

# ACT-R model fitting and outcome analysis

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## Abstract

In humans, learning depends on the joint contribution of multiple interacting systems — memory (WM), long-term memory (LTM) and reinforcement learning (RL). The present study aims to understand the relative contributions of these systems during learning as well the specific strategies individuals might rely on. Collins (2018) put forward a working memory-reinforcement learning combined model that addresses this question but it largely ignores long-term memory. We built four ACT-R (single-mechanism RL and LTM, and two integrated RL-LTM, meta-learning RL and parameterized RL bias models) idiographic learning models using the Collins (2018) stimulus-response association task. Different models provided best-fits (LTM: 63%, RL: 1%, meta-RL: 12%, bias-RL:21% of participants) for individual learners which suggests that irreducible differences in learning and meta-learning strategies exist within individuals. Models predicted learning accuracy and rate, and testing accuracy for subjects in their respective groups.

## Objectives

This report describes the four ACT-R models and the learning outcomes produced by the changes in parameters. The report also describes how these models fit behavioral data and details the properties of the best fitting models and parameters. The specific objectives of this project is to test if the RLWM task can be modeled well by a group of pure and combined declarative and RL learning models. After fitting the models to participant data we aim to extract parameters that may explain why and how learning resulted as observed. If the parameters describe individual differences in learning would the parameters predict other behavioral data like working memory capacity and reinforcement learning accuracy?

## ACT-R Models

Below are the 4 ACT-R models tested. **Note that the bolded names appear through-out this document.**

- **RL:** Pure RL model based on learning of production utility in ACT-R. learning rate (alpha) and softmax temperature are the only 2 parameters
- **LTM:** A declarative model that solely depends on storage and retrieval of stimuli, response and outcome in ACT-R's declarative memory. This model depends on decay rate, retrieval noise and
- **meta\_RL:** This is a combined RL - LTM model. Information about trials performed by the RL system is shared and stored in LTM (declarative) for use. An isolated (meta) RL system (a set of productions) learns and determines which sub-system, RL or LTM, is used throughout learning. Which subsystem is preferred depends on the specific set of parameters.
- **biased:** This is a combined RL-LTM model. Information about trials performed by the RL system is not shared with the LTM portion of the model. An additional "*strategy*" parameters specifies a **bias** towards the RL model at the 20, 40, 60, and 80 percent of learning and test trials.

## Approach

The models are fit to behavioral data and the best-fitting model and set of parameters is selected by comparing BIC. The lowest BIC value determines the winning model. To assess the quality of the fit model and parameters RLWM task learning features were compared to the model outcomes. The features of interest are: - Accuracy at the end of learning (accuracy after 12 stimulus presentations) - Accuracy at test - Change in accuracy from end of learning to test - Learning rate - Differences in the learning trajectories of the two set sizes The expectations and outcomes are described below.

## Results

### Model fits

Of the four models compared, the LTM model fit the most number of participants (54) followed by the biased version of the combined RL-LTM model (18) and the meta-RL combined model in third place (10). The RL only model had only one participant that fit it best (figure 1). This is a slight departure from our expectation that the combined RL-LTM models would fit the majority of participants. As observed, this suggests that most learners simply commit to memory the stimulus response associations.

Within each group (groups formed by preferred model types) of participants, there is only 1 RL best fitting combination of parameter values for the alpha and softmax parameters. For the most popular model, LTM, that fit (54) participants, surprisingly, there were only 13 best fitting parameter-value sets for the spreading activation, retrieval noise and memory decay rate parameters. The biased model was the most diverse at 17 parameter sets for (18) participants. The meta-RL model closely followed the biased model in terms of diversity of parameter-value sets at 8 parameter-value sets for (10) subjects. Figures 2 and 3 show the medians and ranges of the BIC values that determined that the LTM model is the best fitting model even when only comparing BIC values for the set of parameter-values that fit participants best in each category of models.

### Assessments of Model fits

Looking at the learning curves for the four models in Figure 4, the differences in learning rates are apparent as are other features like the separation between the two set sizes. In the plot below each data point is the average accuracy, for that number of stimulus presentations, across all parameter combinations. The LTM and RL models predict that an increase in set-size does not diminish learning rate and accuracy. But this analysis washes out the individual differences that could be captured by the diverse set of parameter combinations.

The panels in figure 5 show the mean accuracy for participant behavioral data. The model lines are averages across parameters for that group only. As we are aiming for an individual differences look at these data, collapsing across so much of this variability is uninformative, as was shown above in figure 4, especially if the differences, once fit to actual behavioral data, indicate large differences in learning outcomes or cognitive faculty diagnostics like working memory capacity. Here, only the best fitting sets of parameter combinations

# Counts of participants by mode

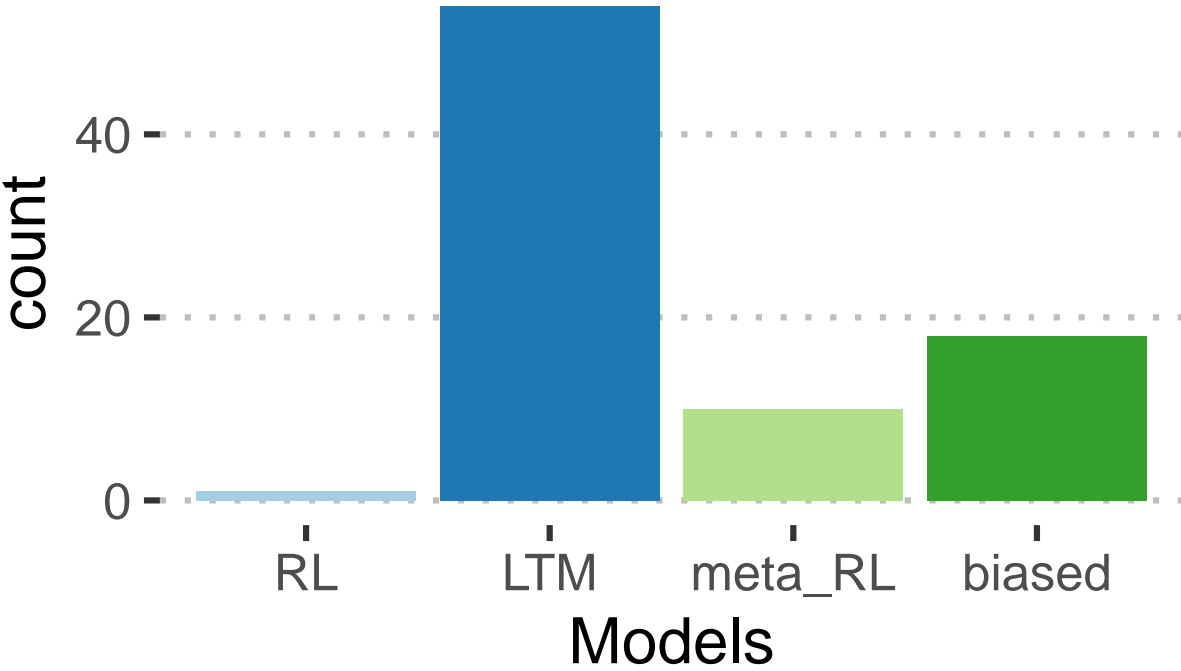


Figure 1: Figure 1.

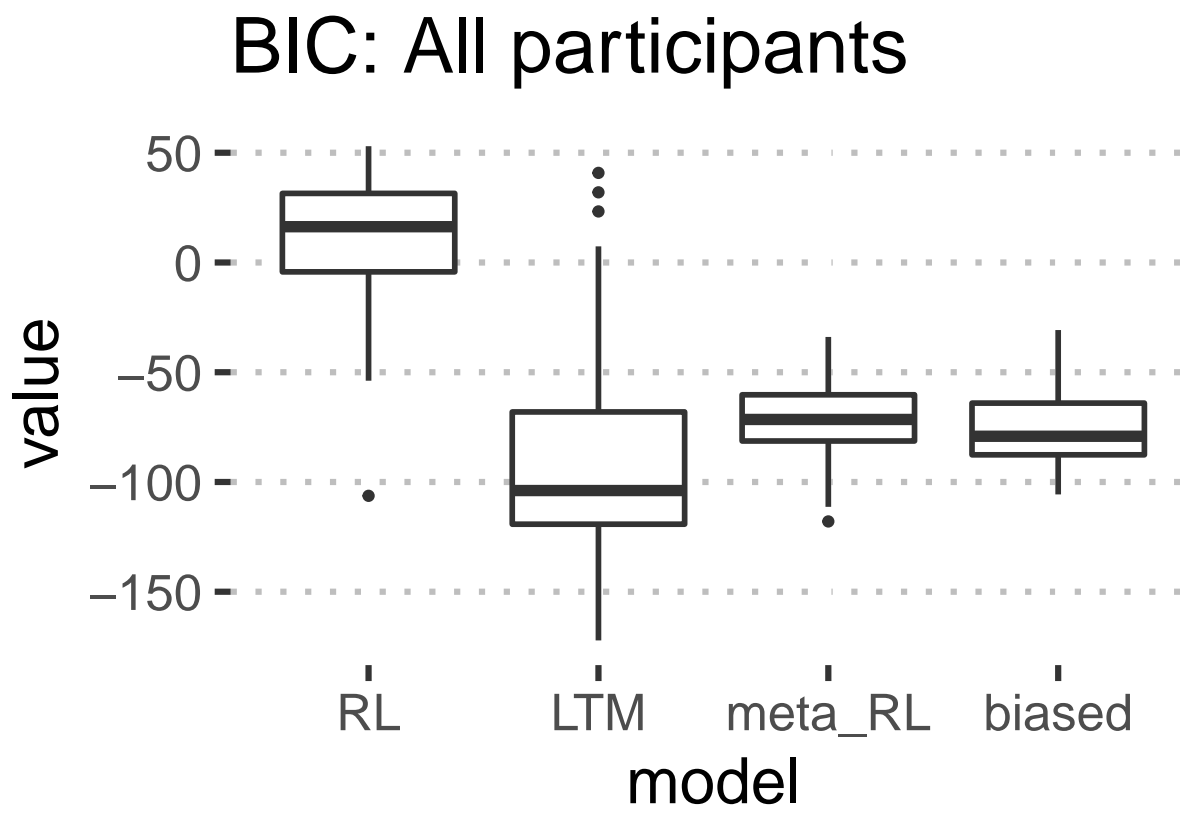


Figure 2: Figure 2.

