

Replication of ‘Cognitive Control Predicts Use of Model-based Reinforcement Learning’ by  
Otto, Skatova, Madlon-Kay & Daw (2014, *Journal of Cognitive Neuroscience*)

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## Introduction

Traditionally, reinforcement learning (RL) and cognitive control have been studied in two distinct literatures. Nevertheless, there are many commonalities between the two systems including analogous computational mechanisms and overlapping neural substrate. One account of reinforcement learning postulates two learning mechanisms for decision making: model-free and model-based learning. The former is a habitual system that directly invigorates and suppresses action based on rewards and punishments, while the latter constructs an action ‘policy’, specifying the optimal choices conditioned on the environmental structure and agent goals. These systems are proposed to work in parallel, each contributing to an agent’s ultimate choice. A two-stage sequential choice task measures aspects of these two systems, and has shown that human choice behavior reflects a mixture of model-based and model-free RL.

Given this mixture of systems, Otto and colleagues were interested in individual differences affecting the contribution of model-based RL system to choice behavior. Making choices in line with model-based rather than model-free RL shares conceptual similarities with cognitive control, which also requires leveraging “higher-order representations to overcome habitual, stimulus-drive action” (Braver, 2012). Seen in this way, the author’s propose that model-free decisions are analogous to prepotent responses, which cognitive control overcomes by upregulating the model-based system. Specifically, they showed that cognitive control relates to a model-based RL metric as measured by the two-stage task previously mentioned. They used two separate paradigms to measure cognitive control in two experiments, including the stroop task in experiment 1, which will be used in this replication.

## Methods

### Power Analysis

The primary finding of interest is a three-way interaction between a model-based RL metric (itself a two-way interaction between reward and transition in the two-stage decision task) and the stroop incongruency effect. This interaction is part of a larger regression model. As such, the effect is a b-value, which the original study found equaled  $-.06(.03)$ . The degrees of freedom are difficult to assess as the study used mixed models with 45 subjects and 120/350 trials in the stroop and decision task respectively. Given that the df will be no more than 45, and to be as conservative as possible, I assessed the effect size of their coefficient t-test using 45 df. Converting this t-value to an effect-size results in a Cohen’s  $d$  of .6. My power analysis using g\*power indicated that I would need fewer than the original samples size for 80% power ( $n=25$ ). For 90% power I would need 32 subjects.

### Planned Sample

This study aims to relate behavior on two separate, previously validated behavioral paradigms. One rule for data collection is to only analyze this relationship after significant effects are achieved for each individual task. While a ‘significant effect’ is clearly defined for the stroop task, such a criteria does not hold for the two step decision task, excepting that we see no mixture of model-based and model-free learning strategies. In addition, individual task significance may require fewer subjects than the statistic of interest. Thus we will prespecify the number of subjects successfully run through the task (allowing for removal of subject failed to reach a performance criteria, outlined below), based on the power analysis above. For 80% power that means  $n=25$ .

There were a number of criteria used by the original authors to exclude subjects, particularly when the sample was collected on mTurk. Subjects in the original experiment were excluded if they exhibited an error rate greater than 25% on the stroop task. The authors do not indicate if this is the average error rate across both blocks (congruent and incongruent blocks), but we will assume it is, allowing for greater than 25% error rate on either particular block. In addition if the subject misses more than 10 deadlines in the stroop task or 20 deadlines in the two-stage task they will be excluded. Participants were also excluded if their probability of repeating a second-stage choice given a reward was less than 50% for the second-stage choices ( $P(\text{stay}_i | \text{win}_{i-1})$ ). That is, given a choice between two second stage stimuli, participants must choose the previously rewarded second-stage response at least 50% of the time. This criterion is defensible as the main dependent variable of interest, the probability of repeating the same first-stage choice, is logically independent of second-stage choice behavior.

I also included catch-trials in my experimental design which were used to further exclude subjects. There were six catch trials during the decision-making task which required subjects to either respond to the left or right, or do nothing. If subjects failed more than one of these catch trials they were excluded.

## **Materials**

Stimuli will be composed of colored words, fractal images, and monetary reward signs. The experiment code will employ the jspsych library, and analysis will use the R statistics package, making use of the lme4 package and the “esticon” function in the doBy package. Amazon Mechanical Turk will be used for subject recruitment and payment. Subjects will be paid a base pay of \$1.5 with a possible bonus contingent on their performance on the two-stage decision task ranging from \$0-\$1 USD. I will be using a lower base pay than the original authors used for their mechanical turk sample (base pay = \$2) because I am using the stroop task to assess cognitive control, which is significantly shorter than the task they used in their online experiment.

