Computational Modeling of Cognitive Control in a Flanker Task

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Abstract

Cognitive control refers to the ability to adjust our thoughts and behaviors in order to achieve internalized goals. In the past, researchers have proposed several models of cognitive control to account for the characteristic patterns of response times observed in the tasks (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001). The goal of this study is to evaluate empirical validity of such models in an experiment. To that end, we compared two models of cognitive control, the conflict monitoring model and the expectancy-based model. Each model was implemented in two different modeling frameworks, neural networks and simple linear models. The relative fits of the four models were then evaluated and compared based on observed data from a flanker task experiment. The model comparison results showed that performance of the simple linear models was entirely comparable to that of the neural network models. We also constructed and fitted hierarchical Bayesian latent mixture versions of the linear models to investigate individual differences. The result suggests that no single model of cognitive control, whether conflict monitoring or expectancy-based, would be able to account for individual performance on the task.

Keywords: cognitive control; computational modeling; neural networks; hierarchical Bayes; latent mixture modeling; model comparison.

Introduction

The ability to control our attention, which is called cognitive control, has been an important topic in the study of human cognition. The conflict-monitoring theory of Botvinick et al. (2001) has been one of the most popular approaches to account for cognitive control behavior. The theory posits that a conflict monitoring system in the anterior cingulate cortex detects conflict and sends out a signal to the dorsolateral prefrontal cortex to activate cognitive control. This theory provided a neural network model to reproduce experimental data, inspiring other researchers to develop their own models of cognitive control (e.g., Verguts & Notebaert, 2008). The neural network model has been believed to be an elegant way to explain cognitive control mechanisms and their effects on the performance in congruency tasks. It was also shown by simulations that the models fit well the response time data reported by other studies that used congruency tasks. However, although the models were developed to account for observed data, the studies that actually fit those models to their data are rarely found. This suggests that the contribution of the models has been somewhat limited to providing a theoretical framework, despite their potential usefulness in an experimental analysis.

The present study aims to explore two competing theoretical accounts of cognitive control by fitting their computational implementations to experimental data. Although the conflict-monitoring theory has been one of the most influential frameworks for the study of control mechanisms, alternative accounts that explain control related behaviors have been proposed (Egner, Delano, & Hirsch, 2007). Among the alternative explanations of cognitive control, in this study we focus on expectancy-based control that has been tested by recent experiments (e.g., Duthoo, Wühr, & Notebaert, 2013; Jiménez & Méndez, 2013). The expectancy-based control assumes that cognitive control is activated according to the probability that the trial type would be repeated. Therefore, we manipulate the probability of repetition in a cognitive task to observe the effects of expectancy on task performance. The data is then fitted to the two types of models, the conflict monitoring model and an expectancy-based model. The expectancy-based model is created as a modification of the conflict monitoring model with the assumption of expectancy-based control. The comparison of the two models would indicate which model is more likely to reflect the underlying cognitive processes.

We primarily test the neural network models, but there are potential limitations in such models. The neural network models with many parameters that indirectly affect the output might be overly complex to account for behavioral performance in a cognitive task that only has a few dimensions of information (e.g., accuracy rate, response time). In order to test whether the neural network models' complexity is meaningful in experimental studies, we also compare them with relatively simple linear models as baseline benchmarks. The neural network models would demonstrate their usefulness in hypothesis testing if they perform better than the simple models.

Additionally, we also construct and evaluate a hierarchical Bayesian latent mixture model that combines the conflict monitoring model and the expectancy-based model in a single modeling framework, in order to explore individual differences. This model would estimate how much a participant is inclined to a certain control mechanism represented by a model.

Flanker Task

To evaluate the empirical validity of the models, we used a version of the flanker task in which the participants are asked to distinguish the direction of the central arrow, while ignoring the other flanker arrows on the sides. The stimuli are called incongruent when the target arrow and the flanker arrows are pointing to different directions, and are called congruent if all the arrows are the same. Examples of experimental stimuli are shown in Figure 1. The flanker task is very simple, yet feasible of manipulating the designs such as proportion congruency and proportion of repetition (e.g., Gratton, Coles, & Donchin, 1992). Mathematical models' predictions can depend upon the designs selected, so it is important to choose a design appropriate for the purpose of the study.