BIC: best fitting per model

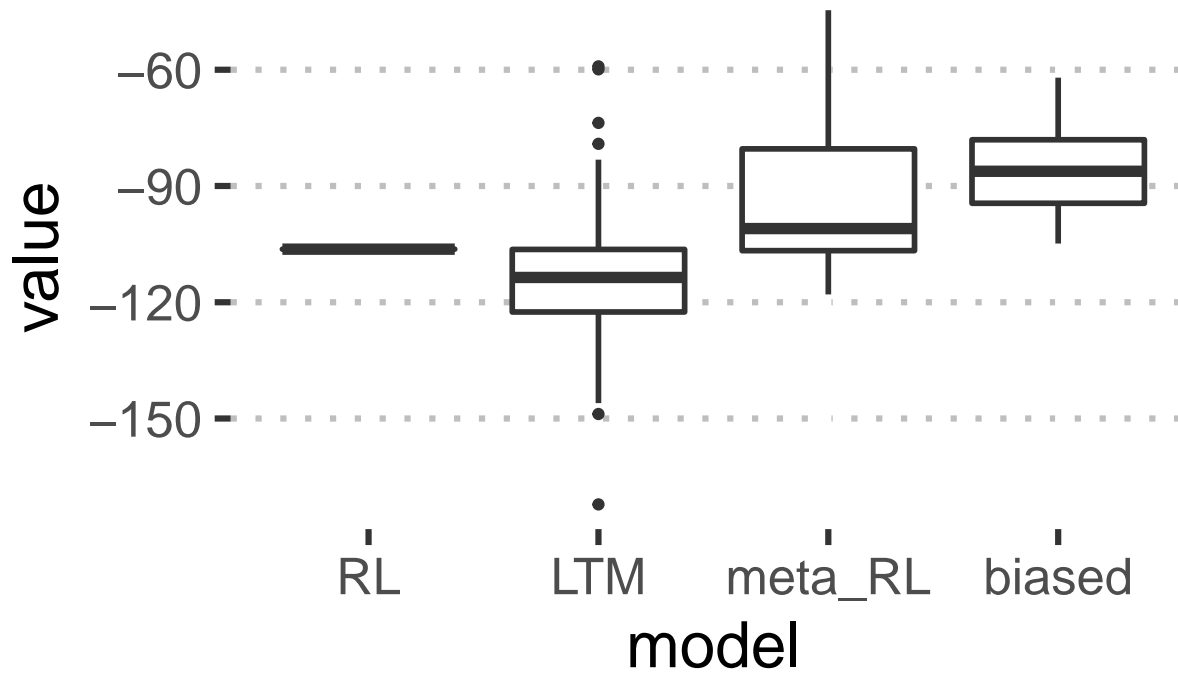


Figure 3: Figure 3.

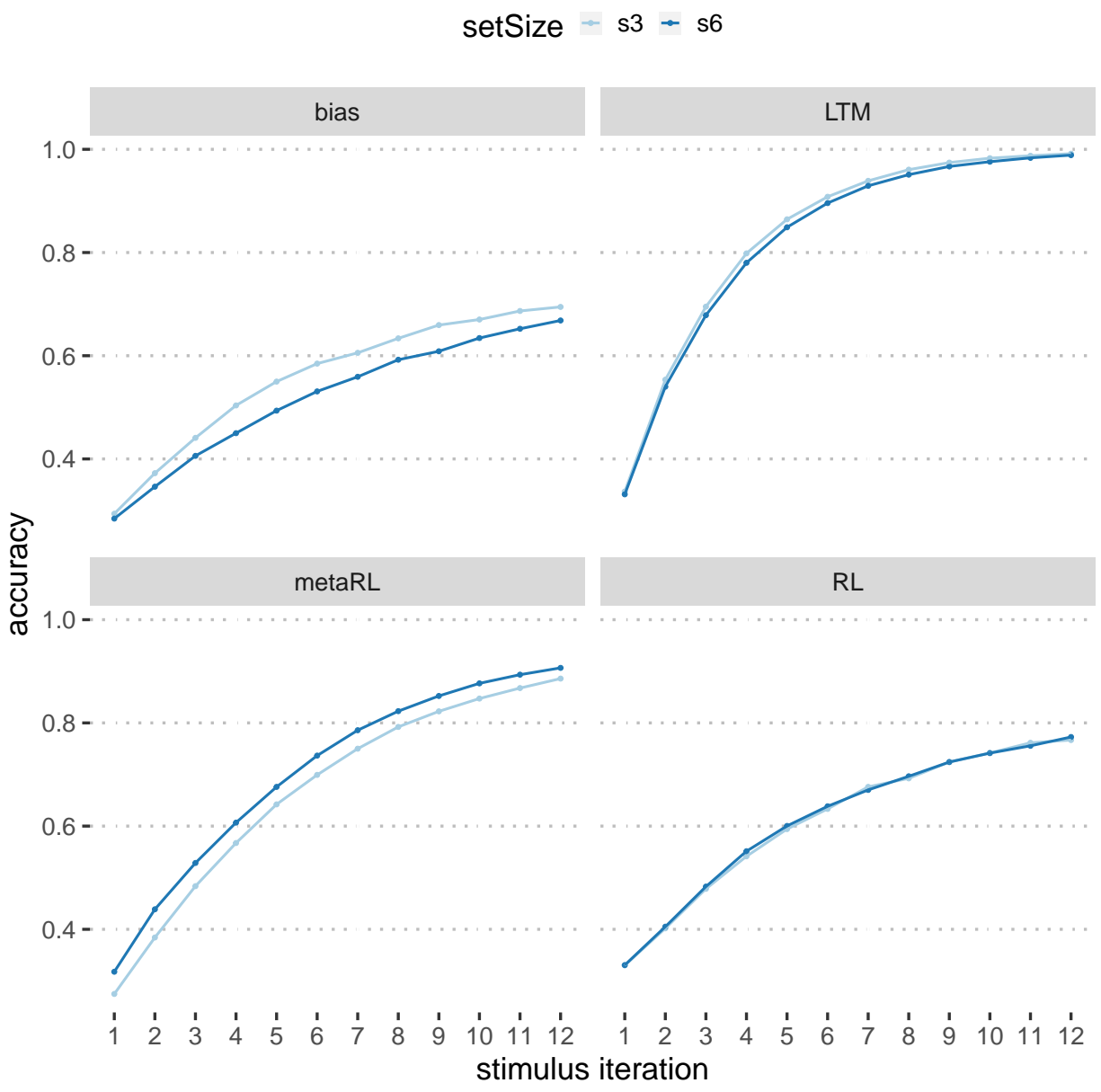
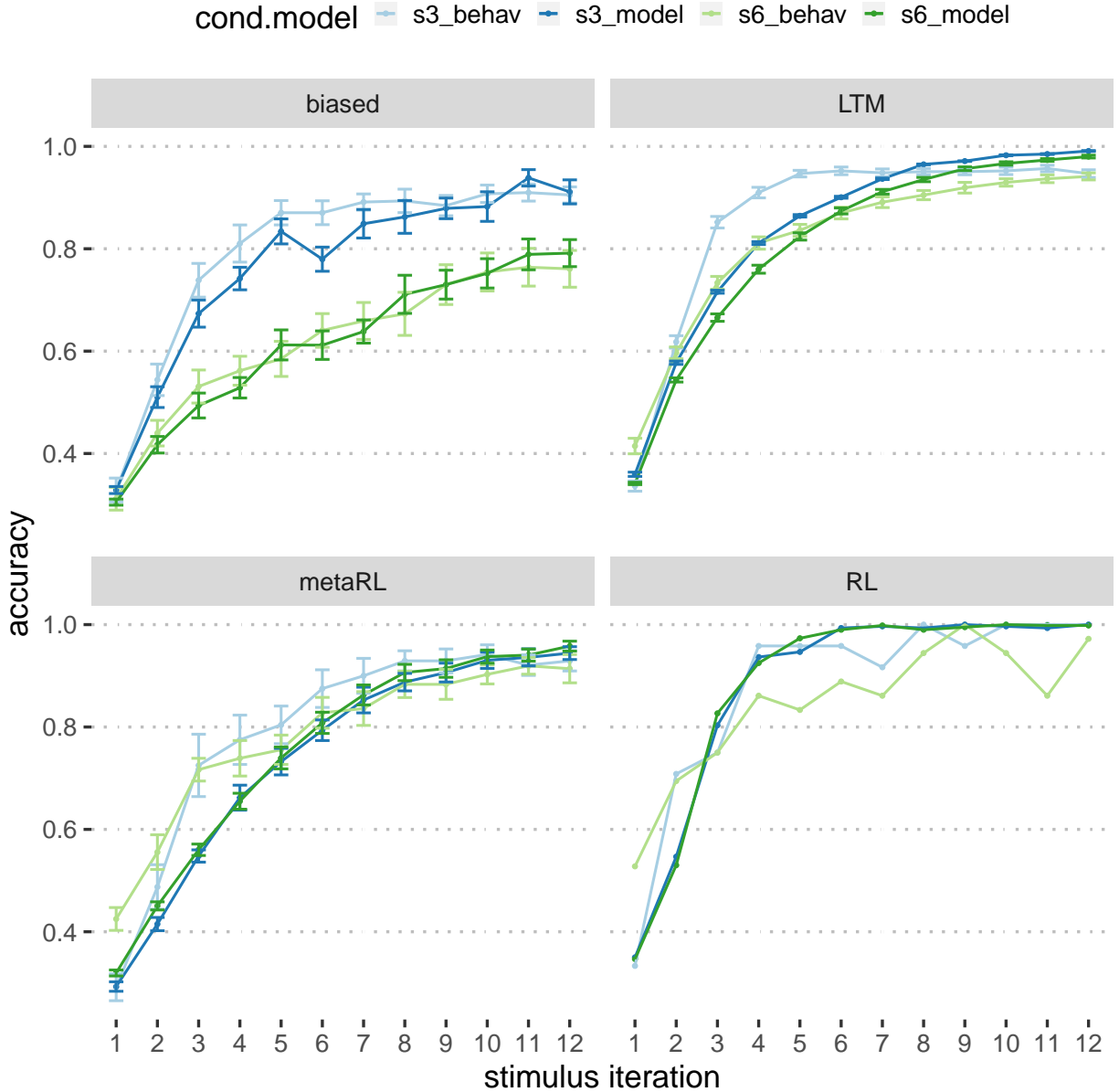
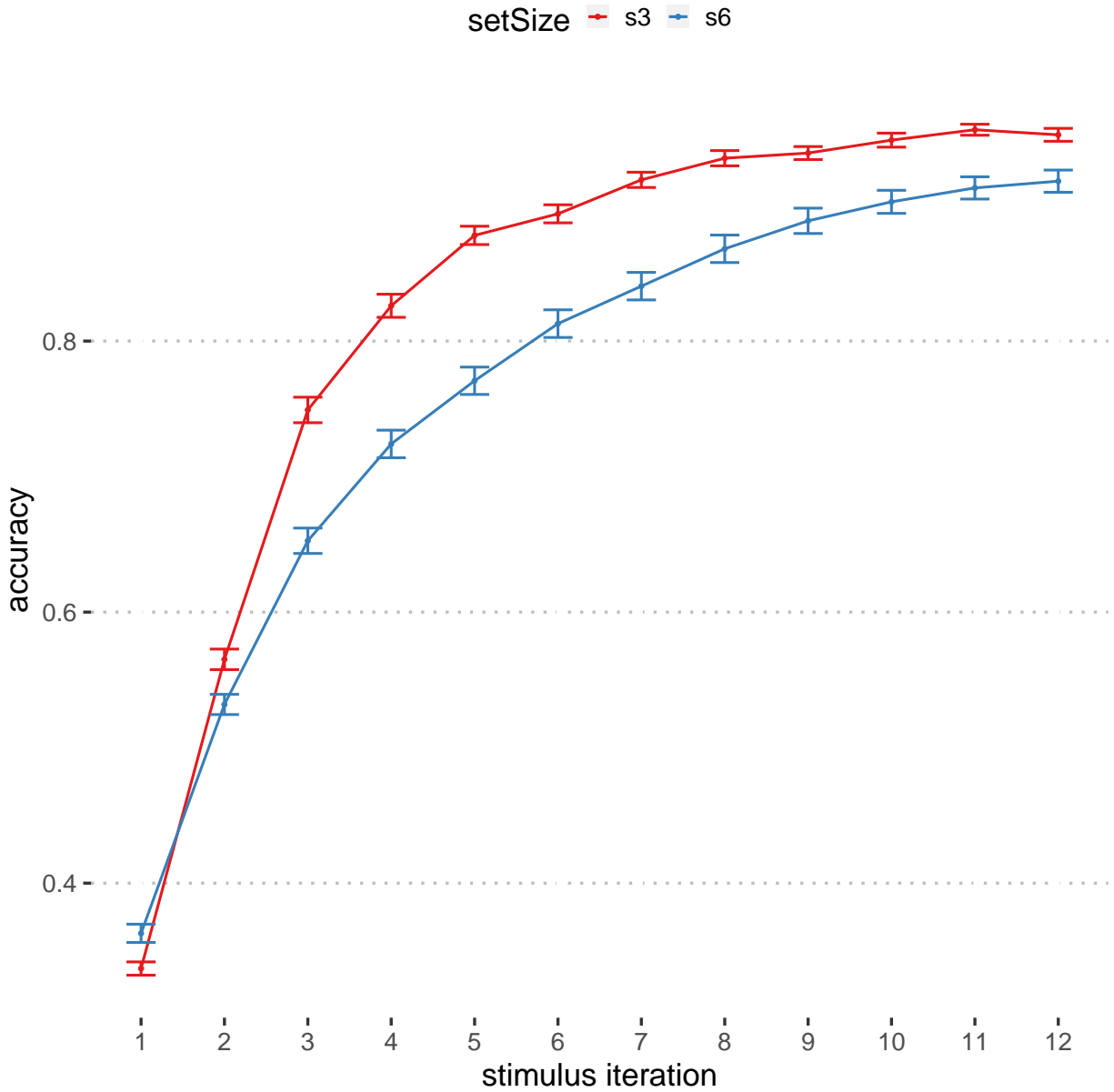