## **Procedure**

For both the stroop and two-stage decision task, subjects will be presented instructions and then given practice blocks of either 24 (for the stroop) or 10 (for the two-stage task) trials. The authors do not mention if they counterbalanced the presentation of two tasks - in this online implementation, the ordering of the tasks will be randomized.

Below is the procedural description of each task, quoted from the task description from the original paper. Bracketed phrases have been added to either clarify or detail the methods used in this replication when they differ from the original.

### **Stroop Task**

“Participants performed a computerized version of the Stroop task (Besner, Stolz, & Boutilier, 1997), which required them to identify, as quickly and as accurately as possible, in which one of three colors the word on the screen was presented. In each trial, before the stimulus, participants saw a fixation cross in the center of the screen for 200 msec. One of three color words (“RED,” “GREEN,” or “BLUE”) was displayed either in red, green, or blue on a black background, in 20-point Helvetica bold font, until participants responded. Participants responded using labeled keys on the keyboard (“b” = blue, “g” = green, “r” = red). There was an intertrial interval of 250 msec. Participants received two blocks, each of 120 trials. In one block (“incongruent infrequent” [referred to as “infrequent”]), 80% of the trials were congruent (e.g., RED in red type) and 20% were incongruent (e.g., RED in blue type), whereas in the other block type (“incongruent frequent” [referred to as “frequent”]), these proportions were reversed. [The order of the blocks were randomized across participants.] Participants were not informed about the differences between the blocks and were given a short break between blocks. Before each experimental block, participants received a block of 24 practice trials. In the practice trials, but not the experimental trials, participants received feedback on the screen indicating whether their response was correct or not. Trials in which participants made errors were excluded from analysis.”

### **Two-step Decision-making Task**

“Each participant undertook 200 trials of the two-stage decision task (Figure 1A) described in detail by Daw et al. (2011). On each trial, an initial choice between two options labeled by [fractal shapes] led probabilistically to either of two second-stage “states,” represented by different colors. Each first-stage choice was associated with one of the second-stage states and led there 70% of the time. In turn, each of the second-stage states demanded another choice between another pair of options labeled by [fractal shapes]. Each second-stage option was associated with a different probability of delivering a monetary reward (vs. nothing) when chosen. To encourage participants to continue learning throughout the task, the chances of payoff associated with the four second-stage options were changed slowly and independently throughout the task, according to Gaussian random walks [(mean 0, SD .025)]. In each stage, participants had 2 sec to make a choice. [Interstimuli and intertrial intervals were both 1000 ms, and monetary reward was presented for 500 msec.]”

### **Analysis Plan**

The analysis followed the original authors as closely as possible. I have supplemented the original description where ambiguities occur. These supplements are indicated by brackets.

“For each participant, we first estimated their Stroop incongruency effect (IE) on correct trials for incongruent trials in each block type using a linear regression with RTs as the outcome variable and explanatory variables that crossed the [block type (infrequent vs. frequent) with an indicator of congruency (congruent vs. incongruent)]. Before being entered into the regression, RTs were first log-transformed to remove skew (Ratcliff, 1993) and then z-transformed with respect to RTs on all correct trials. Furthermore, the linear model contained an additional nuisance variable to remove the influence of stimulus repetitions, documented to facilitate faster RTs (Kerns et al., 2004). Each participant’s individual regression yielded two coefficients of interest: the IE for the incongruent-infrequent block and the IE for the incongruent-frequent block. [These IE were kept in log-space for further analysis]. To assess model-based and model-free contributions to trial-by-trial learning, we conducted a mixed-effects logistic regression to explain participants’ first-stage choices on each trial (coded as stay or switch relative to previous trial) as a function of the previous trial’s outcome (whether or not a reward was received on the previous trial and whether the previous transition was common or rare). Within-participant factors (the intercept, main effects of reward and transition, and their interaction) were taken as random effects across participants, and estimates and statistics reported are at the population level. To assess whether these learning effects covaried with the Stroop effect, the four variables above were each additionally interacted, across participants, with the infrequent IE and frequent IE, entered into the regression as z-scores. The mixed-effects logistic regressions were performed using the lme4 package (Pinheiro & Bates, 2000) in the R programming language. Linear contrasts were computed in R using the “esticon” function in the doBy package (Højsgaard & Halekoh, 2009). The individual model-based effects plotted in Figure 2A and B are the estimated per-participant regression coefficients from the group analysis (conditioned on the group level estimates) superimposed on the estimated group-level effect.”

