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ORIGINAL INVESTIGATION

A cognitive model-based approach to testing mechanistic explanations for neuropsychological decrements during tobacco abstinence

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Abstract

Rationale Cigarette smokers often experience cognitive decrements during abstinence from tobacco, and these decrements may have clinical relevance in the context of smoking cessation interventions. However, limitations of the behavioral summary statistics used to measure cognitive effects of abstinence, response times (RT) and accuracy rates, may restrict the field's ability to identify robust abstinence effects on task performance and test mechanistic hypotheses about the etiology of these cognitive changes.
Objectives The current study explored whether a measurement approach based on mathematical models of cognition, which make the cognitive mechanisms necessary to perform choice RT tasks explicit, would be able to address these limitations.
Methods The linear ballistic accumulator model (LBA: Brown and Heathcote, Cogn Psychol 57(3):153-178, 2008) was fit to an existing data set from a study that evaluated the impact of overnight abstinence on flanker task performance.
Results The model-based analysis provided evidence that smokers' rates of mind wandering increased during abstinence, and was able to index this effect while controlling for participants' strategy changes that were related to the specific experimental paradigm used.
Conclusion Mind wandering is a putative explanation for cognitive withdrawal symptoms during smoking cessation and may be indexed using the LBA. More broadly, the use of formal model-based analyses in future research on this topic has the potential to allow for strong and specific tests of mechanistic explanations for these symptoms.

Keywords Smoking · Tobacco withdrawal · Cognitive modeling · Bayesian models · Response times

Cigarette smoking is one of the most substantial threats to public health in the USA and abroad, causing an estimated 500,000 premature deaths annually in the USA alone (Services, U. D. o. H. a. H 2014), and 6 million worldwide World Health Organization (2015). Given the salience of smoking's negative health consequences, it is not surprising that almost 70% of current US smokers express a strong motivation to quit (Centers for Disease Control and Prevention 2011). However, even with supportive treatment, the majority of those who quit will eventually relapse (Piasecki 2006). Decrements in cognitive functioning are evident after smokers stop using tobacco and have been hypothesized to contribute to smoking cessation outcomes (Ashare et al. 2014; Ashare and Hawk 2012; Evans and Drobes 2009; Kollins et al. 2013; Kollins et al. 2009; Shiffman et al. 1996). Thus, better understanding these cognitive aberrations may be instrumental for reducing relapse rates.

Abstinence effects are typically studied in "executive" domains, such as attention, working memory, and response inhibition, and are assumed to result from pharmacological changes in the neural systems that mediate them (Ashare et al. 2014; Ashare and Schmidt 2014; Benowitz 2010; McClernon et al. 2015). However, effects on executive task performance appear to be modest and variable; Rhodes and Hawk (2016) recently found small to medium sizes, and poor

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test-retest reliability, of abstinence effects across executive domains. Further, these effects may vary depending on the measure used to index performance. Two recent reviews (Ashare et al. 2014; McClernon et al. 2015) found that experiments investigating the same cognitive domains, or even using the same paradigms (e.g., Go/No-Go tasks), may alternately find abstinence effects in response time (RT) latency, RT variability, or accuracy rate.

The instability of these effects may be explained, in part, by limitations of the performance metrics used. Although assumed to index the integrity of cognitive functions probed by a given task, RT and accuracy statistics are determined by a host of processes, including time spent encoding stimuli, motor response speed, retrieval of task rules from memory, and strategy adjustments (Rae et al. 2014; Ratcliff and McKoon 2008; Shahar et al. 2014). The multi-determined nature of these indices presents two major challenges for measuring, and establishing the causes of, abstinence effects on cognition. First, between-study differences in task instructions and parameters may alter participants' strategies, leading to variable effects. For example, individuals often react to task demands by emphasizing either speed or accuracy in their performance (speed/accuracy trade-offs: Bogacz et al. 2010; Rae et al. 2014). If a task encourages highly accurate responding, accuracy effects may be diminished relative to those in paradigms that do not. Further, these trade-offs may be confounded with abstinence manipulations due to task features (e.g., a response deadline that is more difficult to meet when participants are abstinent).

Second, mechanistic hypotheses about the causes of abstinence-related cognitive changes are difficult to test using RT and accuracy alone. One plausible hypothesis is that these changes result, in part, from secondary influences that cause intermittent lapses of attention to the task. During abstinence, smokers often experience negative mood (Kassel et al. 2003; Piasecki 2006) and cravings for tobacco (Shiffman et al. 1996). In turn, negative mood and craving appear to increase rates of "mind wandering" (Sayette et al. 2010; Smallwood et al. 2009; Smallwood and Schooler 2015), defined as the process by which attention momentarily drifts away from the task to unrelated thoughts, leading to acute lapses in performance (McVay and Kane 2012; Smallwood and Schooler 2006). Mind wandering is often inferred from within-subject RT variability (Bastian and Sackur 2013; McVay and Kane 2012), and findings of greater RT variability in abstinence (Ashare and Hawk 2012; Kollins et al. 2009) provide tentative evidence that mind wandering is prevalent in this state. However, as increased RT variability can also reflect inefficiency of processing (Matzke and Wagenmakers 2009; van Ravenzwaaij et al. 2011), this metric cannot easily differentiate mind wandering from other factors (e.g., sustained cognitive impairments due to withdrawal). Hence, RT variability and similar metrics are limited in their ability to quantify the unique contributions of mind wandering to the cognitive effects of abstinence.