Figure 4: Figure 4.

were selected and collapsed. As can be seen in the figure below, the different model types appear to be vastly different and some characteristics of behavioral data have come through, such as the separations of the learning trajectories for the different set sizes in the RL-LTM Biased model fit. It can also be seen that some parameter sets in the LTM model also capture the difficulty associated with increasing set size (solid lines in Fig. 5B). The LTM participants, on average have the highest accuracies for the testing phase in both set sizes but they are nearly indistinguishable from the meta-RL group for accuracy at end of learning. The biased group shows the most separation between the set size 3 and 6 at learning and also lower accuracy at test than LTM. The biased group is negligibly different from the meta-RL group for set size 3 but shows a marked difference at set size 6, closely following the behavioral data.





There are five outcome measures of interest in the RLWM task: accuracy at the end learning, accuracy at test, learning rate characterized as number of stimulus presentations to reach 85% accuracy and beta estimate for the first 6 trials, the differences in learning of set3 and set 6 and also the level of preserved learning at test for both set-sizes. The following analyses compare the model data with behavioral data.

It is difficult to assess what the model fits are capturing without examining the specific parameter sets more carefully or deducing if membership in a particular model group predicts some other cognitive or learning aspects of the subjects. First, for the cohort of subjects



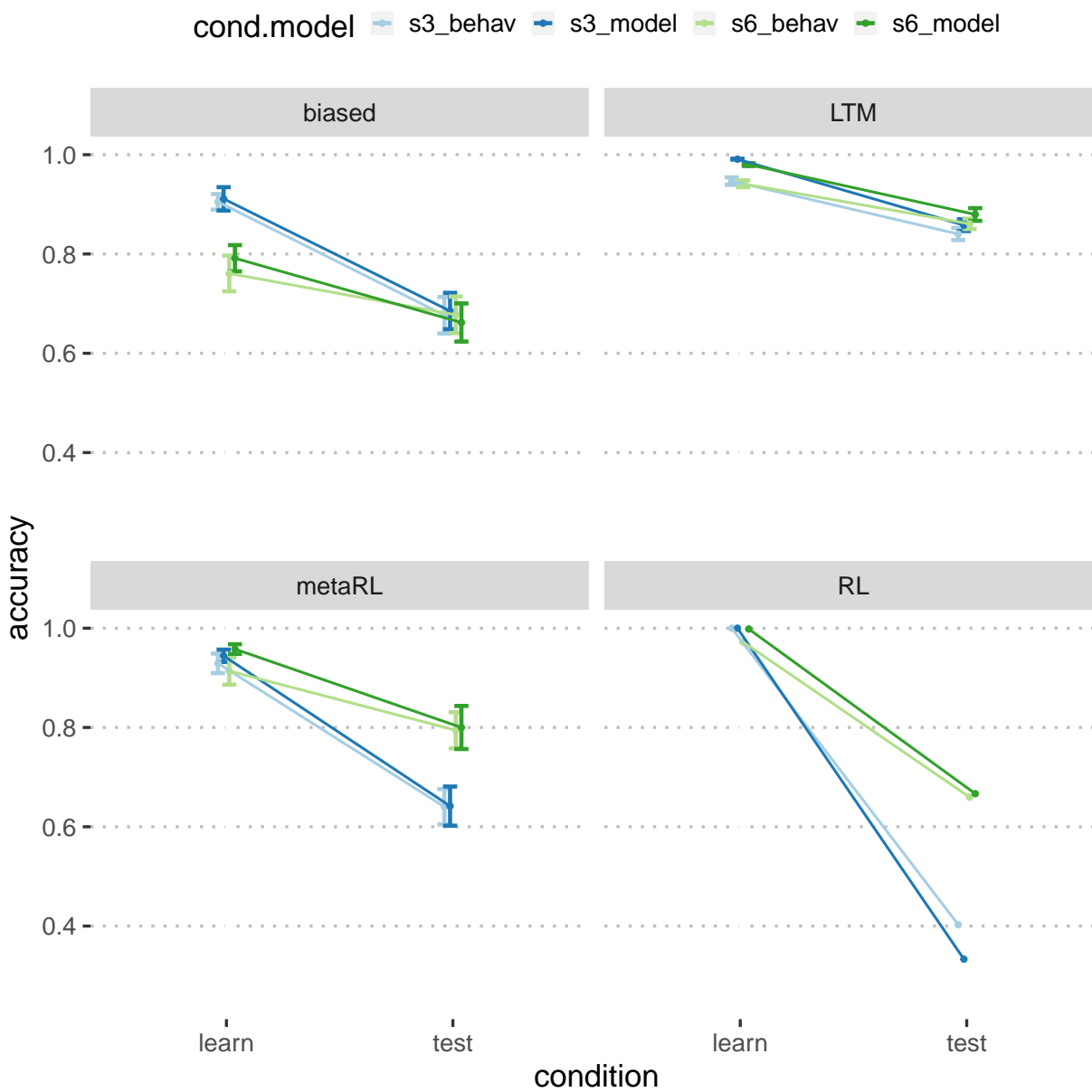


Figure 5: figure 6

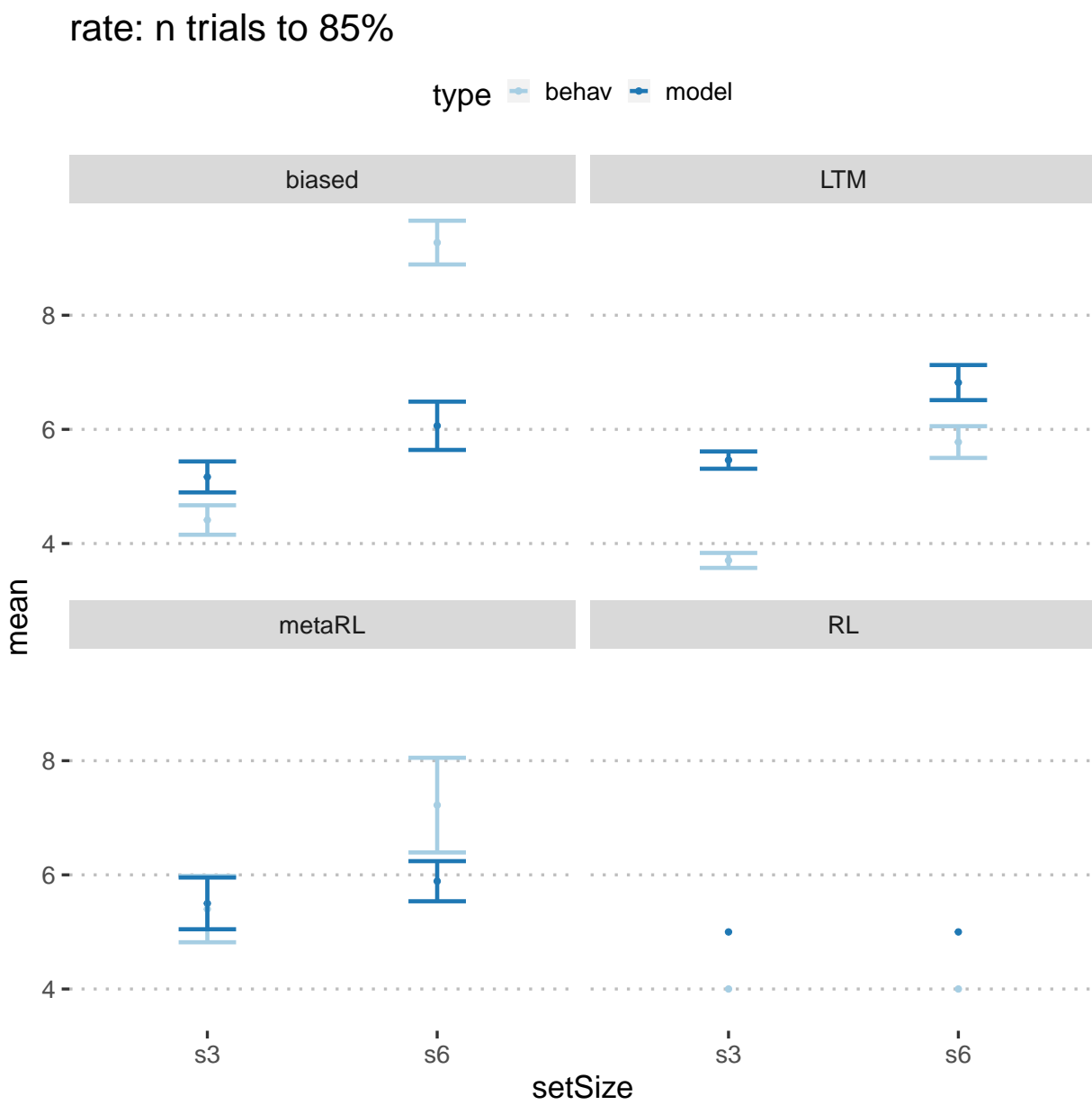


Figure 6: Figure 7.

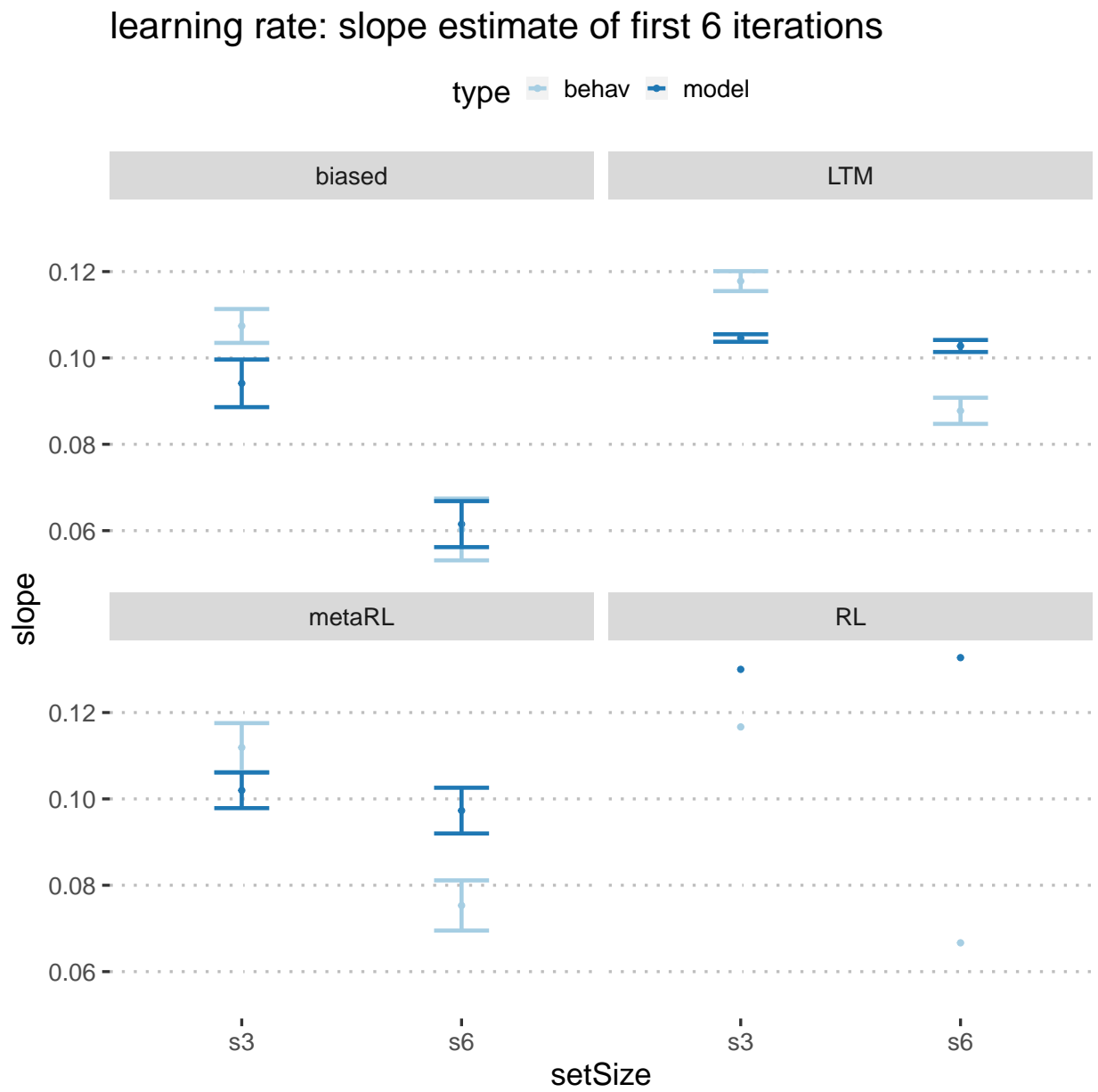


Figure 7: Figure 8.