To summarize, IE effects will be estimated for both stroop conditions for each condition. These effects will then be interacted with a transition type (common/rare) by reward type (rewarded/unrewarded) interaction to predict first-choice switch behavior on the two-stage decision task. The transition x reward coefficient is taken as an index of model-based RL. Thus a negative coefficient for the three way interaction, transition x reward x IE, indicates that enhanced control (as measured by reduced slowing on the incongruent condition, and a lower IE) relates to increased model-based RL.

### **Differences from Original Study**

This study will be conducted on mechanical turk, rather than in person. In other aspects the studies will be identical, save for the specific abstract characters used in the two-step decision making task (though they will still be fractal images), which should cause no differences. The two-step decision making task has been previously conducted online, and was successfully run for experiment 2 of the present study. Trial count and other timing elements will be based on this mechanical turk version. The stroop task will be recreated exactly matching the characteristics of the present study except that block order will not be counterbalanced, but randomized across subjects.

The demographic character of the replication may differ from the study’s population. However, there is no theoretical basis for this to affect the outcomes of the study. Additionally,

the particular mapping between performance and pay is unclear. Here we will linearly relate pay to feedback such that chance performance yields \$0 and perfect 75% performance yields \$1.

## (Post Data Collection) Methods Addendum

### **Actual Sample**

31 subjects participated in the mechanical turk study, of which 21 made it into the final analysis. Of the 10 excluded, 6 failed the catch trial criterion, 1 was removed for failing more >25% of the stroop trials, 2 were removed for failing the two-stage decision task reward sensitivity criterion, and 1 was removed for failing to adequately explore the task space, which was an unplanned criterion, and is explained below. Practical constraints on my funding source limited my sample below the intended 25 subjects.

### **Differences from pre-data collection methods plan**

One additional exclusion criterion was implemented during the course of data collection - any subject that failed to fully sample the task space for the two-stage decision task was excluded. This was assessed by ensuring that subjects both maintained and changed their choices for each combination of transitions and rewards. This exclusion criterion was of practical relevance as mixed-models would not converge with subjects that were both (1) extreme outliers and (2) deterministically choosing actions. Using this criterion I excluded one subject.

Though practically necessary, one could argue that such an exclusion criteria precludes absolute generalization of the results reported here. After all, repeating a first-stage choice when rewarded after a common transition is a defensible strategy in this non-stationary, probabilistic environment. While I tend to think that such absolute decisions are more trivial (based on a somewhat arbitrary strategy decision on the part of the subject), it may be that such subjects represent a different sample of decision-makers such that the current analysis simply could not account for. Given that only one subject fit this criterion, I believe the analysis still is valid, and reflects genuine characteristics of decision-making in the general population.

## Results

### **Data preparation**

Data was prepared separately for the stroop task and the two-stage decision task, and then combined into a final model to explore the interaction of interest: the relationship between the incongruency effect (IE) on the stroop task and model-based choice on the decision task.

The preparatory steps are indicated in the “Analysis Plan” section. Briefly, all incorrect stroop trials and non-responsive two-stage task trials were removed. The reaction times (RT) from the stroop task were log-transformed, and then z-transformed within-subjects. Frequent and infrequent IE’s were obtained for each subject using individual models predicting RT. These IE’s were subsequently standardized across all subjects for use in the full model predicting choice behavior.

### Confirmatory analysis

While IE effects were determined using subject specific models, a group mixed-model was used to assess overall significance of the stroop effects. The model predicted the z-transformed, log RTs based on a block (infrequent/frequent) x congruency interaction, with stimulus repetition as a nuisance variable. Additionally, within-participant factors (the interaction as well as the influence of stimulus repetition) were taken as random effects. Stroop results reproduced the typical findings - I found significant IE's for both the frequent (102 ms,  $t=10.36$ ) and infrequent (163 ms conditions,  $t = 10.19$ ), with the infrequent IE significantly greater than the frequent IE ( $t = 3.2$ ). Note that the IEs reported are averages calculated across the individual subject IEs converted back from log space. Table 1 reports the full pattern of median RTs and standard deviations in this experiment (calculated across individual mean RTs) and the original paper (ambiguous exactly how these were calculated).