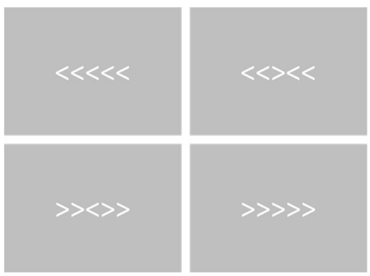

Figure 1: Experimental stimuli of an arrow flanker task.

In the arrow flanker task, the stimuli are more quickly responded to when the task-irrelevant flanker arrows are the same with the task-relevant central arrow (e.g., >>>>>), than when they differ from each other (e.g., <<><<). This difference in the response time between congruent and incongruent stimuli is called the congruency effect. The activation of cognitive control is often measured by another phenomenon that is called the congruency sequence effect (CSE), which indicates a reduction of the congruency effect after an incongruent trial (Gratton et al., 1992). A typical response time pattern of the CSE is shown in Figure 2, in which the combinations of the previous and the current trial type are denoted by the combinations of c (previous congruent), i (previous incongruent), C (current congruent) and I (current incongruent). For example, cI indicates an incongruent trial after a congruent one. It is shown that the congruency effect after a congruent trial (cI – cC) is larger than that after an incongruent trial (iI – iC).

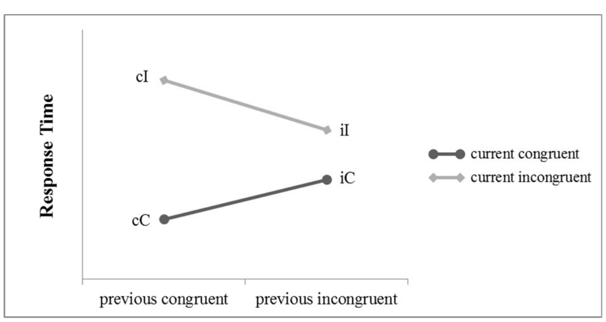

Figure 2: Illustration of the congruency sequence effect (CSE).

The conflict monitoring account explains this effect by an elevated level of control after the detection of a high conflict trial (i.e., incongruent trial). High level of control enhances performance in the next trial, reducing the difference in response time between incongruent and congruent trials (i.e., the congruency effect). An alternative explanation provided by the expectancy-based control is that the CSE is generated with the repetition expectancy, with which the same trial type as the previous one is expected. This prior belief reduces the congruency effect after an incongruent trial, by allocating more attention to the task-relevant information in anticipation of another incongruent stimulus (Gratton et al., 1992).

Both of the two control mechanisms can account for the CSE, but there is a major difference in the way they do. The expectancy-based control expects the CSE only when a repetition is expected. That is, the CSE would not occur under the alternation expectancy. This difference in the prediction is discussed in greater detail in the section below.

Computational Models

Again, the purpose of the present study is to discriminate the two different theoretical accounts of cognitive control, namely, expectancy-based control and conflict-driven control, by way of computational modeling of observed data. To that end, we employed two models, a conflict monitoring model and an expectancy-based model. Further, each model was implemented in yet two different modeling frameworks, neural networks and linear models.

Neural Network Models

These are the same neural network (NN) models of cognitive control proposed by Botvinick et al. (2001), as shown in Figure 3.

The six input units of the network represent the direction of the arrows in the left, the center, and the right position of the franker task in Figure 1. They are connected to the corresponding output units. If the input to an output unit reaches a threshold, a response is made. Random noise is applied to each unit's activity level to produce variable responses including errors. The three control units distribute attentional resources to each input unit. When the level of control is higher, more attention is allocated to the central, target arrow (see Botvinick et al., 2001, for further details). Inspired by this neural network model, in the present study we created two variations of the model, each implementing a different theoretical account of cognitive control, a conflict monitoring NN model and an expectancy-based NN model.

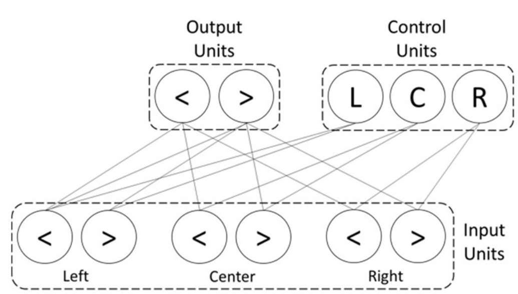

Figure 3: Neural network (NN) model of cognitive control for an arrow flanker task.

Conflict Monitoring NN Model (CM_NN): This model is essentially the same as that proposed by Botvinick et al. (2001) with little major modifications. In the present model (CM_NN), the level of control in $(t+1)^{th}$ trial is updated on each trial as follows:

$$C_{t+1} = \lambda C_t + (1-\lambda)(aE_t + b) \quad (1)$$

where $0 < \lambda < 1$, $E_t = -a_1 a_2 w_{12}$, a_1 and a_2 indicate the activation of the two output units, and w_{12} indicates the inhibitory weight between them. For simplicity, w_{12} is fixed to -1 (Blais, Robidoux, Risko, & Besner, 2007). The symbols a and b represent scaling parameters.

The input to the control units are distributed based on the value of C_t. The attention to the central arrow (i.e., the control unit "C" in Figure 3) is identical to the C_t value, but its range is restricted to (1,3). The attention to the flanker arrows (i.e., the control unit "L" and "R" in Figure 3) are (3-C_t)/2 each for the left and the right arrows. Therefore, the attention is evenly distributed with minimal control, and concentrated to the target arrow with maximal control. The input from the control units are fed to the input units according to the connection weights between them. The range of the connection weights we set were (1,4), similar to previous studies (e.g., Botvinick et al., 2001).

Expectancy-based NN Model (EB_NN): In this neural network model of expectancy-based control, we modified the above model CM_NN so that the level of control would be dependent on the expectancy. This idea was previously proposed in Yu and Cohen (2008) to account for sequential effects in congruency tasks as the effect of repetition expectancy. There are two trial types in the flanker task, a congruent type and an incongruent type. The model assumes that subjects believe that there is a fixed probability u of observing a repetition of either trial type (congruent or incongruent). Let X_t be a set of binary observations ($x_1,\ldots, x_t$), where x_t = 1 if the congruency is repeated, and x_t = 0 if the congruency is alternated in the t^{th} trial. According to the model, u is updated as,

$$u_{t+1} = \lambda u_t + (1-\lambda)(x_t + a) \quad (2)$$

where $0 < \lambda < 1, -0.3 < a < 0.3$, and the initial belief u_0 is set to 0.5. The range of u_t is constrained to (0,1). The symbol a in the above equation is a scaling parameter.

The input to the control units are determined by the u value. That is, the input to the unit "C" is 1+2 $\mathrm{p}(Incongruent)$, where $\mathrm{p}(Incongruent)$ = u if the previous trial was incongruent, and $1-u$ if the previous trial was congruent. The attention input to the flanker arrows is equal to 1- $\mathrm{p}(Incongruent)$ for each for the left and right arrows.

Linear Models

In addition to the two NN models, we also constructed and evaluated two simple linear models to serve as baselines, to answer the question of whether the complex structural configurations of the NN models are necessarily justified to account for behavioral data.

Conflict Monitoring Linear Model (CM_LN): In this model, the level of conflict from the previous trial, E_t, is simplified to a binary value, as E_t is 0 if the previous $(t-1)^{th}$ trial was congruent, and 1 if it was incongruent. The perceived level of conflict in the current trial is defined as

$$C_{t+1} = \lambda C_t + (1-\lambda)(E_t + a) \quad (3)$$

where $0 < \lambda < 1$ and $-0.3 < a < 0.3$. E_t in this model is simplified to be 0 after a congruent trial, and 1 after an incongruent trial. The range of C_t is constrained to (0,1). The symbol a is a scaling parameter.

In the conflict monitoring model (Botvinick et al., 2001), a high level of conflict accelerates the response to an incongruent trial, and decelerates the response to a congruent trial, on average. The response time RT_t in the linear model follows the same concept:

$$RT_t = \beta_0 + \beta_1 C_t + \beta_2 I(incong)(1-\beta_3 C_t) + \varepsilon \quad (4)$$

where $\beta_0 > 0$, $\beta_1 > 0$, $\beta_2 > 0$, $0 < \beta_3 < 1$, and $0 < C_t < 1$. As in the expectancy-based model, $I(incong)$ is 1 for an incongruent trial, and 0 for a congruent trial, and ε is a normal error following Normal $(0,\sigma^2)$.

Expectancy-based Linear Model (EB_LN): In this model, given the observations up to $(t-1)^{th}$ trial, X_{t-1}, the belief $\mathrm{p}(x_t|X_{t-1})$ about the t^{th} trial is transformed into the response time RT_t as follows:

$$\begin{aligned} RT_t(x_t) = \beta_0 + \beta_1[1-\mathrm{p}(x_t|X_{t-1})] + \\ \beta_2 I(incong) + \beta_3[1-\mathrm{p}(x_t|X_{t-1})]I(incong) + \varepsilon \end{aligned} \quad (5)$$

where $\beta_0 > 0$, $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$, $x_t = \{0,1\}$, $\mathrm{p}(x_t = 1|X_{t-1}) = u$, and $\mathrm{p}(x_t = 0|X_{t-1}) = 1-u$. In the above equation, $I(incong)$ is equal to 1 for an incongruent trial and 0 for a congruent trial, and ε is a normal error following Normal $(0,\sigma^2)$.

Model Predictions

All four models introduced above, with appropriate choices of model parameters, can be shown to reproduce the congruency sequence effect (CSE) in Figure 1. Interestingly however, expectancy-based control can also yield a *reversed* CSE. To show how, if an alternation of trial types is observed for most trials, the subject would expect a congruent trial after an incongruent trial, and expect an incongruent trial after a congruent trial. This alternation expectancy would then lead to a stronger cognitive control and thus a smaller congruency effect after a congruent trial, as opposed to the standard CSE. Consistent with this hypothesis, the CSE was observed only when the repetition of trial types was expected, in an experiment where subjects explicitly reported their expectations (Duthoo et al., 2013).

Examples of model predictions are shown in Figure 4. The linear models in Eqs. (4) and (5) were used for simulating response time, with the parameter values fixed as β_0 = 450,

β_1 = 60, β_2 = 150, β_3 = 0.7, λ = 0.7, α = 0.1, and σ = 50 for CM_LN, and as β_0 = 450, β_1 = 60, β_2 = 40, β_3 = 40, λ = 0.8, α = 0.1, and σ = 50 for EB_LN.

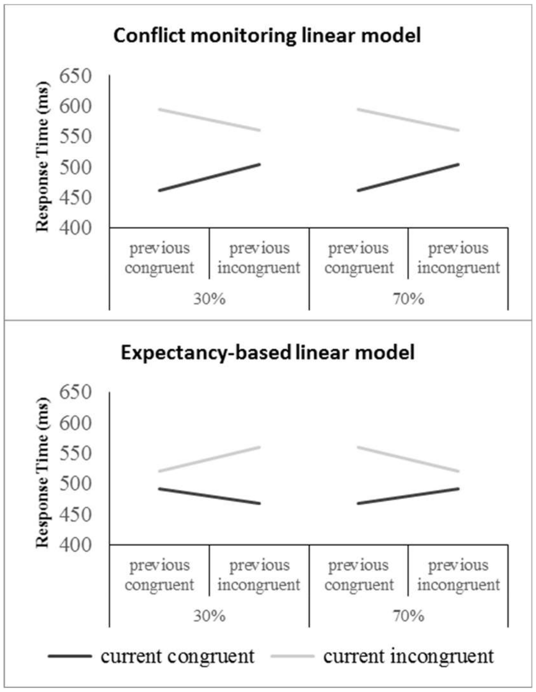

Figure 4: Predicted response time patterns by the conflict monitoring linear model (CM_LN) and the expectancy-based linear model (EB_LN). The percentages below the x axis indicates the proportion of repeating trials in the simulations.

Note Figure 4 that the conflict monitoring model generated the CSE regardless of the proportion of repetition, whereas the expectancy-based model generated the CSE only when the proportion of repetition is high (70%). Under 30% proportion of repetition, the expectancy-based model generated a reversed CSE. It is straightforward to show that these qualitative patterns are also predicted by their neural network counterparts, CM_NN and EB_NN.

Experiment

A flanker task experiment was conducted to empirically evaluate two different theoretical accounts of cognitive control, namely, conflict monitoring and expectancy-based. The computational implementations of the hypotheses and their predictions, as discussed in the previous section, suggest that the key is to experimentally manipulate the proportion of repeating stimuli. We therefore varied the proportion of repetition in the arrow flanker task. Specifically, we used 30% proportion of repetition for a half of the experimental blocks, and 70% for the other half.

Participants: Twenty-four undergraduate students at the Ohio State University participated in the experiment. All subjects had normal or corrected-to-normal vision.

Stimuli: Stimuli were controlled by the PsychoPy module in Python. The stimuli presented were similar to those in Figure 1. At the beginning of each trial, a white fixation cross (+) was presented at the center of the screen for 800 ms. White colored target stimulus appeared at the same location after 200 ms from the disappearance of the fixation cross, with white flanker arrows on the sides. The arrows remained on the screen for 200 ms. The next trial started after 2 seconds from the onset of the stimulus. All stimuli were presented on a grey background on a LCD monitor.

Procedure: Subjects were required to press the “x” key on the keyboard with their left index finger if the target arrow was pointing to the left, and the “.” key on the keyboard with their right index finger if the target arrow was pointing to the right. They were instructed to make a response as quickly and as accurately as possible. If they failed to respond within 1500 ms after the presentation of the stimuli, or if they made an incorrect response, they heard a beep indicating the error. There was a practice block consisting of 20 trials, followed by 6 experimental blocks of 40 trials each. The practice block had 50% proportion of repetition and 50% proportion congruency. For a half of the participants, the proportion of repetition was 30% for the first three blocks, and 70% for the latter three. To counterbalance the order of the combinations, the other half of the participants performed the task in the reversed order (i.e., 70% before 30%). The proportion of congruent trials was fixed to 50% in every block.

Model Evaluation and Comparison

The four models were fitted to the data using the subplex algorithm in the MATLAB programs provided by Bogacz and Cohen (2004). Model generalizability was evaluated in 6-fold cross-validation using 5 blocks as training data, and the remaining block as test data, which repeated six times. Parameter values were found through multiple optimization runs, each with a randomly chosen starting value.

The model fit was measured by the cost function value as defined:

$$cost = \sum_{i=1}^{N} \left(\frac{e_i - m_i}{e_i}\right)^2 \qquad (6)$$

where m_i is a predicted statistic value and e_i is an observed one. A lower cost value indicates a better model fit. The test statistic included the accuracy rate, the response time (RT) for cC, iC, cI, and iI trials each, and the standard deviation. The statistics were separately calculated for the data from different proportion of repetition. For the linear models, the accuracy rate was assumed to be 100%, because they only generate response time as the output.

Model fits of the four models to observed RT data were evaluated in terms of their cost function values. For the two neural network models, the average cost function values over 24 participants were 0.049 (SD = 0.092) for the conflict monitoring model (CM_NN) and 0.060 (SD = 0.036) for the expectancy-based model (EB_NN), whereas for the two linear models, the average values were 0.020 (SD = 0.024) and 0.025 (SD = 0.029) for CM_LN and EB_LN, respectively. In short, the result shows that performance of the linear models is entirely comparable to (and even better than) that of neural network models. This somewhat unexpected finding suggests that the neural network models might be too overly complex to be considered necessary to account for cognitive control behavior in the flanker task.

However, this does not mean that we can simply replace the neural network models with the linear models in the general context. The advantages of the former, unlike the latter, lie in their ability to describe within-trial dynamics of behavioral data that can be associated with brain activity. For the present study, the linear models were sufficient because they were used primarily to model the behavioral data from a single task.

Hierarchical Bayesian Modeling

The modeling analysis above revealed considerable individual differences. That is, some subjects showed lower cost function values with the conflict monitoring models, while others showed lower values with the expectancy-based models. To evaluate theoretical significance of the individual differences, we developed a hierarchical Bayesian latent-mixture model by combining the two linear models. (The neural network models are not amenable to Bayesian modeling, since they do not have explicit likelihoods.) Hierarchical Bayesian latent-mixture modeling is ideally suited for our purpose as it allows us to represent and estimate the relative compositions of multiple cognitive processes in a unified and integrated manner (Lee & Wagenmakers, 2014). For instance, we can get an estimate of the probability that a participant's data is consistent with the expectancy-based model vs the conflict monitoring model.

The hierarchical Bayes model is shown in Figure 5. The z_i ~ Bernoulli ($\emptyset_i$) parameter is an indicator variable that determines which of the two models to use to predict the behavior of the i^{th} subject. The conflict monitoring linear model (CM_LN) is used if $z_i = 0$, and the expectancy-based linear model (EB_LN) is used if $z_i = 1$. The observed response time y_{it} of each subject is predicted by the RT_t of the selected model. RT_t in Eq. (4) and (5) is rewritten as $RT_{it} = \mu_{it} + \varepsilon_i$, where $\varepsilon_i \sim$ Normal $(0, {\sigma_{it}}^2)$. The parameters related to the effect of control, β_1, β_3, λ, and a are given a hierarchical structure that determines their distribution, Normal $(\mu_\theta, \sigma_\theta^2)$. Each parameter θ had hyper parameters μ_θ and σ_θ that constrain the parameter distribution of all subjects. The parameter distributions are truncated based on the parameter ranges shown in the descriptions of the linear models above.

The hierarchical Bayesian model in Figure 5 was fit to the data using Markov Chain Monte Carlo (MCMC) sampling, using 100,000 posterior samples after a burn-in of 5,000. A plot of the mean z_i for each subject, that represents the probability of expectancy-based control, is shown in Figure 6.

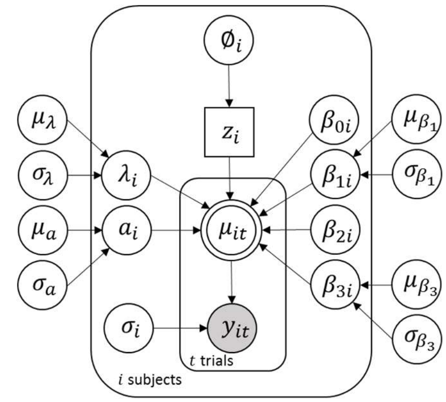

Figure 5: Hierarchical Bayesian latent-mixture implementation of the linear models in Eqs. (4) and (5).

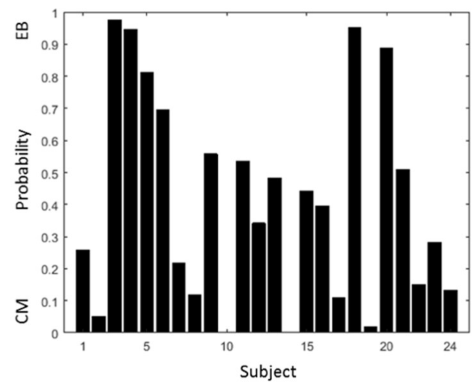

Figure 6: Probability of expectancy-based (EB) control estimated as mean z_i values based on the hierarchical Bayesian latent mixture model in Figure 5. The label 'CM' on the y-axis stands for conflict monitoring.

Each of the 24 subjects was then classified into either a conflict monitoring (CM) or expectancy-based (EB) group, using the threshold of 0.5. There were 15 participants in the conflict monitoring group, and 9 participants in the expectancy-based group. Figure 7 depicts the RT profiles for each group.

The solid lines in Figure 7 are observed data, and the dotted lines are the posterior predictive means from the latent-mixture model in Figure 5. Each group showed the patterns similar to the corresponding model prediction in Figure 4. Participants in the conflict monitoring group seemed to show the CSE in both conditions of the proportion of repetition. On the other hand, the expectancy-based group had a tendency to show a reversed CSE when the proportion of repetition was 30%.

One limitation of this classification scheme is that there are a few participants whose model probabilities are close to 0.5 (see Figure 6). The data from those participants may be explained better by a model without the CSE than by either the CM model or the EB model. This suggests that the classification would not be accurate if the behaviors are not predicted well by the selected set of models.

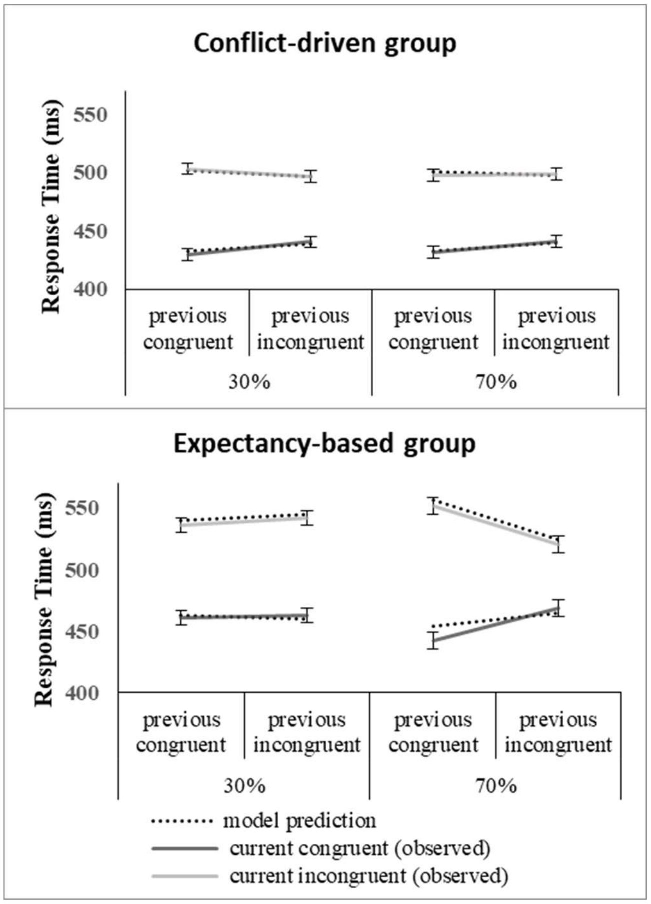

Figure 7: Posterior predictive and observed response times. The predictions are based on the hierarchical Bayesian latent mixture model in Figure 5. The error bars indicate standard errors of the mean.

To summarize the computational modeling results, the linear models performed as well as the neural network models, differentiating the behaviors based on the model predictions. The hierarchical Bayesian latent-mixture model showed significant individual differences in the model probabilities, suggesting multiple control mechanisms underlie the flanker task.

Conclusion

The primary goal of the present study was to explore the empirical validity of two different theoretical accounts of cognitive control, namely, conflict monitoring and expectancy-based, by way of computational modeling. To achieve the goal, we designed and conducted an experiment in which the proportion of repeating trial types was manipulated in an arrow flanker task. We also instantiated each theoretical account of cognitive control in a computational model couched in two modeling frameworks, i.e., neural network modeling and linear modeling. The results taken together showed that the simple linear models can provide equally comparable fits and thus explanations to the data as the neural network models do. An implication is that the neural network models, while popular and widely used given their appeal as a flexible modeling framework, may be overly complex to account for behavioral data in the flanker task. Another main finding of the present study was rather significant individual differences in cognitive control. It seems that there are at least two groups of participants that exhibit different types of cognitive control. This result suggests that there might be a tendency for each individual to prefer a certain control strategy (Braver, 2012). Finally, from the computational modeling standpoint, hierarchical Bayesian latent-mixture analysis employed in the present study could be a useful modeling tool for parsing potentially multiple mechanisms underlying cognitive control on an individual participant (and even trial-by-trial) basis.

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