## separation of the learning cu

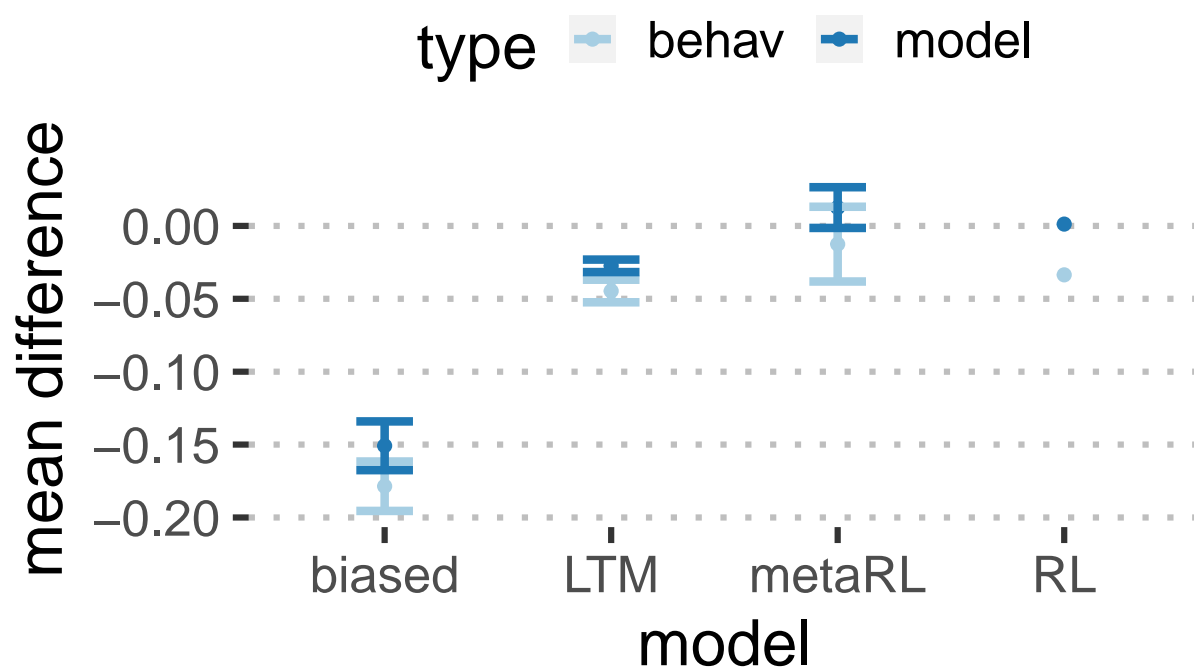


Figure 8: Figure 9.

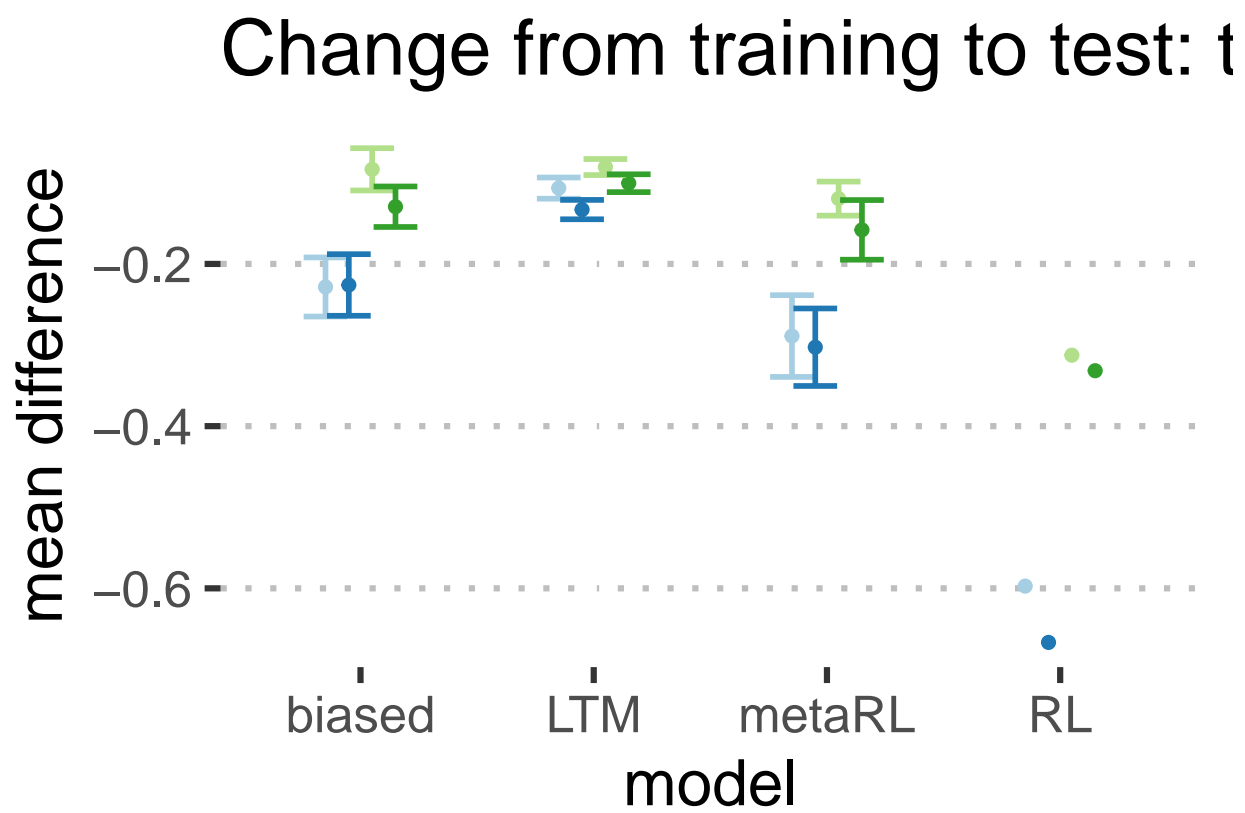
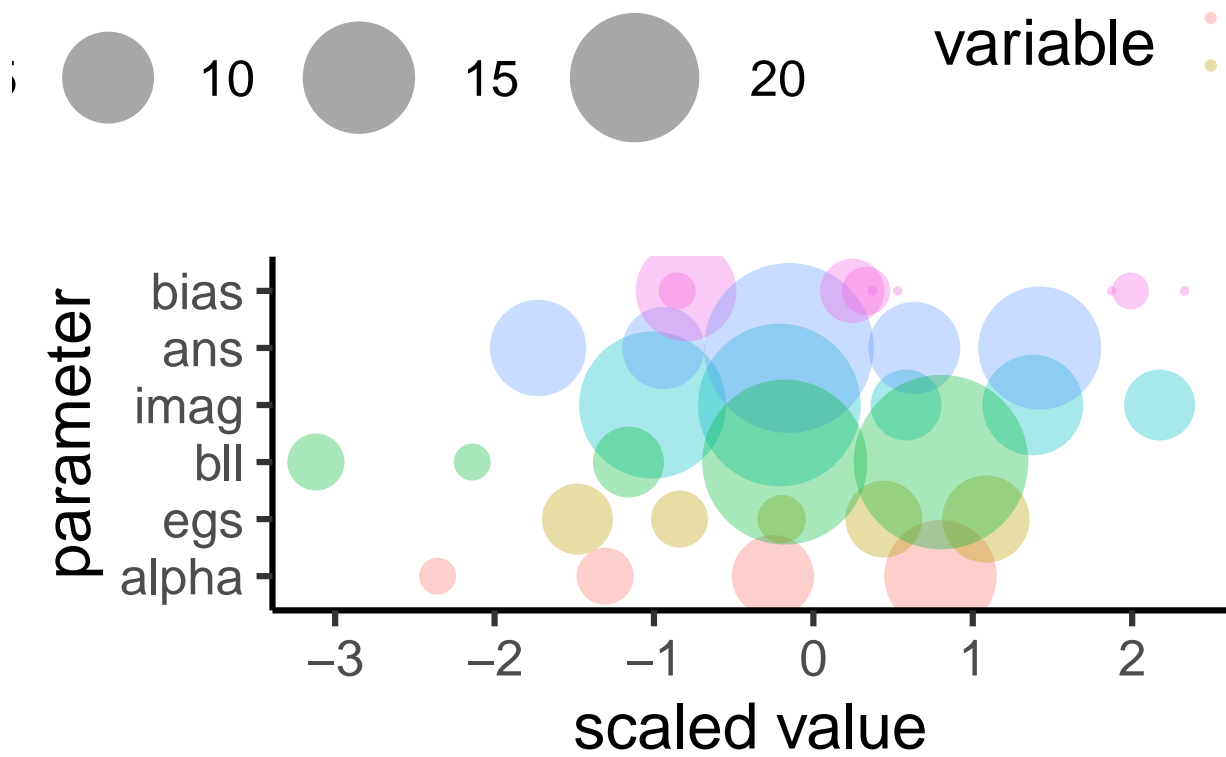


Figure 9: Figure 10.