**Table 1.** Median RTs taken over mean per-subject RTs

<i>Condition</i>	<i>Trial Type</i>	<i>Eisenberg: RT (msec) (SD)</i>	<i>Otto et al.: RT (msec) (SD)</i>
Incongruent infrequent	Congruent	601.86 (99.09)	567.47 (70.86)
	Incongruent	889.43 (173.47)	697.6 (147.86)
Incongruent frequent	Congruent	671.29 (103.86)	573.21 (81.33)
	Incongruent	772.64 (124.68)	602.07 (88.0)

To assess model-based and model-free contributions to choice behavior in the two-stage task, a mixed-model logistic regression was performed to examine the impact of reward (rewarded vs. unrewarded) and transition type (common vs. rare) on the previous trial on the probability of repeating the same first-stage choice:  $P(\text{stay}|\text{transition}, \text{reward})$ . Consistent with the study by Otto et al., and others, I found a main-effect of reward (wald  $z = 1.992$ ), indicating that subjects were more likely to repeat an action after receiving a reward, the hallmark of model-free RL. Additionally, there was a significant reward by transition interaction ( $z = 2.28$ ), indicating that the tendency to repeat an action after a reward was modulated by whether the transition was common or rare, such that repetition was more likely in the common condition. This interaction is reflective of model-based RL, thus the group-level choice behavior reflected influences from both systems. There was also a significant intercept, indicating that subjects had a bias to repeat their previous action, independent of reward. Figure 1 shows the probability of repeating an action in the different conditions.

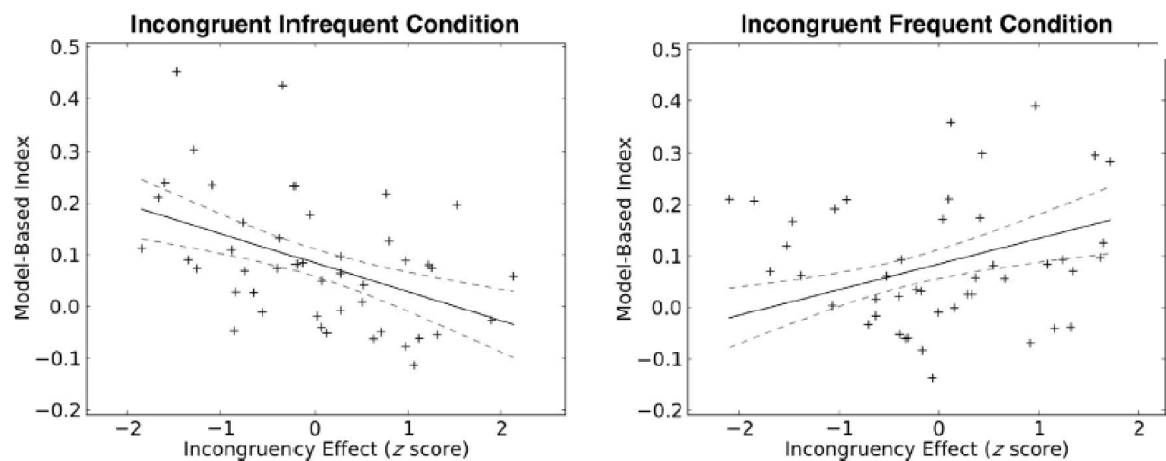
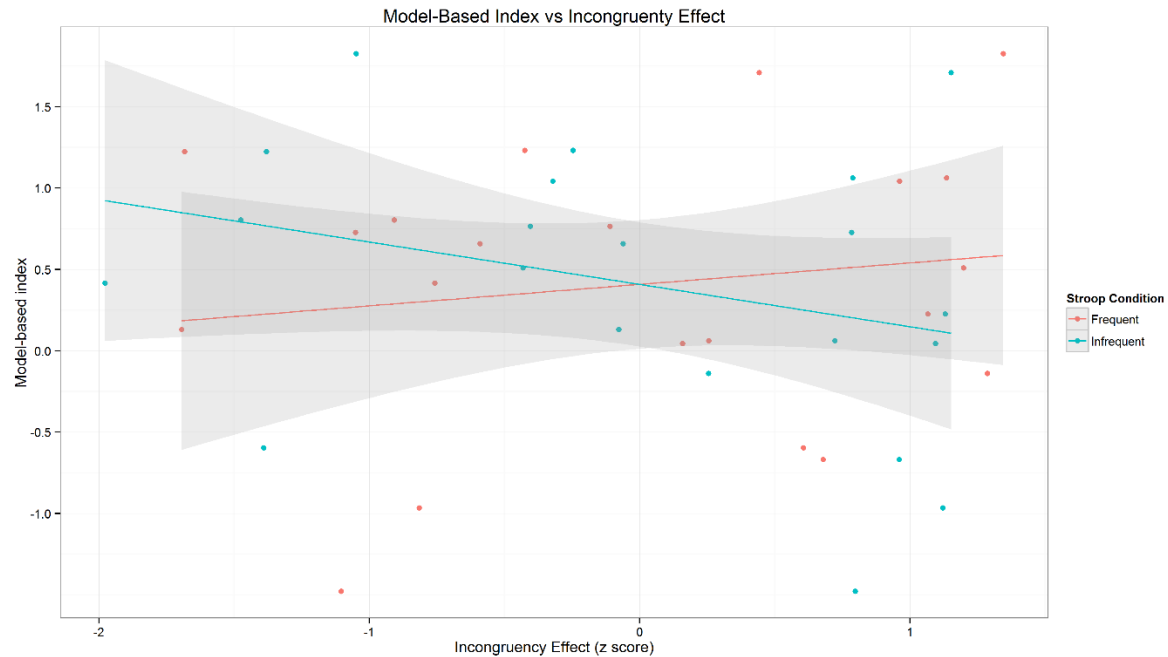
Inconsistent with prior studies, and not predicted by theory was a significant main effect of transition ( $z = -2.75$ ), indicating that subjects were overall less likely to repeat an action if it