Cognitive models from mathematical psychology, which describe the computational and neural mechanisms that allow humans to complete cognitive tasks (Forstmann and Wagenmakers 2015), may be able to better index cognitive changes during abstinence and test mechanistic hypotheses about their causes for two reasons. First, such models provide frameworks where different mechanistic processes that are hypothesized to underlie withdrawal effects (e.g., reduced efficiency vs. mind wandering) can be distinguished, even if they have similar effects on behavioral summary statistics (e.g., RT variability). Second, by formally modeling additional processes that impact these statistics, such models can index mechanisms of interest while controlling for specific features of paradigms used in individual studies. Indeed, cognitive models have recently shown great promise for doing so in multiple clinical conditions (Fosco et al. 2017; Heathcote et al. 2015; Huang-Pollock et al. 2012; Weigard et al. 2016; White et al. 2010).

One such model, the linear ballistic accumulator (LBA: Brown and Heathcote 2008) frames choice RT tasks as a race between two or more response accumulators that gather evidence from a stimulus at a linear rate, or "drift rate," throughout a trial (Fig. 1(a)). For example, in a task where individuals must make a right button-press when presented with a right-facing arrow, the accumulator for a "right" response would race the accumulator for a "left" response. On any trial, the drift rate for the correct ("right") response accumulator is drawn from a distribution with a mean of *vc* and a standard deviation of *svc*, while the drift rate for the error ("left") accumulator is drawn from one with a mean of *ve* and standard deviation of *sve*. The accumulators start at a point drawn independently for each from a uniform distribution between 0 and the parameter *A*, and race to a threshold denoted by *b*, which, when reached, initiates the winning response. As the mean rate for correct responses (*vc*) is (in tasks participants perform above chance) higher than that for error responses (*ve*), the correct accumulator typically wins. Errors occur when between-trial variability causes the error accumulator to reach *b* first. Finally, a *t0* parameter indexes "non-decision" (early perceptual and motor) components of RT.

When the LBA is fit to empirical data, sustained cognitive impairments due to abstinence would be reflected by reduced efficiency of processing, which has been indexed in prior research (Ester et al. 2014) as decreases in *vc* relative to *ve*. In contrast, mind wandering due to abstinence would result in less efficient processing during affected trials (i.e., those in which the smoker is distracted by negative affect), but not unaffected trials, leading to greater drift variability, as captured by *sv* parameters. Previous work has suggested *sv* is a more specific index of mind wandering than intra-individual RT variability, which may occur due to between-trial variability in processing (i.e., *sv*), but may instead occur due to decreased overall efficiency (i.e., *v*) of processing (Hawkins et al. 2015). Indeed,