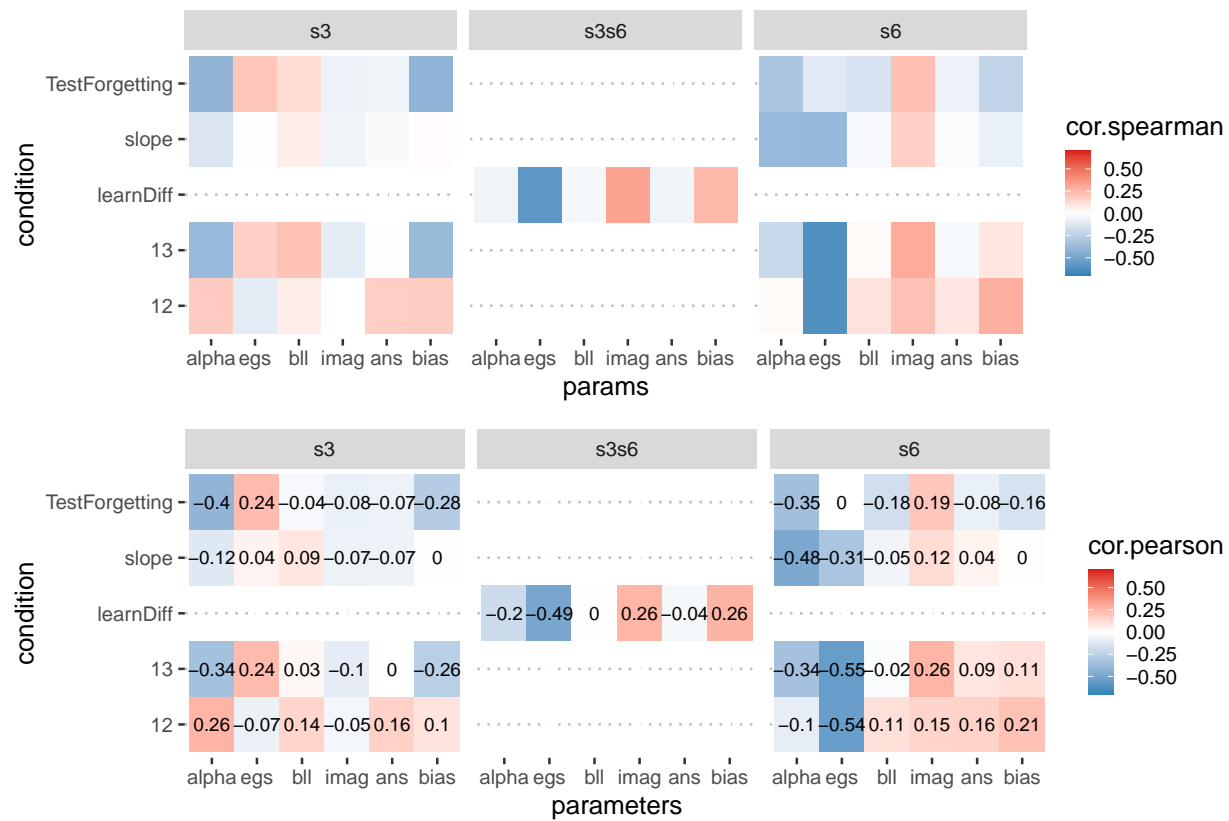
## Parameters

### Parameter spread

Parameter summary: what is the spread of the parameters across participants in the models?



## Individual parameter effects on outcomes

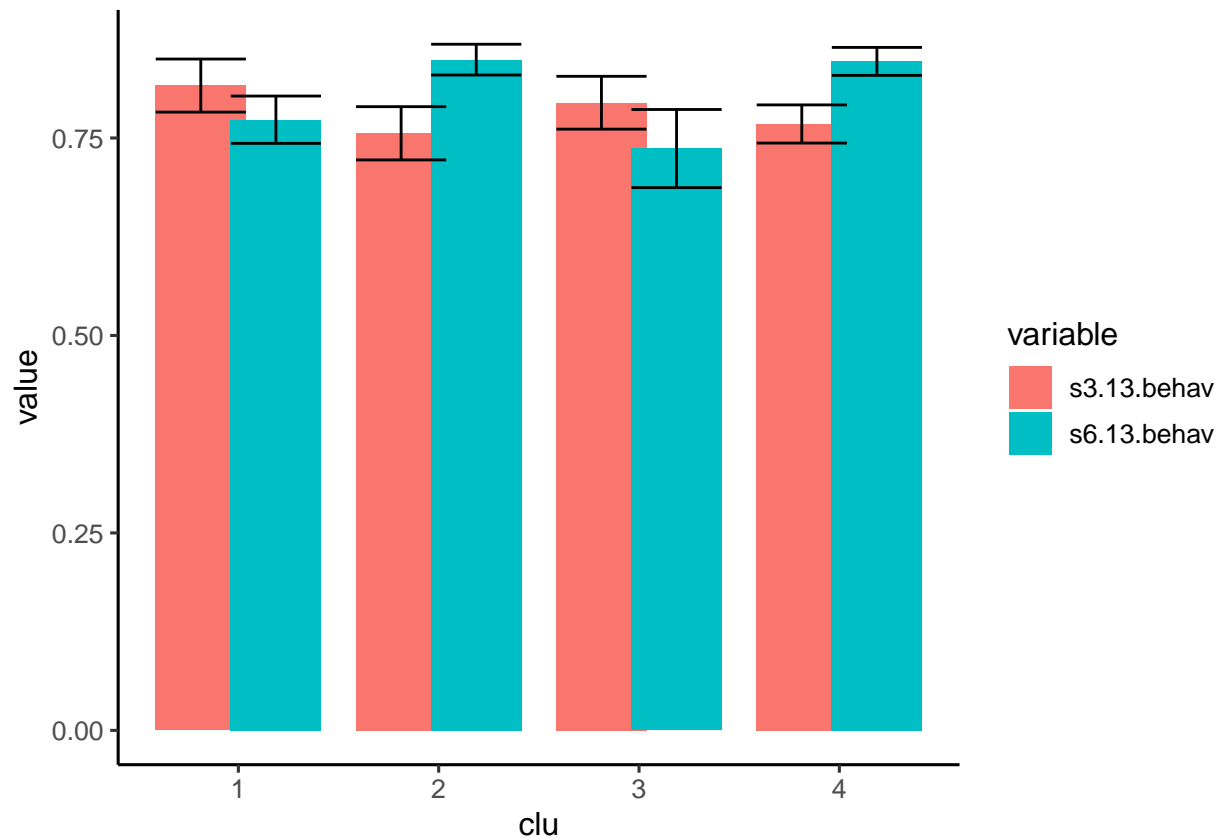


## Combined effect of parameters on outcomes

These plots show that in the biased model, most of the subjects are at very low percentage of RL use. But also, higher rates of RL use or, more even split between RL and LTM indicates a separation between s3 and s6 learning accuracy.

If that is the case, is the inclusion of the RL component a vital part of their learning make-up, however small it is? This plot shows what this group would have looked like if they relied only on LTM.

How about some K-means clustering?

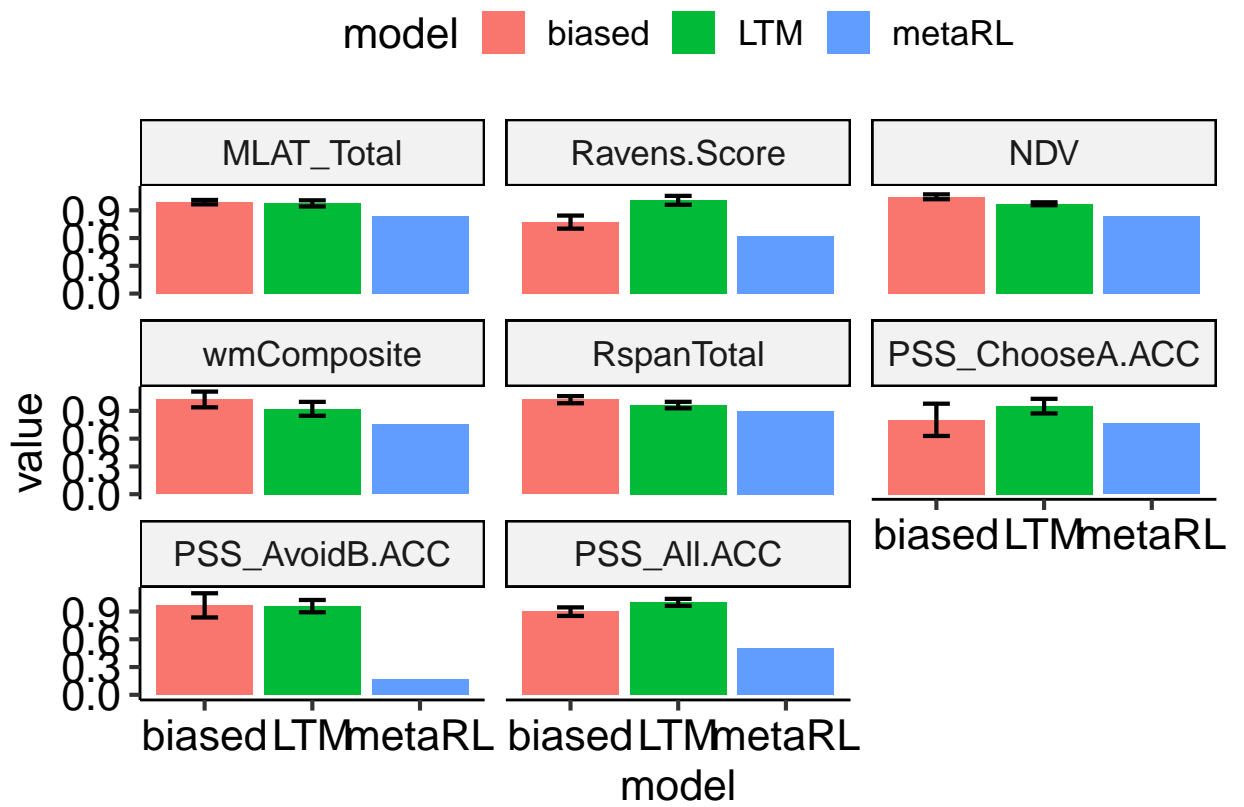


Some specific plans are to estimate the three LTM parameters for all 83 participants and see if they are related to WM, PSS measures. Also, how are the parameters related to the “separation” between s3 and s6?