led to a common transition. This effect was smaller than the others, affecting stay probability by less than 4%, but was reliable, with very low variance ( $b = -.17$ ,  $se = .06$ ).



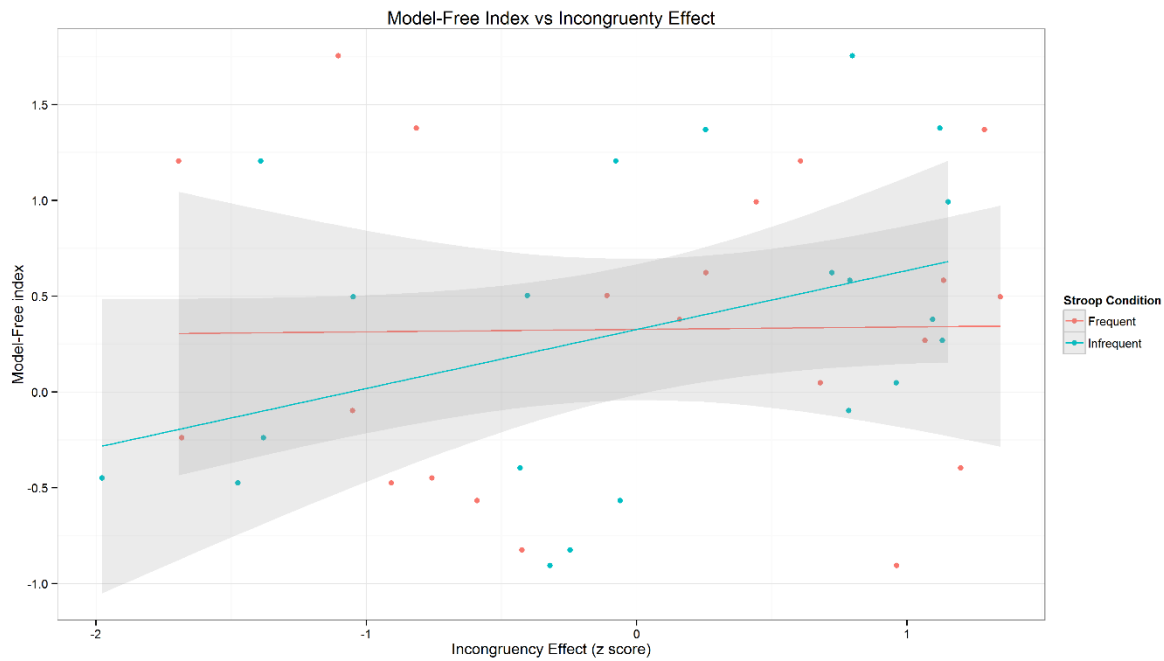
**Figure 1.** Stay probabilities for common transitions (blue) and rare transitions (red) when rewarded (right) and unrewarded (left). Error bars represent confidence intervals. Subjects display a mixture of RL choice strategies, such that they are overall more likely to repeat an action after being rewarded (an indicator of model-free behavior), but also display a reward  $\times$  transition interaction (model-based RL), indicating that they are more likely to repeat an action when rewarded after a common transition, or unrewarded after a rare transition.