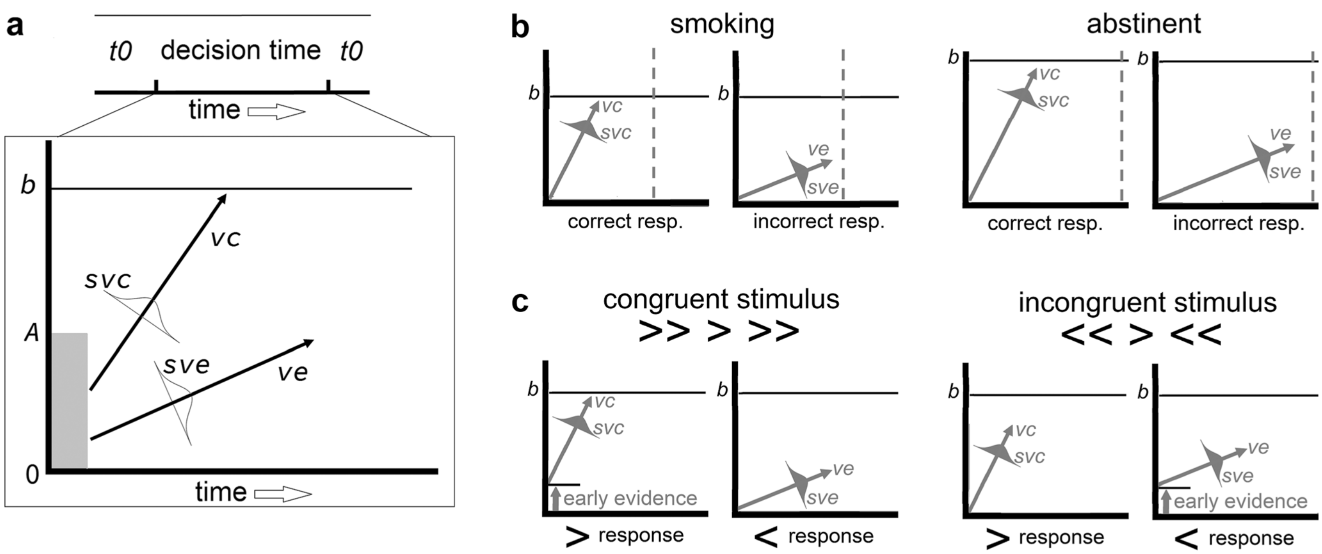

Fig. 1 Representation of the decision-making process as described by the LBA model. (a) Schematic of the model, including a parameter for non-decision time (*t0*), which indexes the amount of time spent on processes that occur before and after the decision process (e.g., perceptual encoding, motor response). During the decision time (enlarged section), mean drift rates for the correct (*vc*) and error (*ve*) responses determine the average rate of evidence accumulation for each respective response, while drift variability parameters (*svc*, *sve*) determine between-trial variability in these rates, which are assumed to be normally distributed. The accumulation processes start at a point drawn from a uniform distribution between 0 and the *A* parameter, and race to a threshold determined by the *b* parameter. (b) The adaptive response deadline (represented by the gray dotted line) in the experimental paradigm of Schlienz et al. (2013) was longer in the abstinent condition than in the smoking condition. This increase in deadline would encourage participants to wait for more evidence to accumulate before making a decision in the abstinent condition, which is reflected by an increase on the *b* parameter. (c) On trials with congruent stimuli, early evidence from the flanking arrows raises that start point of the matching response accumulator, reducing its distance-to-threshold. On incongruent trials, early evidence from the flanking stimuli raises that start point of the mismatching accumulator, leading to faster error RTs and reduced accuracy in this condition

McVay and Kane (2012) found that *sv* was more closely related to self-reported attentional lapses than mean drift (*v*) parameters. Thus, the LBA allows putative mechanisms of cognitive abstinence effects, reduced efficiency, and increased mind wandering, to be discriminated from each other and from other processes that affect RTs (e.g., *t0* or *b*).

In the current study, we aimed to make such discriminations by applying the LBA to archival data from a study in which smokers completed a choice RT task while smoking as usual and following overnight abstinence (Schlienz et al. 2013). The LBA analysis is appropriate for this data set, not only because the study previously found abstinence effects in RT latencies, but also because a study-specific feature of the experimental design may have contributed, in part, to this effect. To equate accuracy between smoking as usual and abstinent conditions, a personalized response deadline (determined by participants' mean RT on a practice block at each session) was used. This deadline was, as predicted, slower during abstinence, and was effective at equating accuracy (Schlienz et al. 2013). Because the deadline gave participants additional time to respond in the abstinent condition, it may have encouraged them to wait for additional evidence to accumulate before making decisions. Such a strategy adjustment is described by the LBA as an increase in *b* (Fig. 1(b)); higher levels of *b* lead to more accurate decisions because they allow more evidence to accumulate, but increase the latency and variance of RTs, as the decision process takes longer (Rae et al. 2014). Hence, the goal of this study was to use the LBA to identify whether changes in one or more putative mechanisms of abstinence effects, reduced efficiency (*vc* - *ve*) or increased mind wandering (*sv*), contributed to abstinence effects in RT, while controlling for strategy changes encouraged by the specific paradigm (*b*).

Methods

Sample and procedure

This study utilized data collected in a previous project (Schlienz et al. 2013) which investigated the effects of abstinence and monetary incentives in a sample of smokers ($N = 25$) aged 18 and older (Mean = 40, SD = 11; Table 1). Participants completed a modified Eriksen flanker task at two study visits: following overnight abstinence (> 12 h), and while smoking as usual. Smoke exposure and compliance with the abstinence manipulation were biochemically verified using an expired carbon monoxide (CO) sample. Following the CO sample and completion of other measures, participants performed the task during EEG data collection. All study

Table 1 Basic demographic and smoking-related characteristics of the study sample, as reported in the original study (Schlienz et al. 2013). Numbers in parentheses indicate the standard deviation unless otherwise noted

N (males:females)	25 (13:12)
Race/ethnicity:	80% Caucasian, 4% Hispanic, 16% Other
Age	40 (11)
Cigarettes per day	22 (7)
Fagerstrom Test of Nicotine Dependence (FTND) score	5.6 (1.1)

procedures were approved by the Institutional Review Board of the institution at which the data were collected, and were in compliance with the Declaration of Helsinki.