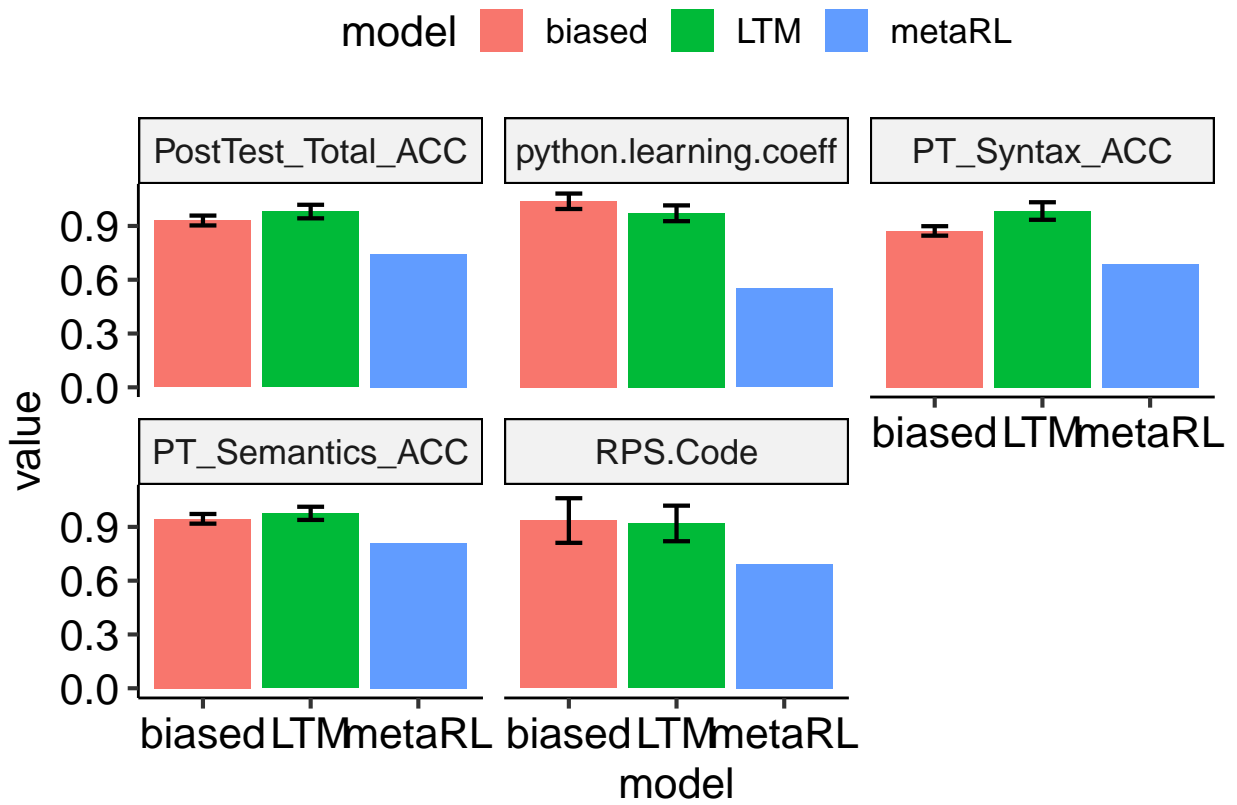
Some more specific things to test might be effect of delay between stimulus presentations. ### What are the differences in learning type in terms of behavioral outcomes in other tasks?

These plots show group effects for uCLIMB subjects only in python and OLCTS measures and behavioral predic-