Next I explored the main effect of interest: the relationship between Stroop IE and model-based RL. To visualize the effect, I extracted the individual subject estimates for the transition  $\times$  reward interaction, conditioned on the group model (my model-based index) and plotted it against the IE for the infrequent and frequent stroop blocks (Figure 2a). The original author's plot is shown as well in Figure 2b. I also examined the relationship between Stroop IE and model-free RL, by looking at individual subject's main effect of reward (Figure 2c).



**Figure 2.** Visualization of the relationship between Stroop IE and components of reinforcement learning. The model-based index is calculated as individual participant's model-based effect size conditional on the group-level mixed-effects logistic regression. (A) Eisenberg results: Infrequent IE marginally predicts model-based index (logit units), while frequent IE is insignificant. Red corresponds to the frequent Stroop block, blue corresponds to infrequent. Shading indicates CI of regression line. (B) Otto et al. results (arbitrary units) demonstrating the same relationship. Dashed lines indicate SE of regression line. (C) Relationship between Stroop IE and a model-free index, calculated analogously to the model-based index. Infrequent IE was significantly related to the model-free index, but not infrequent IE.



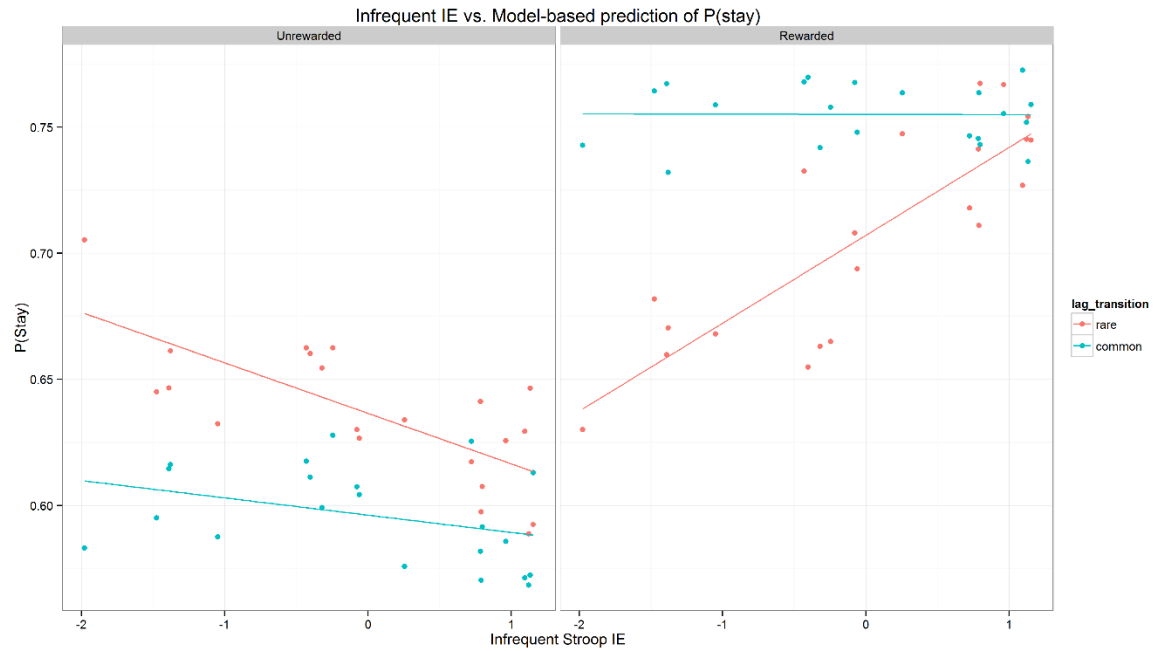


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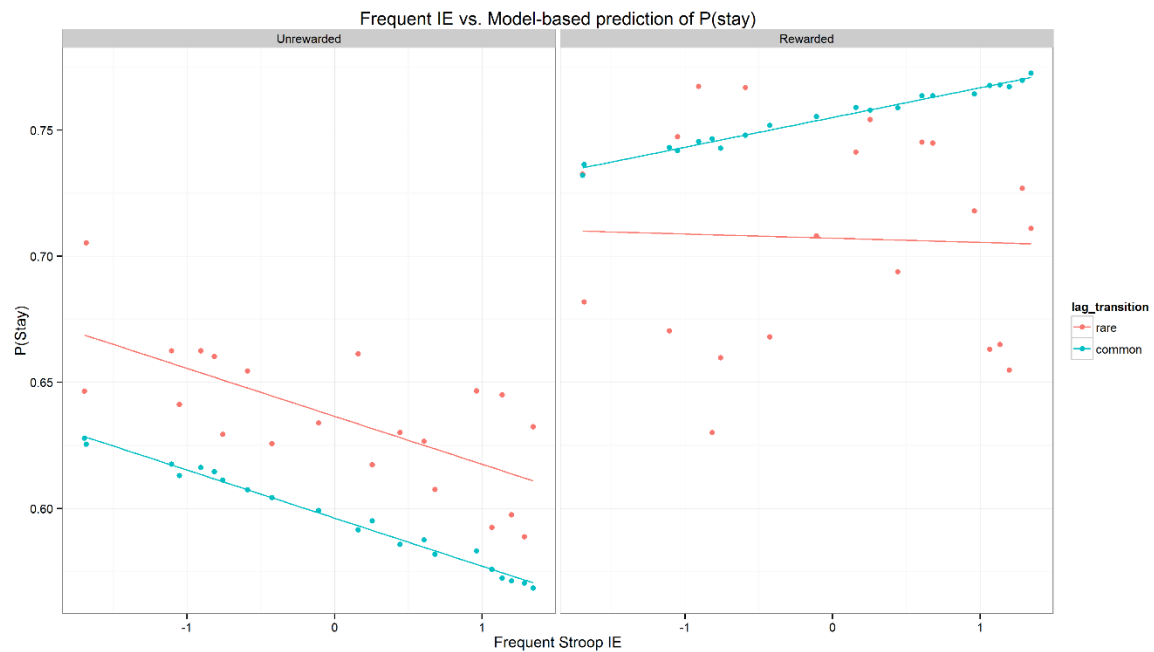
Statistically, I found a marginal three-way interaction between transition type, reward, and infrequent IE ( $b = -.3$ ,  $p = .6$ ), such that greater Stroop interference predicted less model-based choice, replicating the finding of the original authors. However, while the author's found no link between model-free choice and infrequent IE, I found a highly significant positive interaction between reward and IE, such that greater Stroop interference predicted a larger influence of reward on repeating previous choices ( $p < .001$ ). While these results are indicative of a link between control processes as measured by the stroop task and the relative magnitude of the two RL systems, a simpler explanation involving task engagement, or some other gross motivational variable could account for these results. However, such an explanation would predict a similar relationship between RL indices and the IE on the frequent stroop block, which we did not find, instead finding an insignificant *positive* relationship between IE and model-based RL ( $b = .13$ ,  $p > .15$ ), and no relationship with model-free RL. The effect of frequent IE on model-based RL was marginally different than the effect of infrequent IE (linear contrast  $p = .06$ ), demonstrating the specificity of the effect, and undermining a motivational account as an alternate explanation.

## Exploratory analyses

To this point, I have only demonstrated a relationship between the stroop IE and a metric of model-based RL based on a transition by reward interaction, in line with the work by Otto et al. However, this characterization of model-based RL averages over multiple possible choice behaviors. For example, both a decreased  $P(\text{stay}|\text{reward, rare})$ , or an increased  $P(\text{stay}|\text{no reward, rare})$ , could contribute to the interaction coefficient. IE may relate to either, or both of these possible behaviors, which we can disassociate by predicting choice behavior based on IE in all transition (common vs. rare) by reward (rewarded vs. unrewarded) conditions, using the full model from the previous analysis.



**A**



**B**

**Figure 3.** Model predicted stay probabilities for common transitions (blue) and rare transitions (red) when rewarded (right) and unrewarded (left). (A) Infrequent IE differentially relates to choice behavior based on the transition condition. As infrequent IE goes down,  $P(\text{stay}|\text{reward}, \text{rare})$  goes down and  $P(\text{stay}|\text{no reward}, \text{rare})$  goes up, while  $P(\text{stay}|\text{common})$  does not change. (B) In contrast, greater frequent IE affects sensitivity to reward in both conditions equally.

Figure 3 clarifies the relationship between IE and behavior, which are statistically captured in the full model used to describe the relationship between the two tasks. We see that the probability of repeating a choice after a common transition is unrelated to infrequent IE. In contrast, the probability of choice repetition after a rare transition demonstrated the model-based crossover with low infrequent IEs. This relationship also explains the interaction between infrequent IE and reward, as  $P(\text{stay}|\text{reward})$  is much greater than  $P(\text{stay}|\text{no reward})$  for subjects with a higher IE.

## Discussion

### Summary of Replication Attempt

The reduced sample size limits our statistical power, but all results trend towards a successful replication of the main effects first reported by Otto et al. The stroop task was successfully replicated, including the significant IE difference between frequent and infrequent blocks. In my sample reaction times were overall slower, and the IE was more pronounced. Both of these effects are most likely due to the mechanical turk testing environment.

I also replicate previous reports on the two-stage decision task, demonstrating that people's choices reflect a mixture of model-free and model-based RL at the group-level. This pattern largely held for individuals, with a positive model-free index for 13/21 subjects and a positive model-based index for 16/21 (Daw et al. (2011) found 14/17 and 10/17 had positive indices, respectively). We also found a small, but significant effect of transition type that was not predicted by theory or reported by Otto et al. Given that this effect has not been seen in multiple replications of the basic two-stage decision task it is likely an anomaly of my particular sample.

Most relevant for the replication was a marginally significant negative relationship between model-based RL and infrequent IE, replicating the principle finding of the original paper. However, I also found that model-free RL was positively, and robustly, related to infrequent IE. An additional visualization clarified the relationship between IE and RL, indicating that lower IE was related to more model-based behavior regardless of whether the subject received a reward.

### Commentary

While I replicated the broad finding that cognitive control predicts the relative contribution of model-based and model-free RL, the presence of a significant relationship between model-free RL and IE, which was not found by the original authors, requires a different interpretation than first forwarded. The original author's frame the comparison between cognitive control and RL as the upregulating of a goal-directed, context-sensitive system over an independent habitual response. Thus, increased cognitive control increases the impact of model-based RL, without impacting the model-free system. With this system independence, it is possible for someone's behavior to be overwhelmed by their model-free system, regardless of their individual level of control, as the contribution of the two systems are additive. This explanation makes intuitive sense in the context of addiction and other habitual behaviors, where we feel that we can exert more or less control over our behavior to no effect – the habit is just too strong.

The data reported here tell a different story. Increased cognitive control both increased model-based RL and decreased model-free RL. Cognitive control is therefore related to the *arbitration* between the two systems. It is possible that both RL systems are actually learning in the same way across subjects, but cognitive control allows the successful selection of the model-based system at the time of choice. From this perspective choice isn't an additive mixture of the two systems, but a weighted average. Applying this perspective to habitual behavior, one can imagine that favoring the model-based system such that it determines action selection would require an immense amount of effort when the alternative is a strongly instantiated habit. Thus we could still expect the feeling of exerting more or less control with no apparent effect.

For this replication to be considered successful, the planned number of subjects will have to be collected. Additionally, the original authors ran an analogous experiment using the dot pattern expectancy tasks, which is a more complex and valid measure of cognitive control. This task allowed the authors to rule out the alternative motivational account of the data, and thus would be important to replicate for the same reasons.

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## Notes.

Lme4 was used for the mixed-model analysis as in the original paper. As I mentioned in an email, my model stopped converging for seemingly no reason (clearly I changed something), and precluded me from further analyzing certain aspects of the data (like statistically pursuing whether the relationship between IE and P(stay|reward,rare) was stronger than between IE and

P(stay|no reward,rare), replotting the data with larger labels (sorry!) and reporting the full range of coefficient estimates – I went from memory. It is possible that the times when my models converged were actually problematic as well – after all, it makes no sense for the models to suddenly change. However, the correlation of random effects (and results, as indicated by the plots) all made sense. Additionally, the model-based index pulled out for individual subjects from the random effects were similar to the individual estimates I got running the model for each subject alone. All this is to say that I believe those models were correct, and I have confidence in the plots and statistics reported here. However, unless I can replicate myself (the irony!), I won't be able to pursue this much further. From what I've read [here](#), my convergence problems indicate something like a 'singular solution' that has been overfit. Quote below

“It is very common for somewhat overfitted models (i.e., models that are more complex than the data can support, e.g. because there are too few levels of the random effect — see previous section) to result in singular fits. Technically this means that some of the "theta" (variance-covariance Cholesky decomposition) parameters are exactly zero, which is the edge of the feasible space, or equivalently that the variance-covariance matrix has some zero eigenvalues (i.e. is positive semidefinite rather than positive definite), or (\*almost\* equivalently) that some of the variances are estimated as zero or some of the correlations are estimated as +/-1. This is most commonly (but not always) a problem with small numbers of random-effect levels, as illustrated in [these simulations](#) and discussed (in a somewhat different, Bayesian context) by Gelman [[16](#)].”

I ran the model with MCMCglmm, as per Long's suggestion, which converged. Unfortunately, I have no experience with it and am not really sure how to pull out analogous statistics. I stuck with lmer as it was the original authors use.

Thanks for the great class!  
Ian