Stimuli consisted of a central target arrow pointing to the left (<) or right (>), flanked by congruent (e.g., << < <<) or incongruent (<< > <<) arrows presented with equal probability. Stimuli were presented for 150 ms, followed by a variable response window (1200–1600 ms), visual feedback (300 ms), and inter-trial interval (1000–1400 ms). Participants indicated the direction of the central arrow via button-press, and were encouraged to respond before a personal deadline (mean RT + 0.5 SDRT) determined during a practice block at the start of each session. The study employed this deadline to examine abstinence effects on error-related brain activity by minimizing accuracy differences between sessions, and the deadline was longer in the abstinent session (see Schlienz et al. 2013). As the deadline would likely impact speed/accuracy trade-offs by allowing participants more time to respond in this session, we expected the *b* parameter to increase in abstinence, accounting for this potential confound (Fig. 1(b)). After the practice block, participants completed four 200-trial test blocks; two blocks reinforced correct "fast" responses with a small monetary reward whereas, on the other two, participants were instructed to try their best and were not rewarded. The current study only used trials from non-rewarded blocks because the question of whether cognitive abstinence effects in model parameters varied by incentive conditions was beyond the scope of this study, and addressing it would greatly increase the complexity of the model selection analyses detailed below. To provide the maximum number of trials per condition, as drift variability parameters are difficult to estimate reliably with few trials (Voss et al. 2013), the blocks were collapsed for analysis. RTs after the deadline were included to avoid fitting the LBA to censored RT distributions.

Data analysis

Basic model structure

The *v* and *sv* parameters were allowed to vary between correct (*vc, svc*) and error (*ve, sve*) response accumulators, and *b* was parameterized as positive and equal to the height of the threshold above *A*. Accumulator models have a "scaling" property; a subset of their parameters can be multiplied by an arbitrary amount without changing their predictions. This issue is resolved by fixing a parameter (often *v* or *sv*) to an arbitrary value to constrain the model (Donkin et al. 2009). We fixed *sve* to 1 in models that did not allow *sv* to differ by Smoke Condition, and *sve* for the smoking session in those that did. The choice of this "scaling" parameter was based on the fact that it would likely be the most difficult to estimate, given the challenges of estimating drift variability and the lower number of error RTs. This allowed us to probe differences in *sve* by comparing *sve* in the abstinent session to 1.

Several parameters were allowed to vary between congruent and incongruent conditions. Although incongruent trials result in generally slower RT and poorer accuracy, White et al. (2011) found that a key feature of these trials, in which errors are faster than correct responses, was best described by models that allowed drift rate to change over the time course of the decision. Their model assumed evidence early in the decision process is biased toward the incorrect response by the peripheral arrows, but, as attention narrows on the central target arrow over time, later evidence is more likely to be in favor of the correct response. The standard LBA does not allow drift rates to change over the decision (but see Holmes et al. 2016). However, Heathcote and Hannah (2013) proposed that flanker interference effects, as well as related effects in Stroop and Simon tasks, could be captured by a combination of two factors: an early priming effect that gives a head start to the accumulator corresponding to the interfering information, and a persistent effect that weakens the difference between rates for correct and error responses. Specifically, early evidence is assumed to increase the start point of the accumulator favored by flanking arrows (the correct response in the congruent condition and incorrect response in the incongruent condition; Fig. 1(c)). Because accumulation in the LBA is linear, the start point increase has the same effect as an equivalent reduction in threshold, so the priming effect can be represented as a lower *b* for accumulators corresponding to the flanking arrows. In addition, to accommodate any persistent effect, *v* was allowed to vary by congruency.

Estimation and model selection

To ensure that contaminant RTs would not bias parameter estimates (Ratcliff and Tuerlinckx 2002), RTs < 150 ms were excluded as fast guess trials and RTs > 1200 ms, and were removed as outliers (< 1% of trials). Models were estimated using a hierarchical Bayesian version of the LBA (Turner et al. 2013) in Dynamic Models of Choice (DMC: Heathcote et al. 2017: https://osf.io/pbwx8/; Heathcote et al. 2018), a free set of R (R Core Team 2013) functions for fitting RT models. This approach estimates posterior distributions over individual-level parameter values, as well as parameters representing group-level distributions, which are described by mean (μ) and standard deviation (σ) hyper-parameters. Priors and estimation details are in Supplemental Materials.

Models that allowed all possible combinations of parameters of interest (v, sv, b) to vary between abstinence conditions were estimated and compared with indices of model fit that penalize model complexity. As adding parameters necessarily improves fit, such penalties balance fit with model parsimony. The Watanabe-Akaike information criterion (WAIC: Watanabe 2010) was the primary index used. To determine whether the difference between WAIC scores of two models (ΔWAIC) was credible, the standard error (SE) of the difference was computed with the "paired estimate" method (Vehtari et al. 2016) using the "loo" R package (Vehtari et al. 2016a). We considered models to have "credibly different" fit if ΔWAIC exceeded the SE. This procedure determines *relative* fit; plots comparing empirical data with data predicted by the models (Supplemental Materials) were used to inspect whether models provided an adequate description of behavioral data in an absolute sense.

Hypothesis testing

Evidence for differences between parameter values was assessed by calculating (as described in Supplemental Materials) the proportion of the posterior difference in parameters, averaged over individuals, that was above 0 (P). P quantifies the probability that the posterior difference distribution is consistent with the hypothesis that a difference exists. Ps > .75 were considered positive, but weak, evidence, while Ps > .95 were considered strong evidence.

Correlation analysis

To determine whether abstinence-related parameter changes were correlated with relevant individual differences, several covariates were investigated. First, it was predicted that any abstinence-related changes in sv would be related to negative affect during the abstinent session, consistent with the mind wandering hypothesis. Participants completed the positive and negative affect scale, where they rated the intensity of a variety of positive (e.g., "Interested") and negative (e.g., "Irritable") emotions, at both sessions. We therefore used the negative affect scale in the abstinent session (PANAS-NA), as well as the change in this scale between the smoking and abstinent sessions (ΔPANAS-NA) as covariates. Abstinent session scores were used in addition to change scores because one participant was missing PANAS data from the smoking session, precluding calculation of change scores in the full sample. Second, as response deadline effects were assumed to be accounted for by b, it was predicted that such deadlines selectively correlate with changes in b. We therefore used deadlines in the abstinent condition, as well as changes from the smoking condition (Δdeadline),[1] to test this prediction. As individual-level parameters from hierarchical models are not independent, traditional correlation tests are inappropriate (Boehm et al. under review). Therefore, a "plausible values" analysis (Supplemental Materials: Ly et al. 2017, 2018; Marsman et al. 2016) was conducted to estimate posteriors of the correlation coefficient (r) and P for the presence of a correlational relationship.

Results

Model comparison and fit

Table 2 displays relative fit statistics for all models, named with letters that correspond to their ranking from the best (A) to worst fitting (G). Model A, the least constrained model, did not display credibly better fit than model B (ΔWAIC = 24.49, SE = 25.56), but did display credibly better fit than model C (ΔWAIC = 31.67, SE = 29.18), model D (ΔWAIC = 63.98.1, SE = 55.26), and the remaining models, which fit the data relatively poorly (ΔWAIC > 204.36, SE < 94.99). Therefore, model A appears to be the best-fitting model when compared to all other models except B. Plots of absolute fit (Supplemental Materials) confirmed that both Models A and B described the data well and predicted fast errors on incongruent trials, consistent with prior models (White et al. 2011). The fact that the more parsimonious of the two, model B, displays comparable fit to model A without allowing v to vary, suggests that v differences found between visits in A are spurious. Indeed, relative fit indices, despite penalizing for complexity, can select models that are more complex than necessary (Millar 2018; Spiegelhalter et al. 2014), suggesting that model A may be overfit. We therefore based inferences about abstinence effects on the evidence for, and directionality of, parameter differences in both models. Effects were considered robust if they were present, and in the same direction, in models A and B.

Model parameter differences and correlations

Evidence from model A is reported, but instances in which these results contradicted model B (see Table 3) are noted. Figure 2 displays group μ posteriors for parameters with robust abstinence effects as violin plots. Note that density in these plots reflects relative levels of certainty about the location of the group mean, and not between-subject variability.

[1] The participant with missing PANAS data in the smoking condition was also excluded from the analysis using Δdeadline as a covariate so results from this analysis could be properly compared with the one using ΔPANAS-NA.

Table 2 Ranking of flanker task models by WAIC score from the best- to worst-fitting (A-G). Parameters allowed to vary between smoking and abstinent visits are denoted by "X" and columns to the right denote the WAIC score of the full hierarchical model and the raw standard error (SE) of that score. The average deviance information criterion (DIC: Spiegelhalter et al. 2002) was also calculated for each model to determine whether the rankings produced by WAIC would agree with other accepted indices

Model/rank	*v*	*sv*	*b*	WAIC	SE - WAIC	DIC
A	X	X	X	− 43,540.07	379.29	− 1745.843
B		X	X	− 43,515.58	378.77	− 1743.731
C	X		X	− 43,508.40	379.79	− 1743.654
D	X	X		− 43,476.10	383.90	− 1742.603
E	X			− 43,335.71	383.71	− 1734.293
F			X	− 43,224.32	381.22	− 1731.484
G		X		− 41,473.35	372.06	− 1660.550

Mean drift rate

As expected, there was evidence that *vc* was slower, $P > .99$, and *ve* was faster, $P > .99$, on incongruent trials, indicating that longer RTs and lower accuracy on these trials are due, in part, to poorer evidence quality. There was also evidence for main effects of smoke condition and a smoke x congruency interaction in model A, indicating that participants' efficiency of processing *improved* during abstinence. As an improvement seems implausible, and so likely reflects a tradeoff between parameters caused by overfitting, and as model B did not allow *v* to vary, these effects (discussed in Supplemental Materials) were not considered robust.

Drift rate variability

There was strong evidence that *svc* was greater during the abstinent, relative to smoking, session, $P > .99$. However, effects of *sve* varied between models (Table 3). Although *sve* effects were not robust, effects in *svc* provided unambiguous evidence that between-trial variability in the processing of relevant information increased during abstinence, supporting the hypothesis that mind wandering is more prevalent in this state.

Response boundary

There was evidence for an effect of congruency, $P > .99$, in which *b* for responses with congruent flanking arrows was lower than *b* for those with incongruent ones, and an interaction, $P > .99$, in which the effect of congruency was larger in abstinence. This pattern suggests that flanker effects are due, in part, to reductions in the distance-to-threshold for accumulators congruent with the flanker arrows, and this effect is more pronounced during abstinence. As expected, there was also evidence that *b* was higher in abstinence, $P > .99$, indicating that this parameter accounts for the potential confound of longer response deadlines.

Plausible values correlation analysis

Changes in parameters that displayed abstinence effects (Δsvc, Δb) were entered into plausible values analyses with all covariates (Table 4, Fig. 3). PANAS-NA scores in the abstinent condition displayed evidence of a positive relationship with Δsvc, $P = .94$, and a weaker relationship with Δb, $P = .83$ (Fig. 3(a)). However, ΔPANAS-NA was unrelated to either (Fig. 3(c)). As expected, response deadline in the abstinent condition and Δdeadline were both strongly related to Δb, $P \geq .99$, but not Δsvc, $P < .66$ (Fig. 3(b, d)).

Discussion

In this study, the LBA model (Brown and Heathcote 2008) was fit to data from an experiment assessing effects of tobacco abstinence on flanker performance (Schlienz et al. 2013) to evaluate its utility for testing mechanistic hypotheses about

Table 3 Comparison of directionality of, and evidence for (*P*), between-condition parameter differences for the models A and B. Effects that are inconsistent between models are denoted with an asterisk (*)

Parameter	Model	Congruency effect	Smoke condition effect	Interaction
vc	A	Con. > Incon., $P > .99$	Abst. > Smoke, $P > .99$*	$P = .97$*
	B	Con. > Incon., $P > .99$	*NA*	*NA*
ve	A	Con. < Incon., $P > .99$	Abst. < Smoke, $P > .99$*	$P > .99$*
	B	Con. < Incon., $P > .99$	*NA*	*NA*
svc	A	*NA*	Abst. > Smoke, $P > .99$	*NA*
	B	*NA*	Abst. > Smoke, $P > .99$	*NA*
sve	A	*NA*	Abst. > Smoke, $P > .99$*	*NA*
	B	*NA*	Abst. < Smoke, $P > .99$*	*NA*
b	A	Con. < Incon., $P > .99$	Abst. > Smoke, $P > .99$	$P > .99$
	B	Con. < Incon., $P > .99$	Abst. > Smoke, $P > .99$	$P = .96$

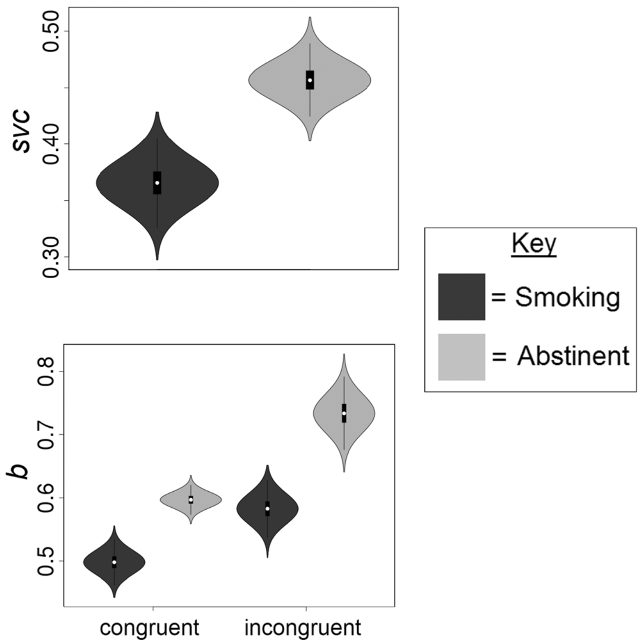

Fig. 2 Posterior distributions of group μ model parameter estimates from model A, the least constrained model, for parameters that displayed robust effects of abstinence (*svc*, *b*). Distributions are displayed as violin plots, which contain a box plot of posterior samples inside a kernel density plot of the same samples. Violin plots of group μ posteriors for other LBA parameters of interest from both models A and B are displayed in Supplemental Fig. 2

abstinence effects, and measuring changes in mechanisms of interest separately from other factors. Models converged on two general changes in the abstinent condition: increases in between-trial variability of evidence accumulation for correct responses (*svc*) and increases in response threshold (*b*). Increases in *b* were predicted to account for the effects of longer adaptive response deadlines in the abstinent condition, a prediction that was strongly supported by the selective correlational relationship between individuals' response deadlines and changes in *b*. However, the increase in *svc* supports the hypothesis that mind wandering, potentially caused by subjective feelings of distress (Kassel et al. 2003; Piasecki 2006) and/or craving (Sayette et al. 2010), may drive abstinence-related cognitive decrements. The magnitude of increases in *svc* was positively correlated with negative affect in the abstinent condition, but was not correlated with *changes* in negative affect from the smoking condition. This disparity may indicate that affect is a moderator, rather than a mediator, of mind wandering effects; individuals who experience negative affect during abstinence may experience greater mind wandering in this state, even if abstinence is not the cause of this affect. Alternately, given the possible unreliability of change scores (Johns 1981), abstinent condition scores may simply have been less noisy. Regardless, evidence for a relationship with mood is consistent with prior work on mind wandering (Smallwood and Schooler 2015).

The results have two main implications for the literature on cognitive abstinence effects. First, they suggest model-based metrics may be better-equipped to test mechanistic explanations about neurocognitive changes during abstinence than behavioral summary statistics used in the current literature. Summary statistics from the original study indicated that cognitive performance was impaired in abstinence, but the effect of increased RT latency (1) did not suggest a specific theoretical mechanism of impairment and (2) could be attributed to both the abstinence-related mechanisms of interest and to response deadlines, a unique feature of the paradigm. The LBA provided a mechanistic explanation for both abstinence effects (mind wandering) and deadline effects (increased caution), and this dissociation was further supported by selective relationships of model parameters with covariates. Thus, application of cognitive modeling to other abstinence paradigms may reconcile variability in the findings of individual studies by indexing processes of interest while controlling for paradigm-specific effects.

Although parameters which measure constructs of interest (e.g., Δ*svc*) may be expected to better predict covariates than other measurements (e.g., ΔSDRT), Pearson correlation (*r*) values for the relationships between covariates and summary statistics (Fig. 3; Table 4) were comparable to *r* posteriors for parameters. However, the study's relatively small sample and use of non-independent individual posteriors makes direct

Table 4 Relevant statistics for covariates used in the plausible values analysis: the negative affect subscale of the positive and negative affect scale from the abstinent condition (Abst. PANAS-NA), the personalized response deadline from the abstinent condition (Abst. deadline), change in the PANAS-NA (ΔPANAS-NA), and change in the response deadline (Δdeadline). All change scores (Δ) were calculated by subtracting the baseline condition from the abstinent condition. ΔMRT $r = r$ for the relationship between changes in mean RT and the covariate; ΔSDRT $r = r$ for the relationship between changes in the standard deviation of RT and the covariate; Δ*sv* median *r* (*P*) = most likely *r* value and *P* value for the relationship between Δ*sv* and the covariate; Δ*b* median *r* (*P*) = most likely *r* value and *P* value for the relationship between Δ*b* and the covariate

Measure	Mean (SD)	ΔMRT *r*	ΔSDRT *r*	Δ*sv* median *r* (*P*)	Δ*b* median *r* (*P*)
Abst. PANAS-NA	16.40 (5.40)	.21	.36	.35 (*P* = .94)	.21 (*P* = .83)
Abst. deadline	0.531 (0.100)	.56	.30	.05 (*P* = .57)	.48 (*P* = .99)
ΔPANAS-NA	1.08 (7.80)	− .02	.07	.00 (*P* = .52)	− .06 (*P* = .62)
Δdeadline	0.055 (0.105)	.87	.42	.11 (*P* = .66)	.84 (*P* > .99)

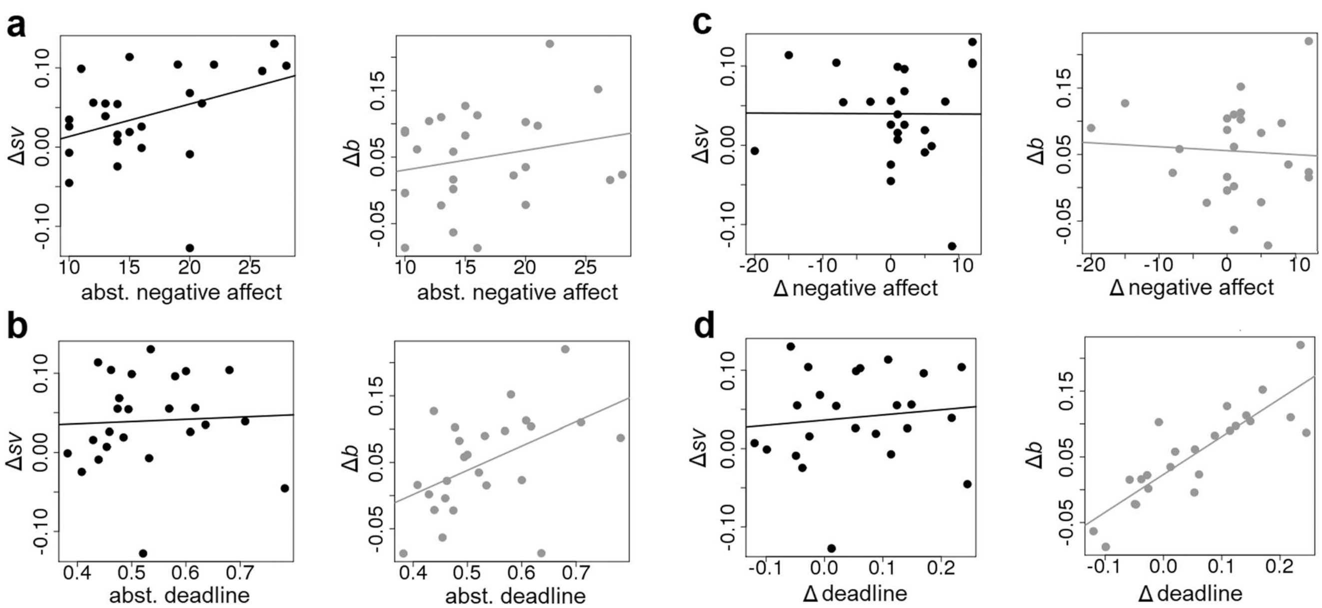

Fig. 3 Scatterplots of the relationship between each covariate used in the plausible values analysis and the mean of individuals' posterior distribution for changes (abstinent visit–smoking visit) in drift variability for the correct response (Δsvc) and response thresholds (Δb). (a) Relationships between model parameter changes and participants' PANAS negative affect scale score from the abstinent condition. (b) Relationships between model parameter changes and participants personalized response deadline from the abstinent condition. (c) Relationships between model parameter changes and change in the PANAS-NA scale score. (d) Relationships between model parameter changes and changes in personalized response deadlines

comparison of the predictive value of parameters and summary statistics difficult. Therefore, the current study advances research aimed at establishing the presence and etiology of cognitive abstinence effects, rather than that on predictive utility, and suggests modeling basic processes that contribute to task performance may be a fruitful alternative to this field's current focus on complex cognitive domains. Indeed, a similar approach to the study of ADHD has recently provided evidence for task-general decrements in cognitive efficiency (Karalunas et al. 2014; Weigard and Huang-Pollock 2017), questioning that field's need to invoke complex "executive" constructs.

Second, the results suggest several future research directions to explore mind wandering as a mediator of abstinence effects. To bolster the assumption that *svc* reflects mind wandering, efforts should be made to link abstinence-related Δsvc to other indices of the construct, such as reports of task-unrelated thoughts (Christoff et al. 2009; McVay and Kane 2009, 2012) and their neural correlates (Christoff et al. 2009; Mittner et al. 2014). Further, experiments that manipulate subjective aspects of tobacco withdrawal, such as negative affect, craving, or cue reactivity (Levin et al. 2006; McClernon et al. 2015; Zelle et al. 2017), would be instrumental in identifying mediators of *svc* effects. Finally, if *svc* is demonstrated to be a specific and reliable index of mind wandering, it may ultimately be useful for identifying individuals who benefit from mindfulness-based interventions, or for monitoring treatment responses for such interventions.

Beyond these implications, results suggested the flanker effect could be explained by a combination of factors: (1) reductions in *b* for responses congruent with flanking stimuli, and (2) decreased *vc* and increased *ve* (i.e., poorer quality of evidence) on incongruent trials. Similar results were reported by Heathcote and Hannah (2013) in a re-analysis of data from the five experiments by White et al. (2011), and account for the difference between the effects of the flanking stimuli on early vs. late evidence. Early in the decision, strong evidence in favor of the response indicated by the flanking stimuli increases the baseline activity of this response accumulator, lowering its distance-to-threshold (*b*). Over time, as attention narrows on the target arrow (White et al. 2011), the influence of flanking stimuli diminishes, but is not eliminated, as reflected by the reduction in evidence quality. Intriguingly, the flanker effect in *b* was greater in abstinence. If the *b* effect reflects the degree to which early evidence is impacted by irrelevant stimuli, this finding may indicate abstinence-related changes in attentional control (i.e., the ability to narrow attention to the target), a possibility that should be explored in future work.

Several limitations should be acknowledged. First, as noted in the original study, the sample was comprised of heavy smokers (Schlienz et al. 2013) and it is unclear whether results would generalize to samples of light or intermittent smokers. Second, as there is evidence that nicotine contributes to cognitive enhancement in non-smokers (Heishman et al. 2010), it is not possible to determine whether the effects observed are unique to abstinence, or are primarily driven by this enhancement. Finally, despite the robust abstinence for effects in *svc*, the direction of the effect in *sve* was inconsistent between models, potentially undermining the interpretation that mind wandering increases in abstinence. However, as noted in previous model-based studies (Mittner et al. 2014), error accumulator parameters (*ve*, *sve*) are often more difficult to estimate and draw inferences from than correct accumulator parameters, especially in paradigms with low error rates. Nonetheless, differences between abstinence effects in *svc* and *sve*, and their links to other indices of mind wandering, should be further explored.

In sum, the current study used a cognitive model-based approach to provide evidence that tobacco abstinence-related cognitive decrements are caused, in part, by increases in mind wandering, and demonstrated the utility of such models for indexing this construct of interest, while assessing, and controlling for, paradigm-specific effects on performance. These findings advocate for future work aimed at probing mind wandering as a plausible mediator of abstinence effects, and argue for the inclusion of cognitive modeling in future research on these effects.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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