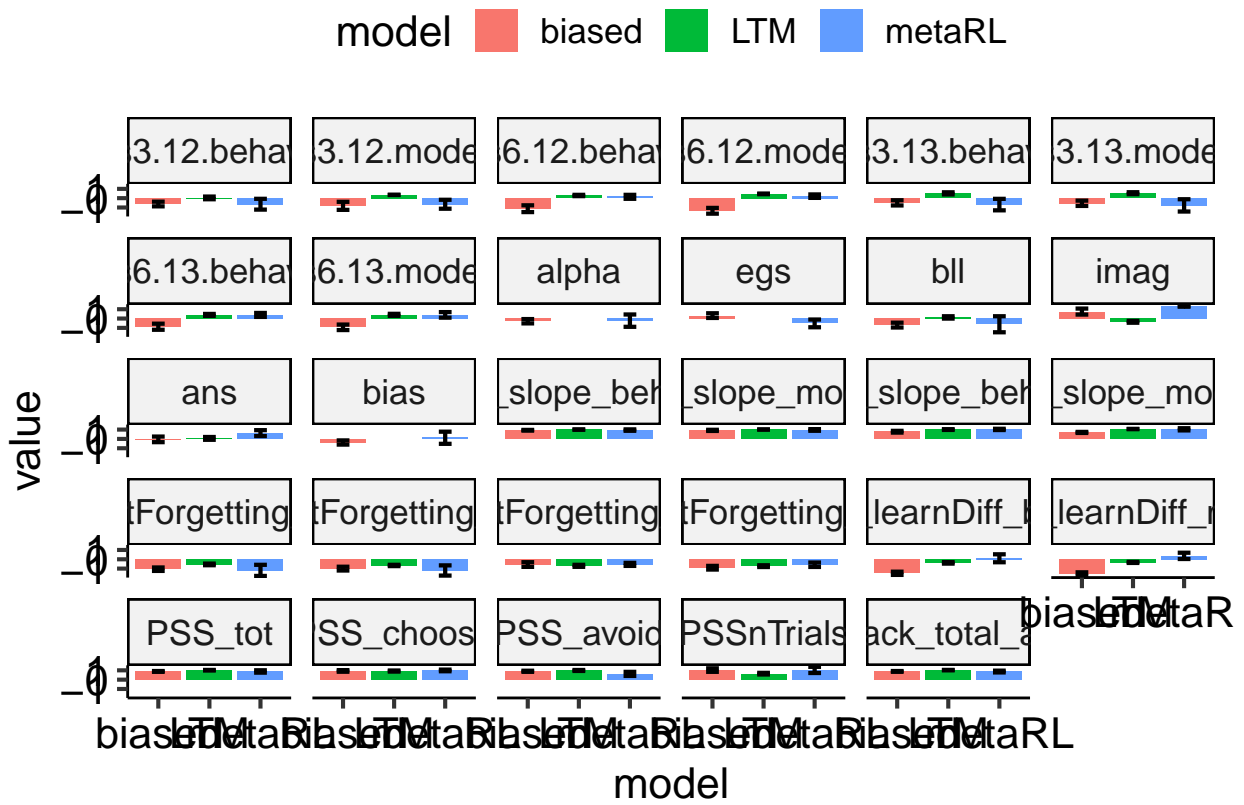


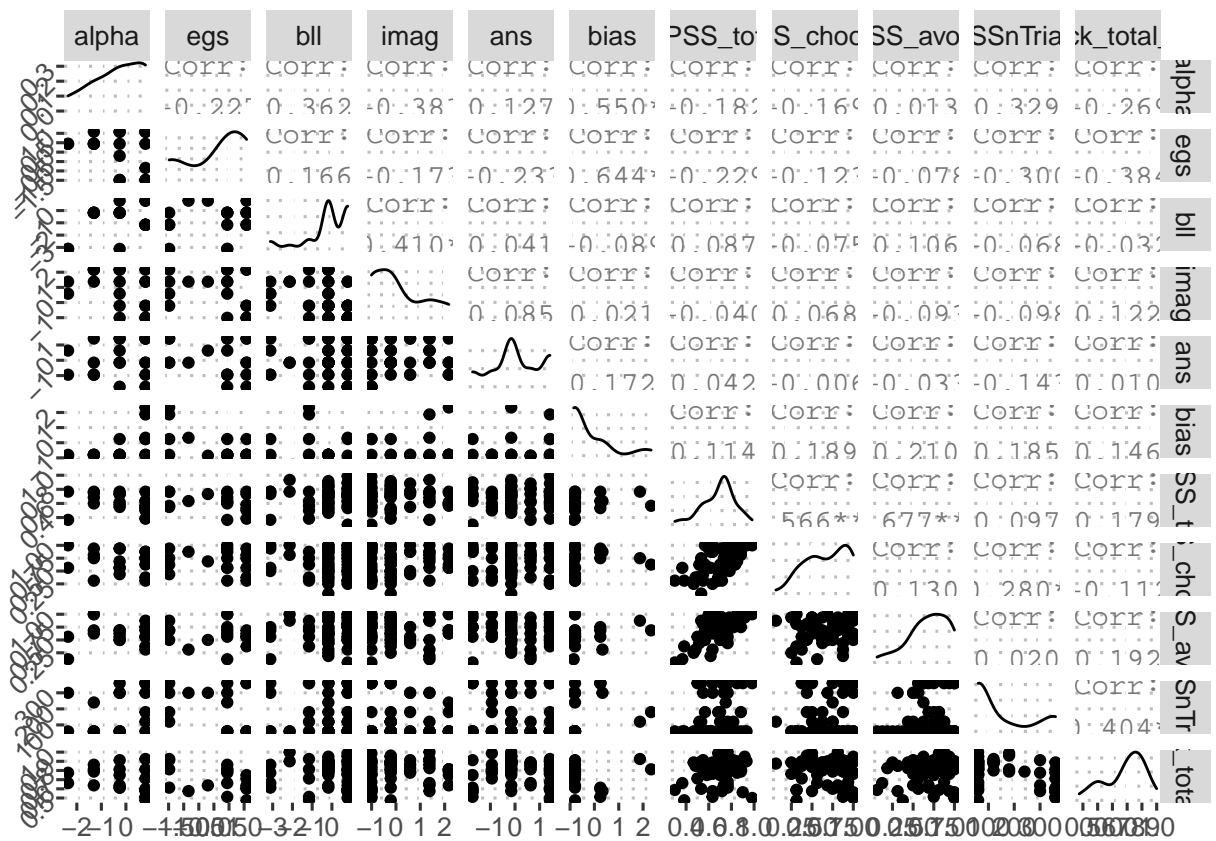


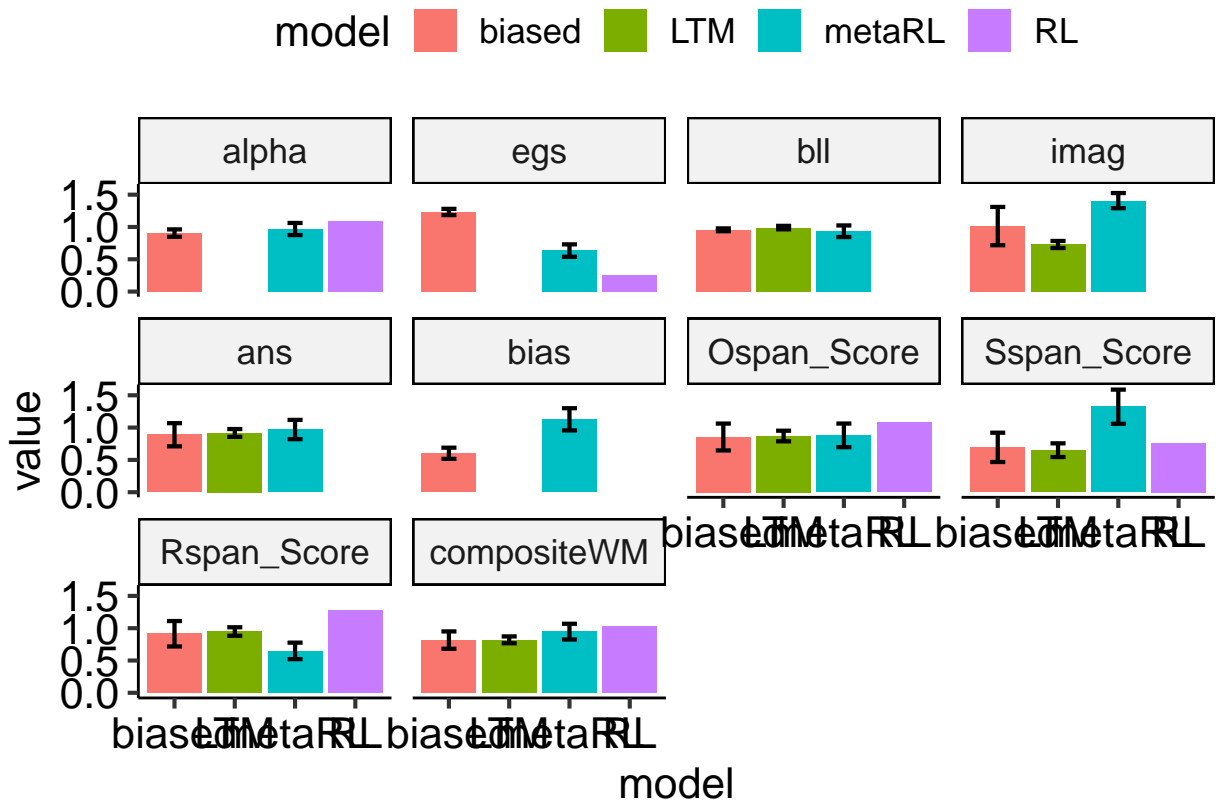
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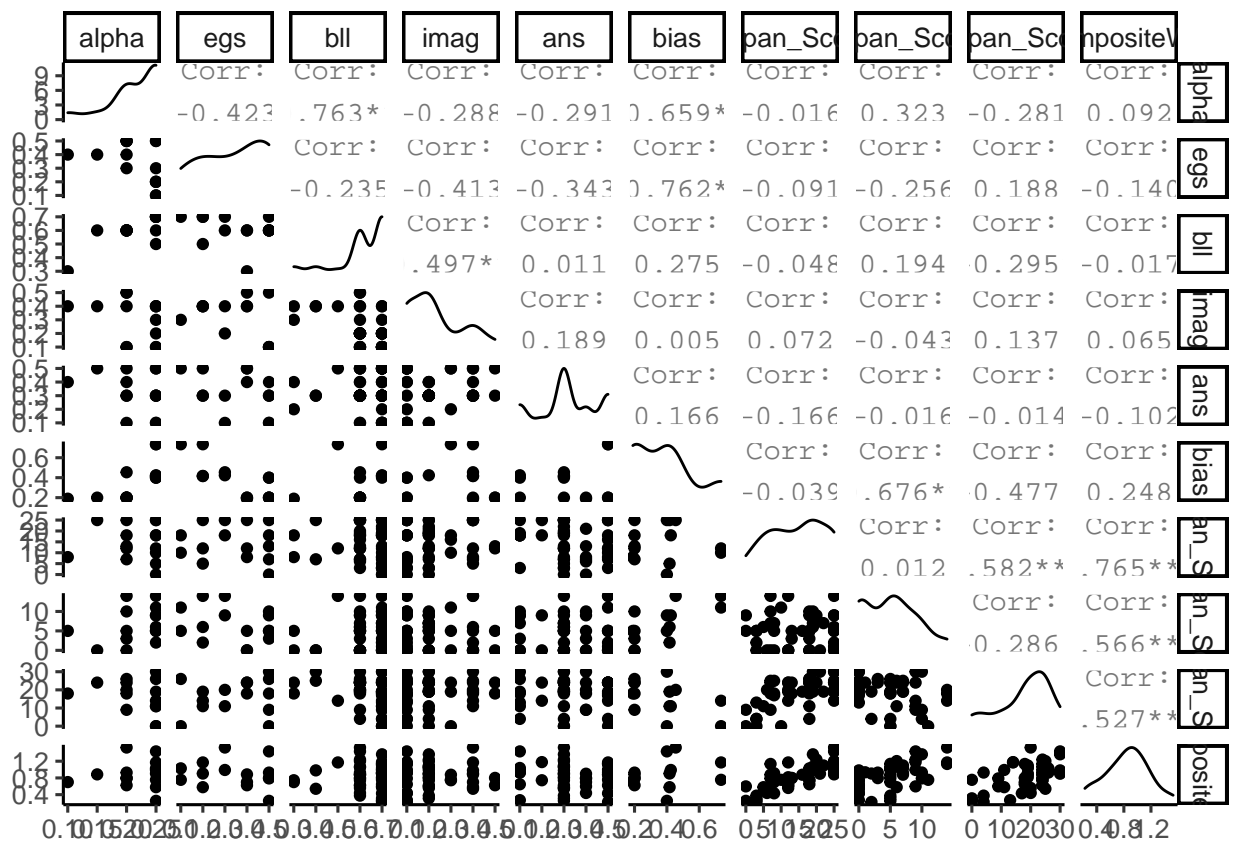


We have 3Back and PSS for a large majority