking group was increased from 10 (N = 20) to 150 (N = 300) in steps of 10, with each step repeating 10,000 times. The final sample size target was 60 per group (N = 120) as we reached 80% power (alpha = .05) between 50 and 60 participants per group.

51 Materials

Fagerström Test for Cigarette Dependence (FTCD). The FTCD (Fagerström, 2012; Heatherton et al., 1991) was used as a self-report measure of nicotine dependence. The Cronbach's alpha estimate (bootstrapped using 10,000 iterations) in this sample was higher than in previous research, $\alpha = .74, 95\%$ CI = [.67, .8].

Visual Probe Task. We used Gorilla (Anwyl-Irvine et al., 2019) to present the visual probe task online and the task is available on the open materials page to preview or clone (http://gorilla.sc/openmaterials/85021).

Each trial started with a 250ms central fixation cross before two images were presented horizontally to the left and right. The content and duration of the two images was controlled by two variables: trial type and SOA. Trial type consisted of three conditions (neutral, smoking, or non-smoking) while SOA consisted of two conditions (200ms or 500ms). At picture offset, a small dot appeared in the location vacated by one of the images. The dot remained on the screen until the participant responded either left (Z key) or right (M key).

After they responded, the next trial began with the screen containing only the fixation cross.

66 The trial procedure is shown visually in Figure 1.

The trial type condition was based on 16 image pairs for neutral trials and 16 image
pairs for smoking and non-smoking trials. For neutral trials, the dot replaced one of the
neutral image pairs. For smoking trials, the dot replaced a smoking image presented next to
a matched non-smoking image. For non-smoking trials, the dot replaced a non-smoking
image presented next to a smoking image.

We used 16 image pairs from the International Affective Picture System (Lang et al., 2008) for the neutral trials. We developed a series of matching smoking and non-smoking images for the smoking and non-smoking trials (Bartlett, 2020). The list of IAPS images is available on the OSF project and our smoking/non-smoking images are available on the Gorilla open materials page.

The trial order was randomised with each picture pair presented four times to cover
each combination of image (left and right) and dot location (left and right). This
combination determined the trial type condition, where a left smoking image, right
non-smoking image, and left dot would produce a smoking trial. For each picture pair, this
process was repeated twice for each SOA condition, producing 384 trials split into two blocks
with 64 trials in each SOA and trial type condition.

183 Procedure

We provided participants with an information sheet and they provided informed
consent by ticking a box. This study was approved by the Faculty of Health and Life
Sciences Ethical Approval board. Participants completed a short questionnaire on their
demographic information, smoking habits, and the FTCD. The next page contained the
visual probe task which began with a set of instructions asking the participant to complete
the task in a quiet environment free of distractions. Participants completed 12 practice trials
which provided feedback on their responses and overall accuracy. After the task, participants

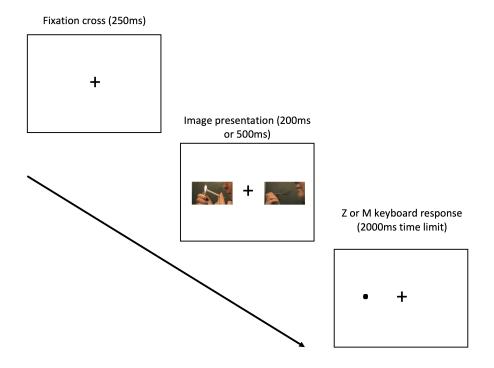


Figure 1. Diagram showing the trial procedure of the visual probe task. Each trial started with a fixation cross lasting 250ms. The fixation cross is then flanked by one of the stimulus pairs on the left and right. The stimuli remained on the screen for 200ms or 500ms depending on the SOA condition. The stimuli disappear and one image is replaced with a small dot. Participants had up to 2000ms to respond whether the dot was on the left or right. The next trial started with a new blank fixation cross.

reported whether they experienced any technical issues, whether they used an ineligible
device, and if they had completed the study before. Similar to Clifford and Jerit (2014), we
asked participants if they had any distractions while they completed the study such as
listening to music. Finally, participants read a debriefing sheet before they were redirected to
Prolific. If the participants successfully reached the end of the study, they were paid £2.

196 Results

Table 1

Mean (SD) values for participant characteristics and scale scores.

	Non-Daily Smokers	Daily Smokers
Age	28.68 (7.71)	31.84 (9.7)
% female	46.67%	26.42%
% white	93%	92%
FTCD	0.52 (1.31)	2.58 (2.17)
Cigarettes per day	2.38 (2.74)	8.59 (6.41)
Age started to smoke	18.51 (3.65)	17.93 (3.47)
Time since last cigarette (minutes)*	2880 (4590)	60 (633.75)

Note. *Due to large skew, these values represent the median and IQR.

197 Participant Attrition and Demographics

218 people accessed the study and 205 completed the experiment and received payment. The final sample was 166 after applying exclusion criteria: 60 non-daily and 106 daily smokers. Participants were excluded for having fewer than 50% of the possible trials (n = 4), experiencing technical issues (n = 16), reporting to smoke every day but not every week (n = 3), and not smoking in the past four weeks (n = 19). The total number equals 42 as some participants met more than one criterion.

Table 1 displays the demographic information. Daily smokers smoked more cigarettes
per day and had a higher FTCD score. Non-daily smokers exemplified infrequent smoking as
the median time since their last cigarette was 48 hours, while it was only one hour for daily
smokers. Figure 2 shows the distribution of FTCD scores and cigarettes per day.

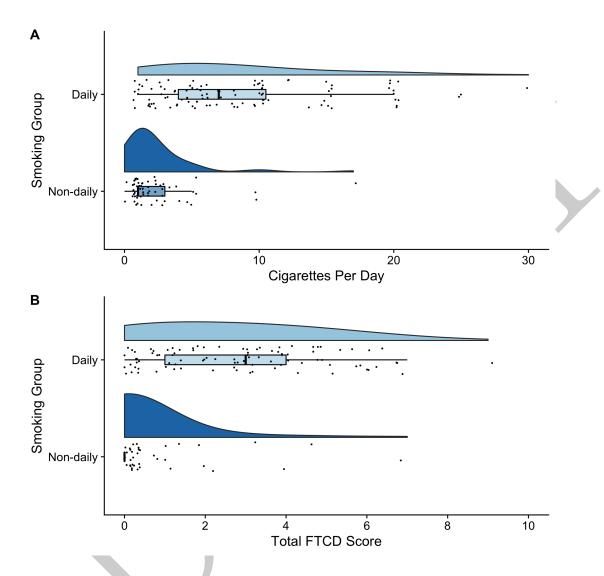


Figure 2. Two different measures of nicotine dependence: (A) number of cigarettes per day and (B) FTCD score. The data are presented as raincloud plots (Allen et al., 2019). The top element for each group represents the distribution of scores through the density. The bottom element presents the individual data points with a superimposed boxplot.

Data Processing

The R code is available on the OSF (https://osf.io/am9hd/). We removed incorrect responses in addition to responses faster than 200ms as they represent preemptive responses.

We considered outliers as any response outside 2.5 times the median absolute deviation for each participant, SOA, and trial condition (Leys et al. 2013). This meant we removed 9.72% of the total possible trials, with the median number of excluded trials for each participant being 23 (range 7 - 98).

For the confirmatory analyses, we focused on smoking/non-smoking image pairs and excluded the neutral pairs. Originally, we planned on conducting exploratory analyses to create orienting and disengagement indices (Salemink et al., 2007) by subtracting the mean RT to neutral trials from smoking trials (orienting) or non-smoking trials (disengagement), but a coding error meant we did not have matching numbers of neutral trials in the 200ms and 500ms SOA conditions. Therefore, we focused on our confirmatory analyses and excluded neutral trials.

After removing outliers, we calculated the mean RT to probes that replaced non-smoking images and the mean RT to probes that replaced smoking images. We then calculated the difference between these two values as our attentional bias index (non-smoking - smoking), where positive values mean faster average responses to smoking images. For each participant, this produced two values: one for the attentional bias index using a 200ms SOA and one using a 500ms SOA.

⁸ Confirmatory Analyses: Attentional Bias Towards Smoking Cues

The mean (SD) attentional bias index in the 200ms SOA condition was 1.95ms (22.31) for daily smokers and -0.30ms (18.57) for non-daily smokers. In the 500ms SOA condition, the mean bias index was 0.21ms (21.93) for daily smokers and -2.06ms (12.67) for non-daily smokers. This was in the opposite direction to our hypotheses as we expected non-daily smokers to display greater attentional bias towards smoking images than daily smokers. The results are displayed in Figure 3.

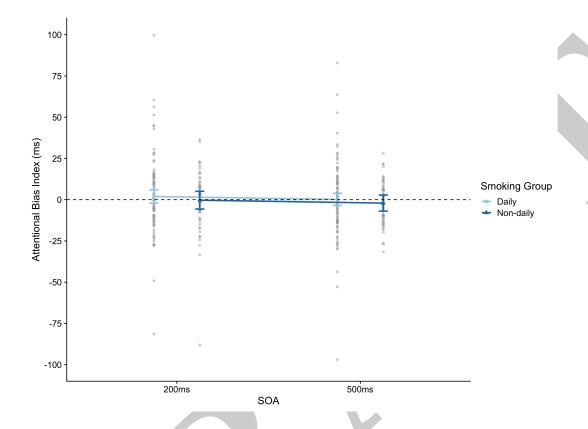


Figure 3. Interaction plot showing the mean attentional bias index for daily and non-daily smokers by SOA condition. The error bars represent the 95% CI around the mean. Positive values indicate greater attentional bias towards smoking cues. The grey points show the individual scores per condition.

We used a 2x2 mixed ANOVA with SOA as a within-subjects IV and smoking group as a between-subjects IV. The mean attentional bias index was the DV. There was not a significant effect of SOA (F (1, 164) = 0.58, p = .448, $\hat{\eta}_G^2$ = .002) or smoking group (F (1, 164) = 0.97, p = .325, $\hat{\eta}_G^2$ = .003). There was also no significant interaction between the two factors, F (1, 164) = 0.01, p = .996, $\hat{\eta}_G^2$ < .001. This did not support our prediction that non-daily smokers would show greater attentional bias towards smoking images than daily smokers.

Exploratory Analyses: No Meaningful Difference in Attentional Bias

To demonstrate there was no meaningful difference between daily and non-daily 243 smokers, we performed equivalence testing on the two comparisons of interest: the difference 244 between daily and non-daily smokers at each SOA condition. You cannot directly provide 245 evidence in favour of the null hypothesis using traditional null hypothesis significance testing. 246 Equivalence testing applies two one-sided tests to user-defined boundaries representing 247 effects you consider too small to be practically or theoretically meaningful (Lakens et al., 248 2018). If both tests are statistically significant, you can conclude your observed effect size is 249 statistically equivalent to zero based on your boundaries. 250

There are different approaches to setting the boundaries for your smallest effect size of 251 interest. We used Cohen's $d = \pm 0.41$ based on the small telescopes method (Lakens et al., 252 2018). This is where you use the effect size that the largest previous study had 33% power to 253 detect (in our case, Vollstädt-Klein et al. (2011) with two groups of 25 and 26 participants). 254 The small telescopes method is appropriate when previous research did not define their 255 smallest effect size of interest, so it represents the effect size large enough to be detectable in 256 the original study (Simonsohn, 2015). Considering alternative choices for the effect size 257 boundaries, our conclusions below hold when we use the larger effect size from our power 258 analysis (10ms) but not when we use the smaller effect size (5ms). Given we are arguing 250 differences in attentional bias in daily and non-daily smokers may be smaller than reported 260 in previous research, we focus on the results using the small telescopes method. 261

For the 200ms SOA condition, the two one-sided test procedure was significant,
demonstrating that the difference in attentional bias towards smoking images between daily
and non-daily smokers was statistically equivalent to zero, t (141.65) = -1.91, p = .029.
Similarly, the 500ms SOA condition was statistically equivalent to zero, t (163.91) = -1.89, p= .03. The equivalence testing procedure is presented in Figure 4, showing that the 90%
confidence interval around the mean difference crosses zero, but does not cross the effect size

boundaries of $d = \pm .41$ (expressed here in raw units).

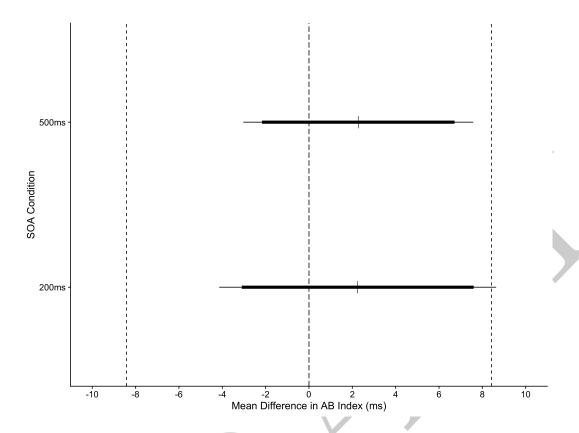


Figure 4. The thin vertical lines show the mean difference in attentional bias index between daily and non-daily smokers in each SOA condition. The thick horizontal black lines represent the 90% confidence interval for the two one-sided test procedure. The thin horizontal black lines represent the 95% confidence interval. The dashed vertical lines represent the equivalence boundaries in raw scores.

$_{269}$ Exploratory Analyses: Including trial type as an additional IV

In our preregistration protocol, we focused on the attentional bias index as our
outcome for confirmatory analyses, calculating it from the difference between smoking and
neutral trials. While there were no meaningful differences between smoking groups, both
peer-reviewers questioned whether participants first showed an attentional bias effect
towards smoking images. Therefore, we performed exploratory analyses where we included
trial type as an additional within-subjects IV instead of calculating the difference in RT

between each condition.

We used a 2x2x2 mixed ANOVA using RT as our DV, trial type and SOA as within-subject IVs, and smoking group as a between-subjects IV. The only significant effect was SOA (F (1, 164) = 13.03, p < .001, $\hat{\eta}_G^2$ = .002), which in isolation is not theoretically meaningful to us. None of the other effects were statistically significant.

Although there were no significant effects including trial type, we quantified whether
participants showed an attentional bias effect towards smoking images using the persons as
effect sizes approach (Grice et al., 2020). Instead of a blanket mean difference between
groups or conditions, you can quantify how many participants behaved consistent with
theoretical predictions. In this context, we can ask how many participants showed faster RTs
to smoking trials compared to non-smoking trials.

For each participant, we coded whether the difference in RT was negative (faster 287 responses to non-smoking images) or positive (faster responses to smoking images), then 288 calculated the percentage showing a positive effect for each smoking group and SOA 289 condition. Participants rarely deviated from 50% showing the expected faster responses to 290 smoking images. 50% of daily smokers in the 200ms and 52.83% in the 500ms SOA condition 291 showed faster responses to smoking images. 53.33% of non-daily smokers in the 200ms SOA 292 condition showed faster responses to smoking images, while 43.33% responded faster to 293 smoking images in the 500ms SOA condition, suggesting more participants responded faster to non-smoking images. We visualised these results in Figure 5 where each line represents a participant and the colour shows whether they responded faster to smoking or non-smoking 296 images for each SOA condition and smoking group. Collectively, these exploratory analyses 297 suggest participants did not display the predicted attentional bias effect towards smoking 298 images. 299

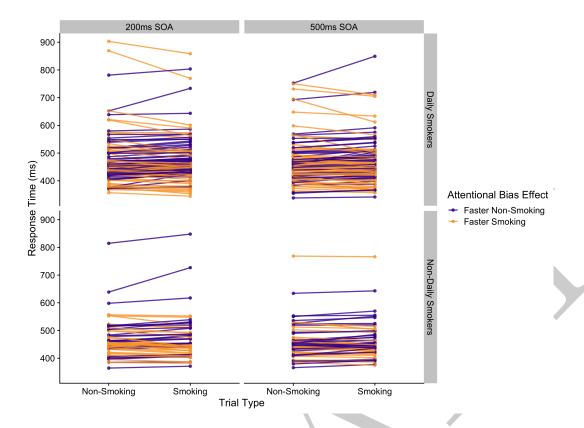


Figure 5. A dot plot visualising whether each participant showed the predicted attentional bias effect towards smoking images. Each line represents one participant where their average RT to non-smoking and smoking images is connected. Positive colour-coded slopes show participants who responded faster to non-smoking images while negative colour-coded slopes show participants who responded faster to smoking images. Each panel represents the combination of smoking group and SOA condition.

Exploratory Analyses: Visual Probe Task Reliability

We calculated Cronbach's alpha for the attentional bias index across the 16 stimulus pairs which was poor for both the 200ms ($\alpha = .29, 95\%$ CI = [.00, .58]) and 500ms ($\alpha = .19, 95\%$ CI = [.00, .42]) SOA conditions.

We reported internal consistency estimates for comparison with previous studies, but they assume the items or trials are presented in the same order (Parsons et al., 2019). As cognitive tasks randomise trials, internal consistency may not be the best approach. An alternative is a permutation approach to calculating split-half reliability (Parsons, 2020).

This randomly splits the data set into two halves many times and calculates the average

correlation between each half. Using 5000 iterations, poor reliability was also reflected in the

split-half estimate (corrected using the Spearman-Brown formula) for the 200ms (r = .56,

95% CI = [.37, .7]) and 500ms (r = .47, 95% CI = [.27, .62]) SOA conditions.

312 Discussion

We hypothesised that non-daily smokers would display greater attentional bias towards 313 smoking cues than daily smokers. Some studies found that non-daily smokers exhibited 314 greater attentional bias (Bradley et al., 2003; Hogarth et al., 2003; Mogg et al., 2005), 315 whereas others found that daily smokers displayed greater attentional bias (Chanon et al., 316 2010; Vollstädt-Klein et al., 2011; Zack et al., 2001). Using traditional methods that 317 calculate an attentional bias index from average differences in RT, there were no significant 318 differences, and using equivalence testing showed there was no meaningful difference in 319 attentional bias in daily and non-daily smokers. 320

We may have found null results as previous research could have problems with inflated 321 effect sizes due to low statistical power. The previous largest sample was 51 smokers in 322 Vollstädt-Klein et al. (2011). Splitting these into 25 and 26 participants, a sensitivity power 323 analysis indicates that this sample size would be sensitive to detect effect sizes of Cohen's d 324 = 0.80 (alpha = .05, beta = .20). Incidentally, Schäfer and Schwarz (2019) showed that the 325 median Cohen's d in a random selection of 684 non-pre-registered articles was 0.80. In the 326 long-run, our study would have 99.80% power to detect an effect size of 0.80. Therefore, it is unlikely the effect size between daily and non-daily smokers is this large, or we would have had enough power to detect it. Our study had the largest known sample size to investigate 329 attentional bias with 60 non-daily smokers and 106 daily smokers. A sensitivity power 330 analysis shows that this was sensitive to detect effect sizes of Cohen's d = 0.46. Our study 331 was sensitive to detect an effect size of almost half the size of Vollstädt-Klein et al. (2011). 332

Our results were statistically equivalent to zero, meaning there may not be a meaningful
difference in attentional bias between smoking groups, at least in its current implementation
where the effect is assumed to represent stable trait-like group differences.

Contemporary theories suggest attentional bias may not be a trait-like phenomenon 336 that can produce stable differences between groups. Field et al. (2016) suggested that 337 attentional bias varies depending on how substance cues are being evaluated. The theory 338 suggests that rather than being a stable trait between groups, it fluctuates with the incentive 339 value of a cue which makes within-group differences more important. Begin et al. (2016) found that laboratory measures like the visual probe task did not predict smoking behaviour in the real-world. However, ecological momentary assessment of craving and awareness of smoking cues did predict smoking behaviour. Therefore, the null results in our study may be 343 a product of the fluctuating nature of attentional bias (Field et al., 2016). In smaller 344 samples, attentional bias could fluctuate one way or the other, but in larger samples like our 345 study, the differences could cancel out and converge to a mean difference around zero. Therefore, future research may benefit from investigating which factors affect the momentary 347 evaluation of substance cues and the subsequent expression of attentional bias. 348

Using the visual probe task to measure factors that affect the momentary evaluation of 349 substance cues may be problematic though. There are vocal critics of the task due to its 350 questionable level of internal consistency (Ataya et al., 2012; Schmukle, 2005; Waechter et 351 al., 2014). Our study also had suboptimal levels of internal consistency and split-half 352 reliability. Researchers rarely report the reliability of cognitive tasks unless it is the main focus of the article (Parsons et al., 2019), which means it is difficult to assess how reliable the tasks were in previous smoking research. Experimental measures are designed to produce reliable differences between groups or condition, not consistently rank individuals (Hedge et 356 al., 2018). This means if researchers plan to use the visual probe task across multiple 357 measurements - such as in cognitive bias modification or the evaluation of substance cues -358

then its poor reliability is problematic. Future research should use eye-tracking as a direct measure of attentional bias as it produces larger effect sizes (Field et al., 2009), has higher internal consistency (Price et al., 2015), and higher criterion validity (Soleymani et al., 2020).

362 Limitations

Our sample may have been more diverse than typical undergraduates in age and
education, but it still contained predominantly white participants. Non-daily smoking is
more prevalent in ethnic minority groups (Fagan & Rigotti, 2009; Levy et al., 2009) and the
health implications of smoking disproportionately affect non-white smokers (St.Helen et al.,
2019). Therefore, future research would benefit from recruiting a larger proportion of
non-white smokers for the results to generalise beyond mostly white smokers.

The online nature of the study meant participants' smoking levels could not be verified objectively using measures like Carbon Monoxide (Wray et al., 2016), but Ramo et al. (2011) demonstrated that smoking-related information collected online has good reliability and validity. Relatedly, as participants completed the study online, there was no control over their smoking behaviour before and during the study. This lead to idiosyncrasies as some smokers reported to smoke while they were completing the study. Although this may represent a more naturalistic environment for the smokers, our study had less control over smokers' deprivation levels.

377 Conclusion

The purpose of our study was investigate the conflict in attentional bias results
between daily and non-daily smokers. We expected non-daily smokers to show greater
attentional bias towards smoking images than daily smokers. Greater attentional bias in
non-daily smokers would have helped to explain why they find it difficult to quit smoking
while showing fewer signs of nicotine dependence. However, there were no significant effects,
and using equivalence testing, we found that there was no meaningful difference in

attentional bias between daily and non-daily smokers. The results can be interpreted in line
with contemporary theories of attentional bias where there may not be stable trait-level
differences between smoking groups in attentional bias. Future research should focus on
investigating how attentional bias fluctuates over time using more reliable measures than the
visual probe task.



Disclosures

390 CRediT Contributions

Conceptualization (JEB, RJ, NW); Methodology (JEB, RJ, NW); Formal analysis

(JEB); Investigation (JEB); Data curation (JEB); Writing - original draft (JEB); Writing
Review & editing (JEB); Supervision (RJ, NW).

Data, code, and materials

The data and code to reproduce these analyses are available on the OSF (https://osf.io/am9hd/). The visual probe task was created in Gorilla and the task can be found using the open materials page (http://gorilla.sc/openmaterials/85021)

398 R Package Acknowledgements

The results were created using R (Version 4.1.3; R Core Team, 2020) and the 399 R-packages afex (Version 1.0.1; Singmann et al., 2020), cowplot (Version 1.1.1; Wilke, 2019), 400 dplyr (Version 1.0.10; Wickham et al., 2020), qqplot2 (Version 3.3.5; Wickham, 2016), janitor 401 (Version 2.1.0; Firke, 2019), papaja (Version 0.1.1; Aust & Barth, 2020), psych (Version 2.2.3; 402 Revelle, 2019), pwr (Version 1.3.0; Champely, 2020), readr (Version 2.1.2; Wickham et al., 403 2018), shiny (Version 1.7.1; Chang et al., 2020), splithalf (Version 0.8.2; Parsons, 2020), 404 stringr (Version 1.4.0; Wickham, 2019), tibble (Version 3.1.6; Müller & Wickham, 2020), 405 tidyr (Version 1.2.0; Wickham & Henry, 2020), tinylabels (Version 0.2.3; Barth, 2022), and TOSTER (Version 0.4.0; Lakens, 2017).

References 408 Allen, M., Poggiali, D., Whitaker, K., Marshall, T. R., & Kievit, R. A. (2019). 409 Raincloud plots: A multi-platform tool for robust data visualization. Wellcome 410 Open Research, 4, 63. https://doi.org/10.12688/wellcomeopenres.15191.1 411 Anwyl-Irvine, A., Massonnié, J., Flitton, A., Kirkham, N., & Evershed, J. (2019). 412 Gorilla in our Midst: An online behavioral experiment builder. Behavior Research 413 Methods, 52, 388-407. https://doi.org/10.1101/438242 414 Ataya, A. F., Adams, S., Mullings, E., Cooper, R. M., Attwood, A. S., & Munafò, M. 415 R. (2012). Internal reliability of measures of substance-related cognitive bias. 416 Drug and Alcohol Dependence, 121(1), 148–151. 417 https://doi.org/10.1016/j.drugalcdep.2011.08.023 418 Aust, F., & Barth, M. (2020). papaja: Create APA manuscripts with R Markdown. 419 https://github.com/crsh/papaja 420 Barth, M. (2022). tinylabels: Lightweight variable labels. 421 https://cran.r-project.org/package=tinylabels 422 Bartlett, J. E. (2020). Daily and Non-daily Smokers: A Profile of Drive and 423 Cognitive Control Mechanisms [PhD thesis, Coventry University]. 424 https://thesiscommons.org/h9gpe/ 425 Baschnagel, J. S. (2013). Using mobile eye-tracking to assess attention to smoking 426 cues in a naturalized environment. Addictive Behaviors, 38(12), 2837–2840. 427 https://doi.org/10.1016/j.addbeh.2013.08.005 428 Begh, R., Smith, M., Ferguson, S. G., Shiffman, S., Munafò, M. R., & Aveyard, P. 429 (2016). Association between smoking-related attentional bias and craving 430 measured in the clinic and in the natural environment. Psychology of Addictive 431 Behaviors, 30(8), 868–875. https://doi.org/10.1037/adb0000231 432 Bogdanovica, I., Godfrey, F., McNeill, A., & Britton, J. (2011). Smoking prevalence 433

in the European Union: A comparison of national and transnational prevalence

```
survey methods and results. Tobacco Control, 20(1), 1–9.
435
              https://doi.org/10.1136/tc.2010.036103
436
           Bradley, B. P., Mogg, K., Wright, T., & Field, M. (2003). Attentional bias in drug
437
              dependence: Vigilance for cigarette-related cues in smokers. Psychology of
438
              Addictive Behaviors, 17(1), 66–72. https://doi.org/10.1037/0893-164X.17.1.66
439
           Champely, S. (2020). Pwr: Basic functions for power analysis.
440
              https://CRAN.R-project.org/package=pwr
441
           Chang, W., Cheng, J., Allaire, J., Xie, Y., & McPherson, J. (2020). Shiny: Web
442
              application framework for r. https://CRAN.R-project.org/package=shiny
443
           Chanon, V. W., Sours, C. R., & Boettiger, C. A. (2010). Attentional bias toward
444
              cigarette cues in active smokers. Psychopharmacology, 212(3), 309–320.
445
              https://doi.org/10.1007/s00213-010-1953-1
           Clifford, S., & Jerit, J. (2014). Is There a Cost to Convenience? An Experimental
447
              Comparison of Data Quality in Laboratory and Online Studies. Journal of
              Experimental Political Science, 1(2), 120–131. https://doi.org/10.1017/xps.2014.5
449
           Ehrman, R. N., Robbins, S. J., Bromwell, M. A., Lankford, M. E., Monterosso, J. R.,
450
              & O'Brien, C. P. (2002). Comparing attentional bias to smoking cues in current
451
              smokers, former smokers, and non-smokers using a dot-probe task. Drug and
452
              Alcohol Dependence, 67(2), 185–191.
453
              https://doi.org/10.1016/S0376-8716(02)00065-0
454
           Fagan, P., & Rigotti, N. A. (2009). Light and intermittent smoking: The road less
455
              traveled. Nicotine & Tobacco Research, 11(2), 107–110.
456
              https://doi.org/10.1093/ntr/ntn015
457
           Fagerström, K. (2012). Determinants of Tobacco Use and Renaming the FTND to
458
              the Fagerström Test for Cigarette Dependence. Nicotine & Tobacco Research,
459
              14(1), 75–78. https://doi.org/10.1093/ntr/ntr137
460
```

Field, M., & Cox, W. M. (2008). Attentional bias in addictive behaviors: A review of

its development, causes, and consequences. Drug and Alcohol Dependence, 462 97(1-2), 1-20. https://doi.org/10.1016/j.drugalcdep.2008.03.030 463 Field, M., Munafò, M. R., & Franken, I. H. A. (2009). A meta-analytic investigation 464 of the relationship between attentional bias and subjective craving in substance 465 abuse. Psychological Bulletin, 135(4), 589-607. https://doi.org/10.1037/a0015843 466 Field, M., Werthmann, J., Franken, I., Hofmann, W., Hogarth, L., & Roefs, A. (2016). 467 The role of attentional bias in obesity and addiction. Health Psychology, 35(8), 468 767–780. https://doi.org/10.1037/hea0000405 469 Firke, S. (2019). Janitor: Simple tools for examining and cleaning dirty data. 470 https://CRAN.R-project.org/package=janitor 471 Grice, J. W., Medellin, E., Jones, I., Horvath, S., McDaniel, H., O'lansen, C., & 472 Baker, M. (2020). Persons as Effect Sizes. Advances in Methods and Practices in 473 Psychological Science, 3(4), 443-455. https://doi.org/10.1177/2515245920922982 474 Heatherton, T. F., Kozlowski, L. T., Frecker, R. C., & Fagerström, K.-O. (1991). The 475 Fagerström Test for Nicotine Dependence: A revision of the Fagerstrom Tolerance 476 Questionnaire. British Journal of Addiction, 86(9), 1119–1127. 477 https://doi.org/10.1111/j.1360-0443.1991.tb01879.x 478 Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust 479 cognitive tasks do not produce reliable individual differences. Behavior Research 480 Methods, 50(3), 1166–1186. https://doi.org/10.3758/s13428-017-0935-1 481 Hogarth, L. C., Mogg, K., Bradley, B. P., Duka, T., & Dickinson, A. (2003). 482 Attentional orienting towards smoking-related stimuli: Behavioural Pharmacology, 483 14(2), 153–160. https://doi.org/10.1097/00008877-200303000-00007 484 Kang, O.-S., Chang, D.-S., Jahng, G.-H., Kim, S.-Y., Kim, H., Kim, J.-W., Chung, 485 S.-Y., Yang, S.-I., Park, H.-J., Lee, H., & Chae, Y. (2012). Individual differences 486 in smoking-related cue reactivity in smokers: An eye-tracking and fMRI study. 487

Progress in Neuro-Psychopharmacology and Biological Psychiatry, 38(2), 285–293.

```
https://doi.org/10.1016/j.pnpbp.2012.04.013
489
           Kotz, D., Fidler, J., & West, R. (2012). Very low rate and light smokers: Smoking
490
              patterns and cessation-related behaviour in England, 2006-11: Very low rate and
491
              light smokers. Addiction, 107(5), 995-1002.
492
              https://doi.org/10.1111/j.1360-0443.2011.03739.x
493
           Lakens, D. (2017). Equivalence tests: A practical primer for t-tests, correlations, and
494
              meta-analyses. Social Psychological and Personality Science, 1, 1–8.
495
              https://doi.org/10.1177/1948550617697177
496
           Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence Testing for
497
              Psychological Research: A Tutorial. Advances in Methods and Practices in
498
              Psychological Science, 1(2), 259–269. https://doi.org/10.1177/2515245918770963
499
           Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2008). International affective picture
500
              system (IAPS): Affective ratings of pictures and instruction manual. Technical
501
              Report A-8. Gainesville: University of Florida.
502
           Levy, D. E., Biener, L., & Rigotti, N. A. (2009). The natural history of light smokers:
503
              A population-based cohort study. Nicotine & Tobacco Research, 11(2), 156–163.
504
              https://doi.org/10.1093/ntr/ntp011
505
           Mogg, K., Bradley, B. P., Field, M., & De Houwer, J. (2003). Eye movements to
506
              smoking-related pictures in smokers: Relationship between attentional biases and
507
              implicit and explicit measures of stimulus valence. Addiction, 98(6), 825–836.
508
              https://doi.org/10.1046/j.1360-0443.2003.00392.x
509
           Mogg, K., Field, M., & Bradley, B. P. (2005). Attentional and approach biases for
510
              smoking cues in smokers: An investigation of competing theoretical views of
511
              addiction. Psychopharmacology, 180(2), 333-341.
512
              https://doi.org/10.1007/s00213-005-2158-x
513
           Müller, K., & Wickham, H. (2020). Tibble: Simple data frames.
514
              https://CRAN.R-project.org/package=tibble
515
```

```
Parsons, S. (2020). Splithalf: robust estimates of split half reliability.
516
              https://doi.org/10.6084/m9.figshare.5559175.v5
517
           Parsons, S., Kruijt, A.-W., & Fox, E. (2019). Psychological Science Needs a Standard
518
              Practice of Reporting the Reliability of Cognitive-Behavioral Measurements.
519
              Advances in Methods and Practices in Psychological Science, 2(4), 378–395.
520
              https://doi.org/10.1177/2515245919879695
521
           Pennington, C. R., Jones, A., Bartlett, J. E., Copeland, A., & Shaw, D. J. (2021).
522
              Raising the bar: Improving methodological rigour in cognitive alcohol research.
523
              Addiction, 116(11), 3243-3251.
524
              https://doi.org/https://doi.org/10.1111/add.15563
525
           Price, R. B., Kuckertz, J. M., Siegle, G. J., Ladouceur, C. D., Silk, J. S., Ryan, N. D.,
526
              Dahl, R. E., & Amir, N. (2015). Empirical Recommendations for Improving the
527
              Stability of the Dot-Probe Task in Clinical Research, Psychological Assessment,
528
              27(2), 365–376. https://doi.org/10.1037/pas0000036
529
           R Core Team. (2020). R: A language and environment for statistical computing. R
530
              Foundation for Statistical Computing. https://www.R-project.org/
531
           Ramo, D. E., Hall, S. M., & Prochaska, J. J. (2011). Reliability and validity of
532
              self-reported smoking in an anonymous online survey with young adults. Health
533
              Psychology, 30(6), 693-701. https://doi.org/10.1037/a0023443
534
           Revelle, W. (2019). Psych: Procedures for psychological, psychometric, and
535
              personality research. Northwestern University.
536
              https://CRAN.R-project.org/package=psych
537
           Salemink, E., Hout, M. A. van den, & Kindt, M. (2007). Selective attention and
538
              threat: Quick orienting versus slow disengagement and two versions of the dot
539
              probe task. Behaviour Research and Therapy, 45(3), 607–615.
540
              https://doi.org/10.1016/j.brat.2006.04.004
541
           Schäfer, T., & Schwarz, M. A. (2019). The Meaningfulness of Effect Sizes in
542
```

Psychological Research: Differences Between Sub-Disciplines and the Impact of 543 Potential Biases. Frontiers in Psychology, 10, 1–13. 544 https://doi.org/10.3389/fpsyg.2019.00813 545 Schmukle, S. C. (2005). Unreliability of the dot probe task. European Journal of 546 Personality, 19(7), 595–605. https://doi.org/10.1002/per.554 547 Shiffman, S. (2009). Light and intermittent smokers: Background and perspective. 548 Nicotine & Tobacco Research, 11(2), 122–125. https://doi.org/10.1093/ntr/ntn020 549 Shiffman, S., Dunbar, M. S., Li, X., Scholl, S. M., Tindle, H. A., Anderson, S. J., & 550 Ferguson, S. G. (2014). Smoking Patterns and Stimulus Control in Intermittent 551 and Daily Smokers. $PLoS \ ONE, \ 9(3), \ 1-14.$ 552 https://doi.org/10.1371/journal.pone.0089911 553 Shiffman, S., Dunbar, M. S., Scholl, S. M., & Tindle, H. A. (2012). Smoking motives 554 of daily and non-daily smokers: A profile analysis. Drug and Alcohol Dependence, 555 126(3), 362–368. https://doi.org/10.1016/j.drugalcdep.2012.05.037 556 Shiffman, S., Tindle, H., Li, X., Scholl, S., Dunbar, M., & Mitchell-Miland, C. (2012). 557 Characteristics and smoking patterns of intermittent smokers. Experimental and 558 Clinical Psychopharmacology, 20(4), 264–277. https://doi.org/10.1037/a0027546 559 Simonsohn, U. (2015). Small Telescopes: Detectability and the Evaluation of 560 Replication Results. Psychological Science, 26(5), 559–569. 561 https://doi.org/10.1177/0956797614567341 562 Singmann, H., Bolker, B., Westfall, J., Aust, F., & Ben-Shachar, M. S. (2020). Afex: 563 Analysis of factorial experiments. https://CRAN.R-project.org/package=afex 564 Soleymani, A., Ivanov, Y., Mathot, S., & Jong, P. J. de. (2020). Free-viewing 565 multi-stimulus eve tracking task to index attention bias for alcohol versus soda 566 cues: Satisfactory reliability and criterion validity. Addictive Behaviors, 100, 567 106117. https://doi.org/10.1016/j.addbeh.2019.106117 568 St. Helen, G., Benowitz, N. L., Ahluwalia, J. S., Tyndale, R. F., Addo, N., Gregorich,

S. E., Pérez-Stable, E. J., & Cox, L. S. (2019). Black Light Smokers: How 570 Nicotine Intake and Carcinogen Exposure Differ Across Various Biobehavioral 571 Factors. Journal of the National Medical Association, 111(5), 509–520. 572 https://doi.org/10.1016/j.jnma.2019.04.004 573 Tindle, H. A., & Shiffman, S. (2011). Smoking Cessation Behavior Among 574 Intermittent Smokers Versus Daily Smokers. American Journal of Public Health, 575 101(7), e1-e3. https://doi.org/10.2105/AJPH.2011.300186 576 Tong, E. K., Ong, M. K., Vittinghoff, E., & Pérez-Stable, E. J. (2006). Nondaily 577 Smokers Should Be Asked and Advised to Quit. American Journal of Preventive 578 Medicine, 30(1), 23–30. https://doi.org/10.1016/j.amepre.2005.08.048 579 Vollstädt-Klein, S., Loeber, S., Winter, S., Leménager, T., Goltz, C. von der, Dinter, 580 C., Koopmann, A., Wied, C., Winterer, G., & Kiefer, F. (2011). Attention Shift 581 towards Smoking Cues Relates to Severity of Dependence, Smoking Behavior and 582 Breath Carbon Monoxide. European Addiction Research, 17(4), 217–224. 583 https://doi.org/10.1159/000327775 584 Waechter, S., Nelson, A. L., Wright, C., Hyatt, A., & Oakman, J. (2014). Measuring 585 Attentional Bias to Threat: Reliability of Dot Probe and Eye Movement Indices. 586 Cognitive Therapy and Research, 38(3), 313–333. 587 https://doi.org/10.1007/s10608-013-9588-2 588 Wickham, H. (2016). ggplot2: Elegant graphics for data analysis. Springer-Verlag 589 New York. https://ggplot2.tidyverse.org 590 Wickham, H. (2019). Stringr: Simple, consistent wrappers for common string 591 operations. https://CRAN.R-project.org/package=stringr 592 Wickham, H., François, R., Henry, L., & Müller, K. (2020). Dplyr: A grammar of 593 data manipulation. https://CRAN.R-project.org/package=dplyr 594 Wickham, H., & Henry, L. (2020). Tidyr: Tidy messy data. 595 https://CRAN.R-project.org/package=tidyr 596

- Wickham, H., Hester, J., & Francois, R. (2018). Readr: Read rectangular text data. 597 https://CRAN.R-project.org/package=readr 598 Wilke, C. O. (2019). Cowplot: Streamlined plot theme and plot annotations for 599 'qqplot2'. https://CRAN.R-project.org/package=cowplot 600 Wray, J. M., Gass, J. C., Miller, E. I., Wilkins, D. G., Rollins, D. E., & Tiffany, S. T. 601 (2016). A Comparative Evaluation of Self-Report and Biological Measures of 602 Cigarette Use in Non-Daily Smokers. Psychological Assessment, 28(9), 1043–1050. 603 https://doi.org/10.1037/pas0000227 604 Zack, M., Belsito, L., Scher, R., Eissenberg, T., & Corrigall, W. A. (2001). Effects of 605 abstinence and smoking on information processing in adolescent smokers. 606
 - $Psychopharmacology,\ 153 (2),\ 249-257.\ \ https://doi.org/10.1007/s002130000552$