of participants - what are the group differences if any in these outcomes based on model fit?

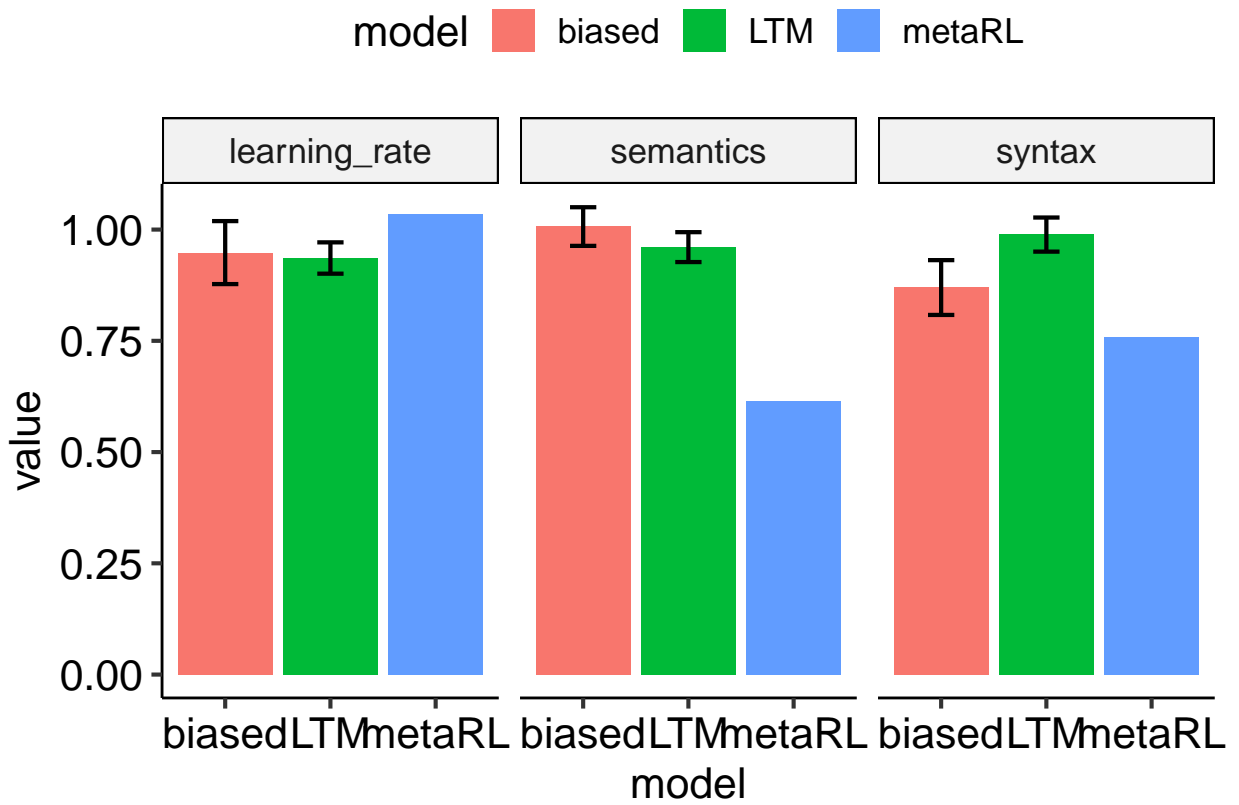








Chantel's request: combine language and programming measures and compare groups.



EEG Beta analysis

Individual plots: