Supplementary Material: Characterizing categorization decision making using visual short term memory representations

Anthea G. Blunden, Dylan Hammond, Piers D. L. Howe, and Daniel R. Little
The University of Melbourne

Abstract

This document contains the supplementary material for Blunden, A. G., Hammond, D., Howe, P. D. L. & Little, D. R. (2020). *Characterizing categorization decision making using visual short term memory representations.* Manuscript submitted for publication.

AND Task: Single change trials

The single change trials in the AND task offer additional non-parametric diagnostic information (Fifić, Little, & Nosofsky, 2010; see also Little, Eidels, Fific, & Wang, 2015, 2018). Diagnostic predictions for each architecture are shown in Figure 1.

In a fixed-order serial self-terminating model, one dimension (either left disc or right disc) is always processed first, followed, if necessary, by the other dimension. If the first dimension that is processed does not involve a change, then a decision can be made and the process will self-terminate. If, however, the first dimension that is processed involves a change, then processing must continue to the second dimension. This leads to the general RT prediction that the first-processed dimension will be approximately the same, whereas the second-processed dimension will be comparatively longer (as it must wait until the first process is finished before it can begin). Further, RTs for the high-magnitude item for the second-processed dimension are comparatively shorter than the low-magnitude item. This is because identifying a large magnitude change is easier than identifying a low magnitude change and so the time taken to switch from the first-processed dimension to the second-processed dimension should be shorter for the HS/SH items.

The single-change items for the AND task also allow for distinction between fixed-order and mixed-order serial processing. While fixed-order processing assumes that the same dimension is always processed first, a mixed-order model assumes that there is variation in which dimension is processed first from trial to trial. Like the fixed-order self-terminating model, the mixed-order model predicts that the redundant stimulus (SS) will have the shortest processing time (as both dimensions lead to a self-terminating stopping rule regardless of which is processed first). The first-processed dimension is still shorter that the second-processed dimension (again, as the second-processed dimension must wait for the first-processed dimension to complete). However, in a mixed-order model, the processing

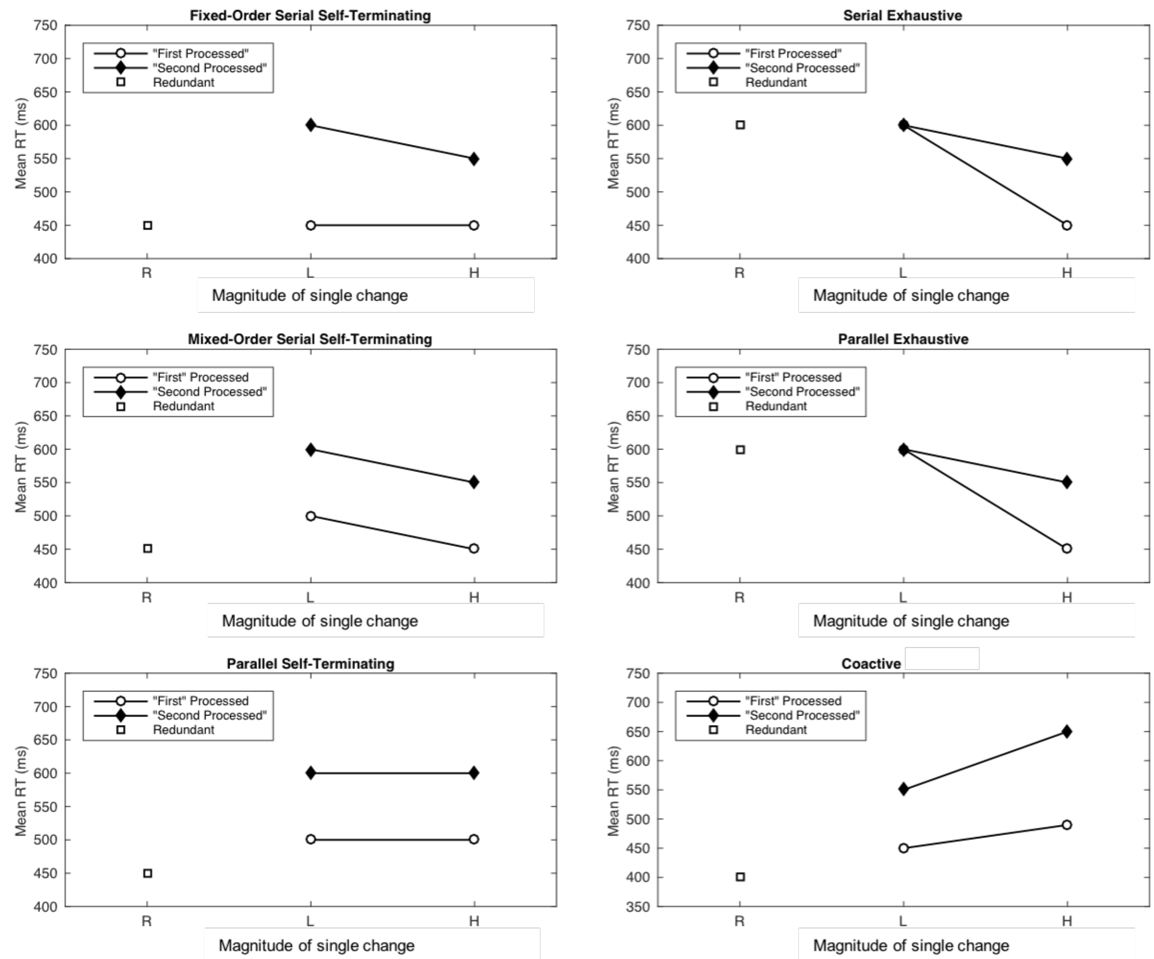

Figure 1. RT predictions for the single-change and no-change items. R = Redundant Stimulus, L = Low salience change, H = High salience change.

time for the high-magnitude stimulus is shorter for both first- and second-processed dimensions. This is because, on average, the time taken to switch from one dimension to the other dimension will be shorter for high magnitude changes compared to low magnitude changes.

For the parallel self-terminating model, processing time is equivalent to the minimum processing time to detect "no-change" across both dimensions. That is, the time it takes to determine whether SL or SH contains an item which has not changed is equivalent for both stimuli. This is also the case with LS or HS. The RTs for low-magnitude and high-magnitude items are therefore equivalent, however, the redundant stimulus should have a faster processing time due to statistical facilitation (Raab, 1962; as there are more chances to self-terminate). Note that parallel and coactive models, the distinction between first-processed and second-processed is less relevant; however, it may be the case that one location is processed faster than the other. This is not a strong or central prediction of the models.

For the serial and parallel exhaustive models, both dimensions must be processed regardless of whether one, or both, dimensions do not involve a change. For the serial exhaustive model, this means that the total processing time comprises the RTs for each individual dimension. The RT for the redundant stimulus should therefore be longer than for the self-terminating models. The parallel exhaustive model predicts that the processing time is equivalent to the maximum processing time across both dimensions. Again, redundant and interior item RTs are longer than for the self-terminating models.

Finally, a general prediction of the coactive model is that the low-magnitude item RTs will be shorter than the high-magnitude items. In the coactive model, each stimulus is represented by a bivariate normal distribution. As one moves from the high-magnitude items towards the left-most corner of the decision space, a greater proportion of the distribution will lie in the single/no-change region. Hence, the chance that a sample will come from the no-change distribution increases for the redundant and low-magnitude items compared to the high-magnitude items, also resulting in a shorter RT for the redundant stimulus and low-magnitude items.

For the AND Task, the mean RTs for the single change items are displayed in Figure 2. For most participants, the RTs for the redundant stimulus was shorter than the other stimuli, suggesting a self-terminating stopping rule. This difference was predominantly significant, excepting the the HS-R comparison for A2 and the SL-R comparison for A4. For A5 the RT for the redundant stimulus was longer than the HS and LS items. For A2 and A3 the RTs for the low-magnitude items were longer than the high-magnitude items, which is consistent with serial processing. However, for A4 the RTs for the low-magnitude items were shorter than the high-magnitude items which could suggest coactive processing. For A5 RTs for the low-magnitude item were shorter on one dimension and longer on the other.

For AND Task single change items, we conducted a series of planned *t* tests comparing low-magnitude and high-magnitude items on both dimensions and comparing the redundant stimulus to the other single change items (see Table 1). For most items the RTs for the redundant stimulus was significantly shorter than the other stimuli, indicating a self-terminating stopping rule[1].

[1]The HS item for A2, SL item for A4 and LS and HS item for A5 were non-significant.

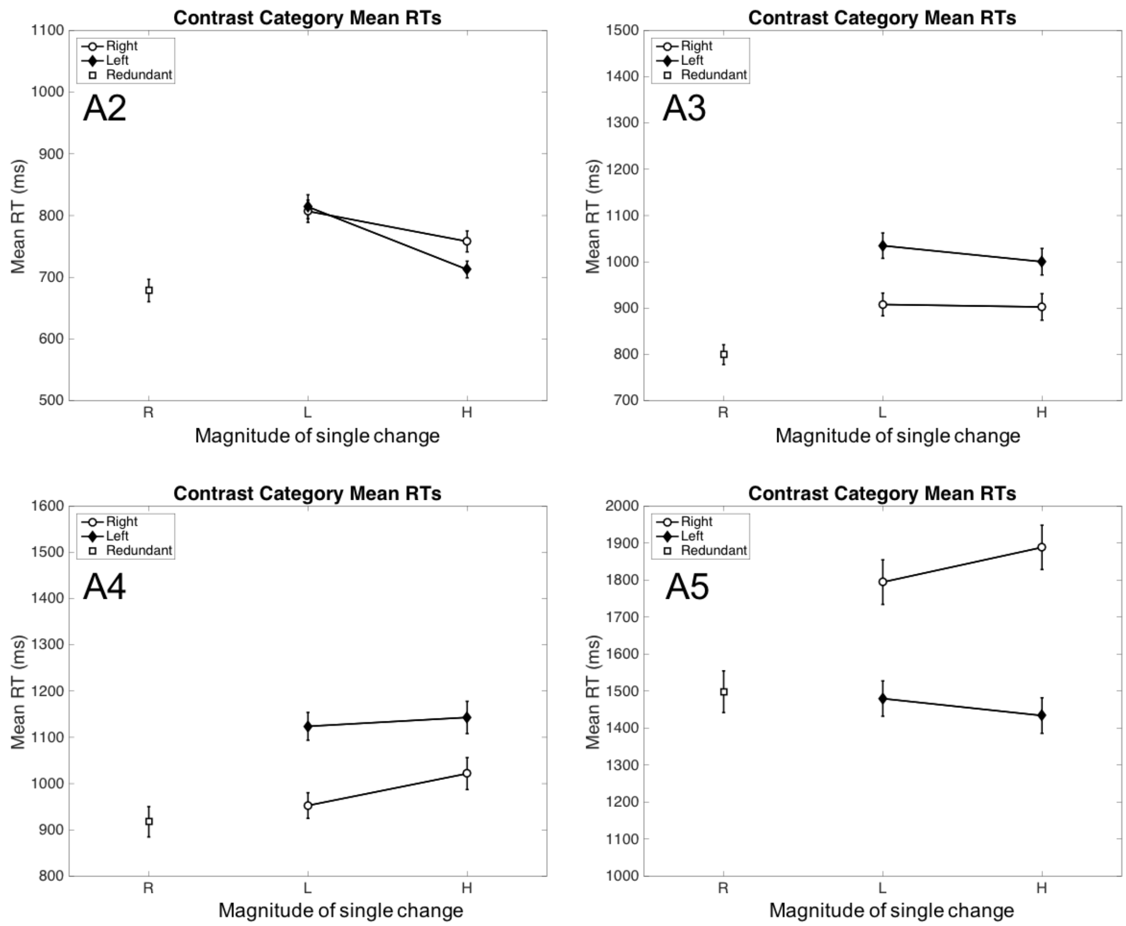

Figure 2. Observed single change item mean RTs for individual participants in Experiment 1: AND Task. Error bars represent one standard error. R = redundant stimulus, I = interior stimulus, E = exterior stimulus.

For A2 the low-magnitude item RTs were significantly longer than the high-magnitude item RTs, indicating serial processing. For the remaining participants there were no significant differences between low-magnitude and high-magnitude items which is consistent with parallel processing, however, caution must be exercised when extrapolating from a null result.

Table 1
Single Change Item Statistical Results for Individual Participants in Experiment 1: AND task

Stimulus Pair	*Mdiff*	*t*	*df*	*p*	*Mdiff*	*t*	*df*	*p*
	A2				A3			
HS - LS	-101.58	-4.34	331	<.001	-34.68	-0.88	332	0.382
SH - SL	-48.97	-1.98	302	0.049	-5.34	-0.14	310	0.887
HS - R	34.06	1.54	300	0.125	200.79	5.37	292	<.001
LS - R	135.64	5.01	287	<.001	235.44	6.45	298	<.001
SH - R	79.54	3.20	280	0.002	103.03	2.8	282	0.006
SL - R	128.51	4.99	278	<.001	108.37	3.25	286	0.001
Stimulus Pair	*Mdiff*	*t*	*df*	*p*	*Mdiff*	*t*	*df*	*p*
	A4				A5			
HS - LS	19.19	0.42	325	0.676	-45.84	-0.68	279	0.499
SH - SL	69.09	1.56	328	0.120	93.99	1.11	201	0.270
HS - R	225.63	4.64	288	<.001	-64.41	-0.88	258	0.382
LS - R	206.44	4.62	295	<.001	-18.57	-0.25	253	0.800
SH - R	104.23	2.14	294	0.033	390.17	4.75	220	<.001
SL - R	35.15	0.83	292	0.410	296.18	3.59	213	<.001

Comparison of the estimated perceptual variance in the free-variance model

To examine whether perceptual variability differed across different change magnitudes (no change, low change, or high change), we extracted the perceptual variability parameters from the best fitting models for most participants from each task. These were the parallel self-terminating model in OR task and the serial self-terminating model in the AND task. We then subtracted the no change variability estimates from the low change variability estimates and the low change variability estimates from the high change variability estimates for the left and right locations. These posterior difference estimates are shown in Figure 3 along with the estimated 95% HDIs. In all cases the HDI's overlap 0.

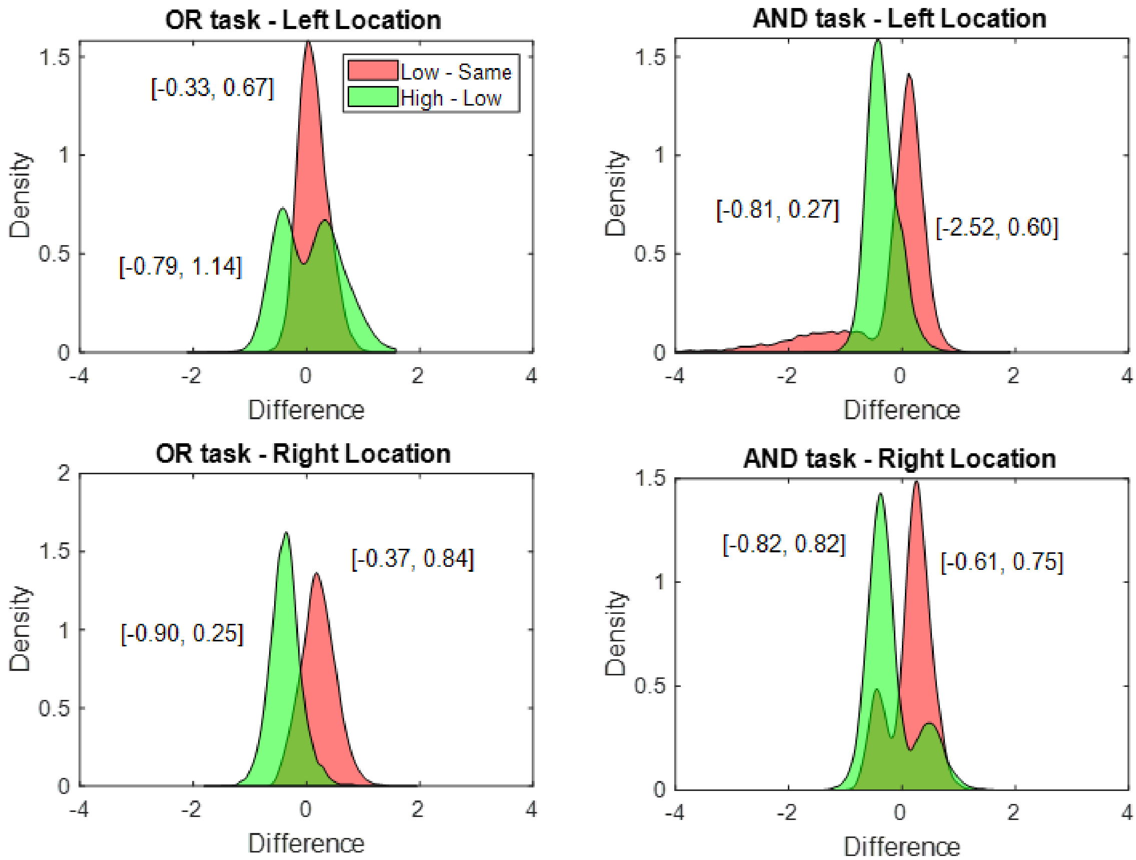

Figure 3. Posterior distributions over the differences in perceptual variance.

Individual Capacity Estimates for Experiment 2

In the primary manuscript, we reported the group capacity estimates. Here we present the individual capacity estimates for each individual participant.

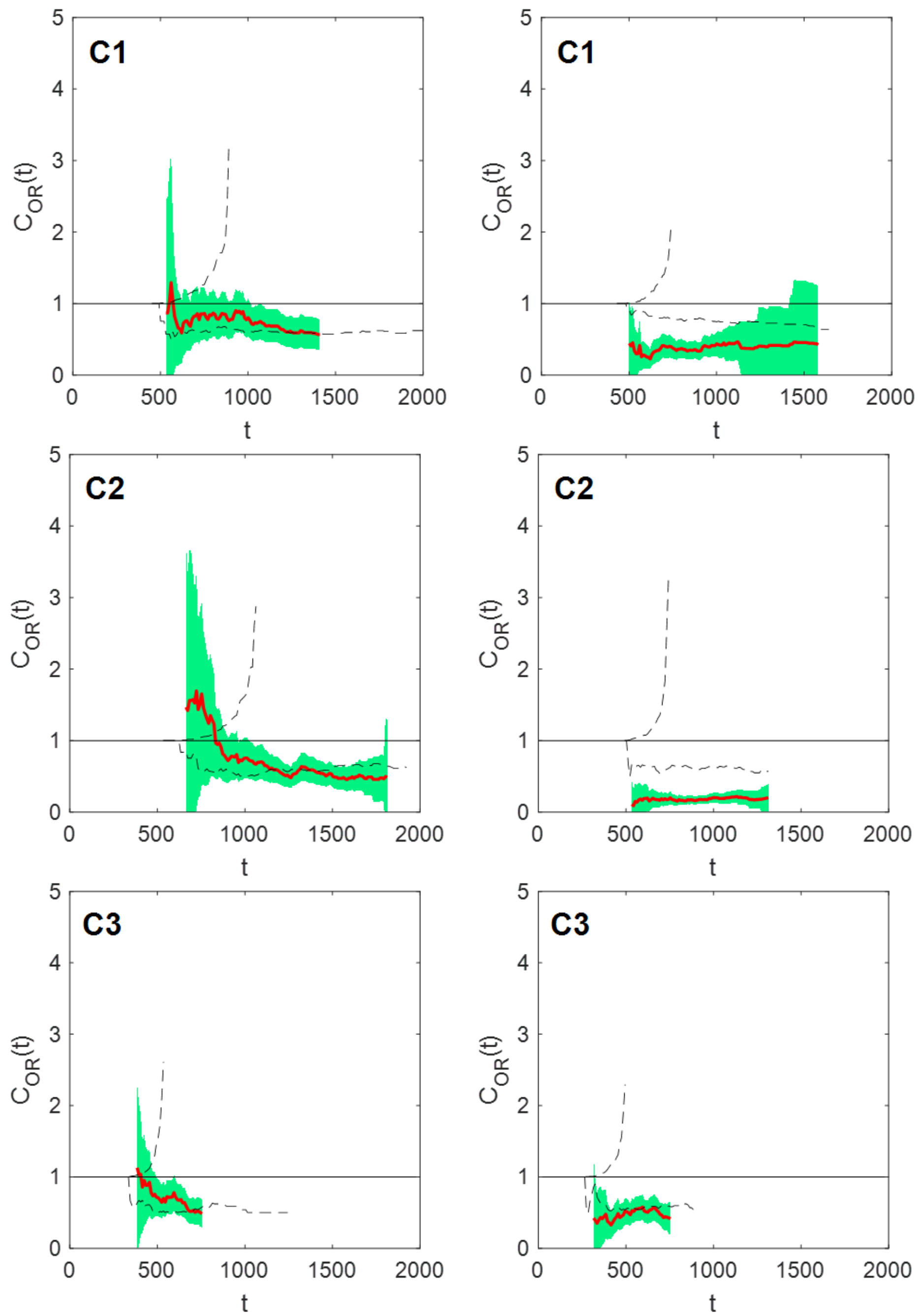

Figure 4. Capacity estimates for each individual participant in the OR condition. Red line represents the capacity coefficient. Black dotted lines represent the Miller (upper) and Grice (lower) bounds, respectively. Left column: redundant target vs single targets+same. Right column: redundant target vs single targets alone.

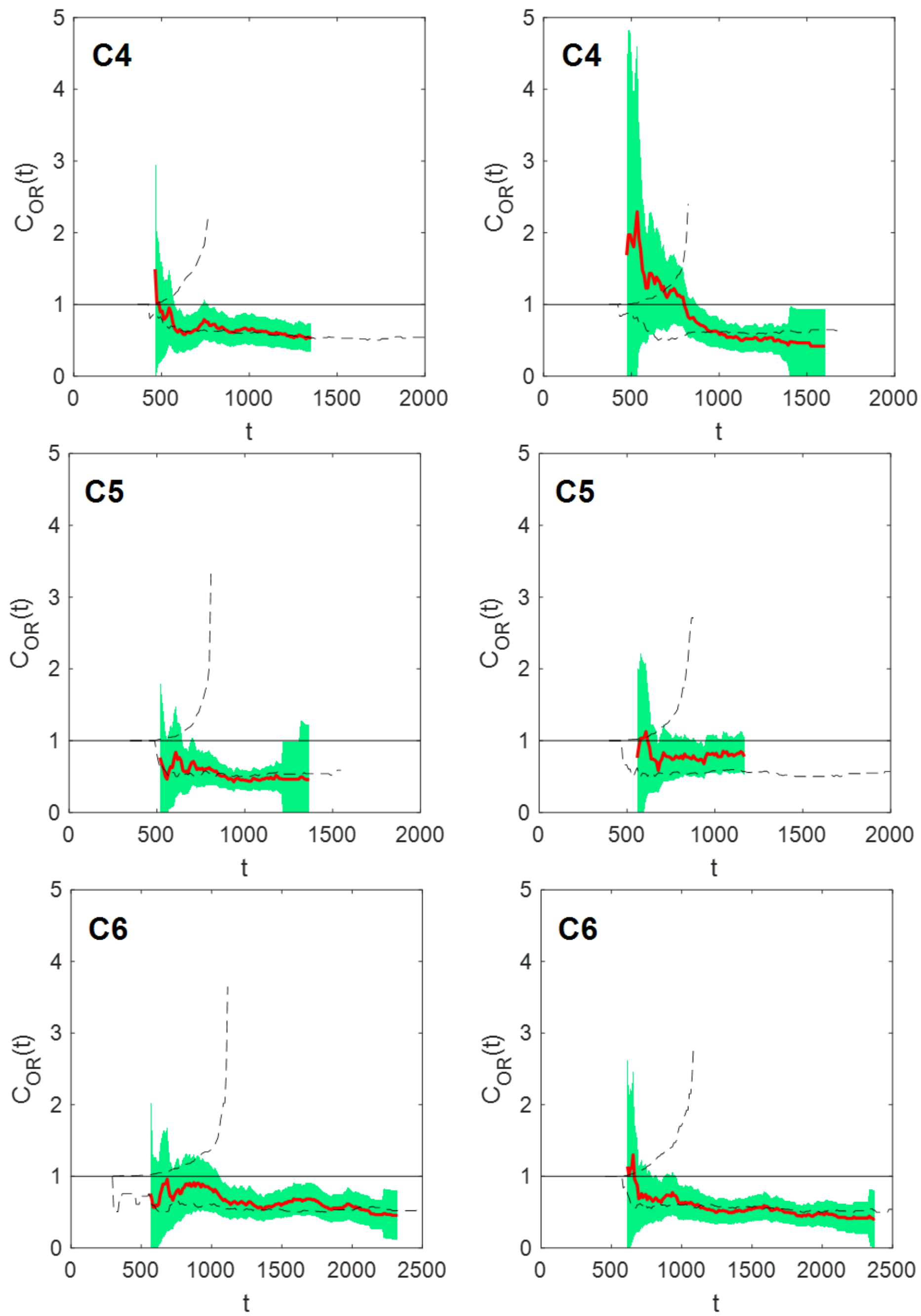

Figure 4. Continued.

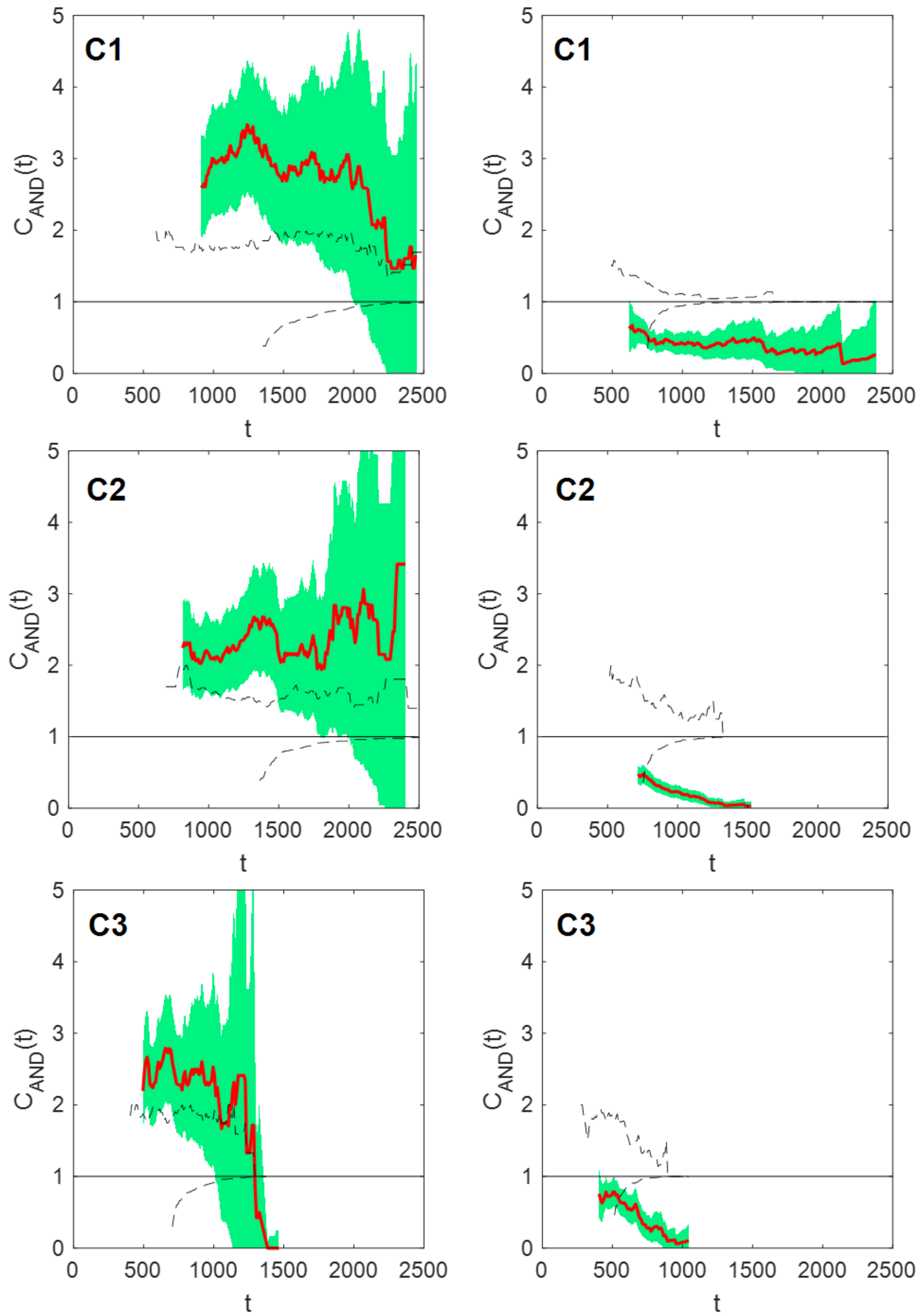

Figure 5. Capacity estimates for each individual participant in the AND condition. Red line represents the capacity coefficient. Black dotted lines represent the Miller (upper) and Grice (lower) bounds, respectively. Left column: redundant target vs single targets+same. Right column: redundant target vs single targets alone.

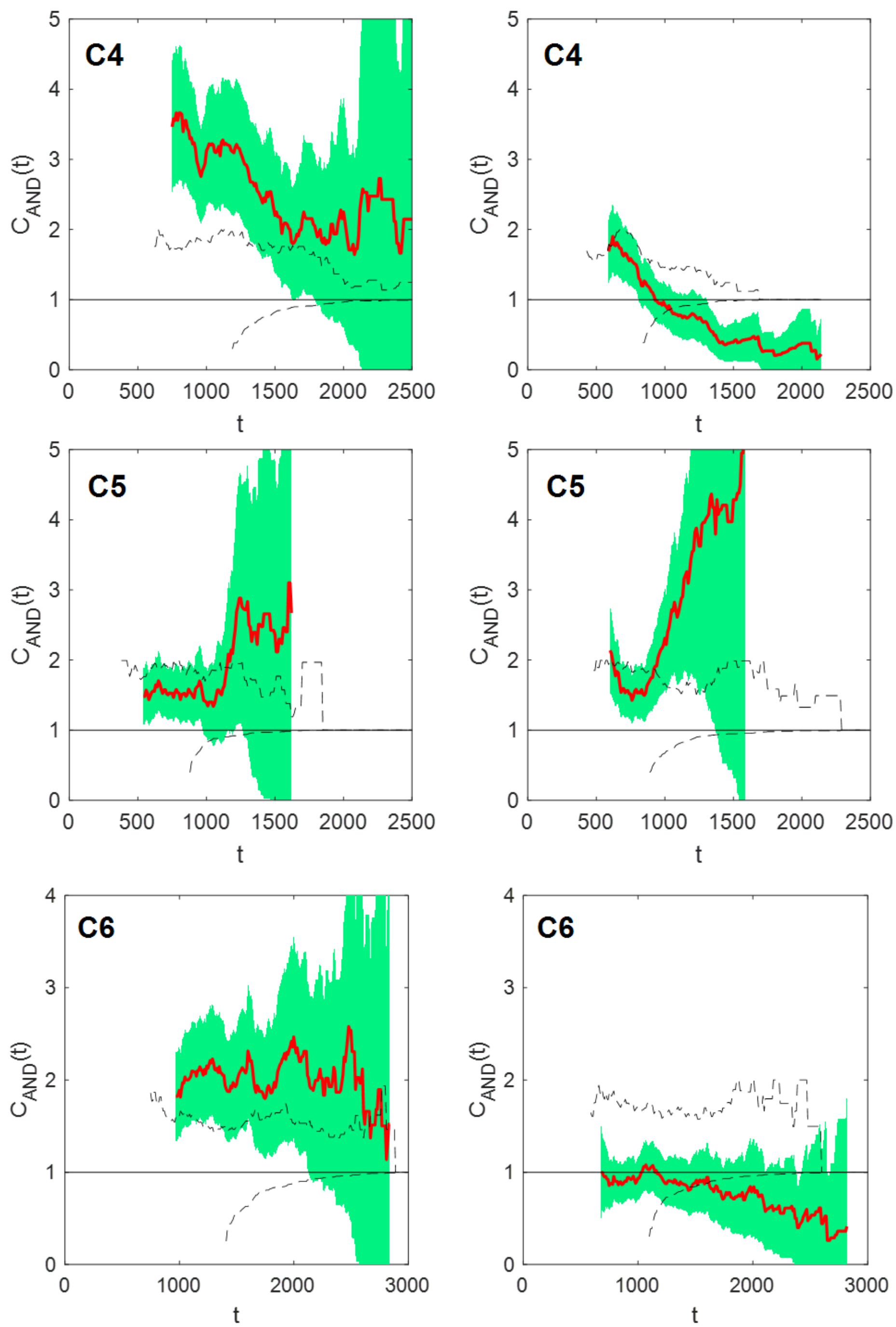

Figure 5. *Continued.*

Posterior Predictive Distributions

In the following posterior predictive distribution plots, each panel captures the data for a single item. The RTs are plotted as a histogram; positive values indicate target category response, and negative values indicate contrast category response. The four items in the top right of each figure belonged to the target category; consequently, most of the RTs should be positive, and any negative RTs indicate an error response for these items. The remaining items belonged to the contrast category and should therefore have mostly negative RTs. Any positive RTs for these items are error RTs.

For each observer, we took 40 samples of parameters from the posterior and generated predictions. Each sample prediction is plotted as a red line. The solid blue line is the prediction based on the average posterior parameters. The likelihood of the average posterior samples is used in the computation of the DIC. The data were binned into 50 msec bins. The posterior predictive densities found using a kernel density estimate with a bandwidth of 10 msec.

OR TASK

The following plots show the posterior predictions from the best-fitting model for each observer from the OR task.

Observer O1: Coactive-min fixed variance model. For the posterior predictions of the coactive-min fixed variance model for observer O1, see Figure 6 below.

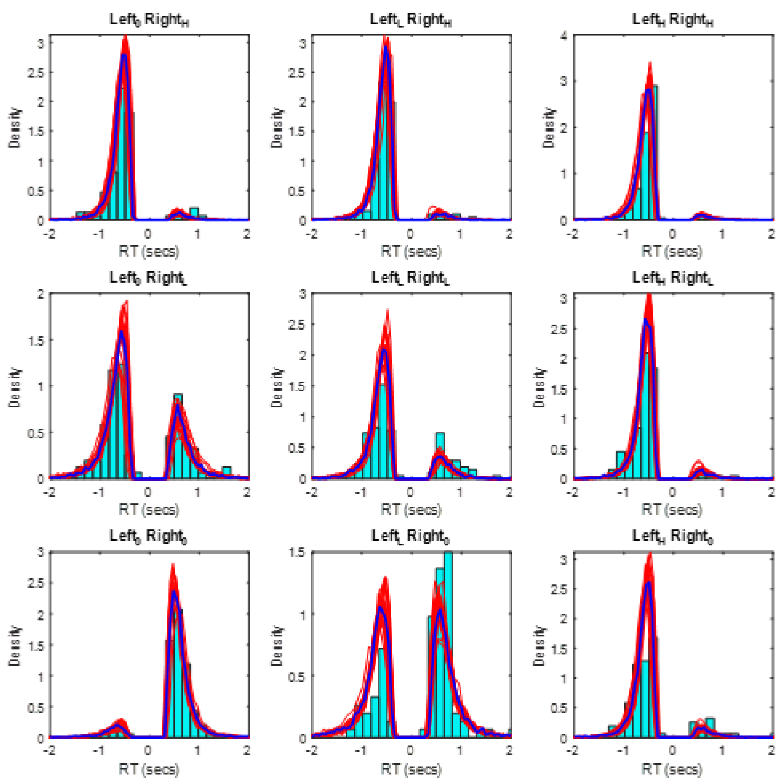

Figure 6. Posterior predictions of the coactive-min fixed variance model for observer O1. Each subplot shows the predictions for one item. Positive RTs indicate target category response. Negative RTs indicate contrast category responses. Data are plotted in the histogram. Each red line indicates a posterior sample. The solid blue line indicates the predictions using the average posterior parameter values.

Observer O2: parallel self-terminating free variance model. For the posterior predictions from the parallel self-terminating free variance model for observer O2, see Figure 7 below.

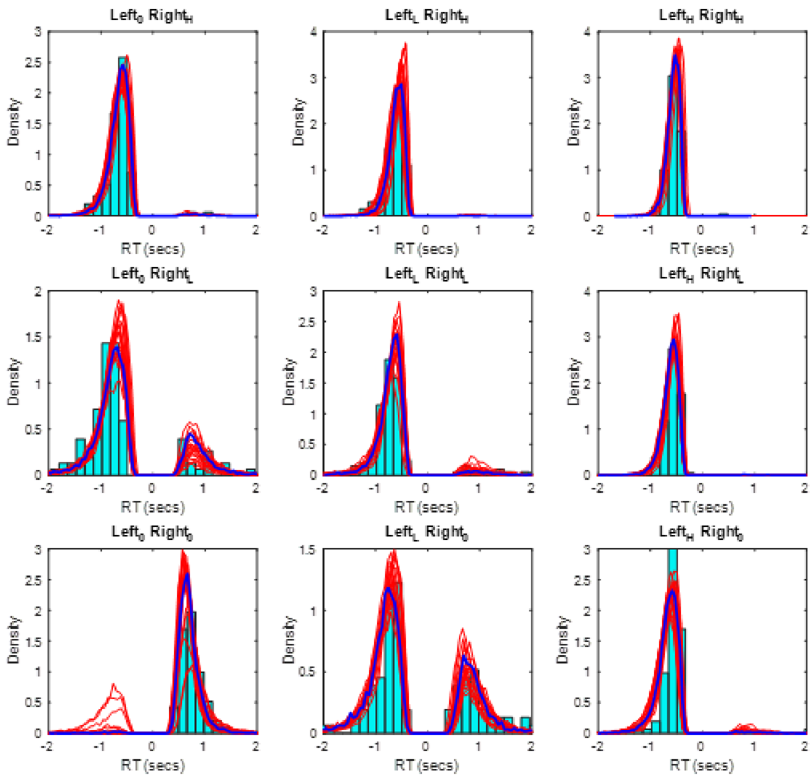

Figure 7. Posterior predictions from the parallel self-terminating free variance model for observer O2.

Observer O3: parallel self-terminating fixed variance model. For the posterior predictions from the parallel self-terminating fixed variance model for observer O3, see Figure 8 below.

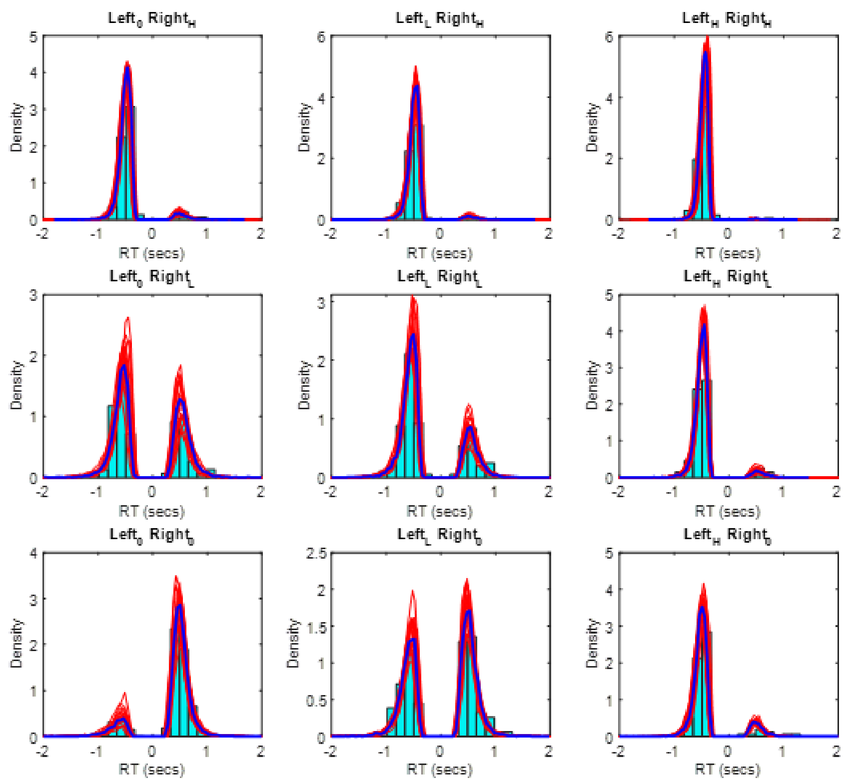

Figure 8. Posterior predictions from the parallel self-terminating fixed variance model for observer O3.

Observer O4: parallel self-terminating fixed variance model. For the posterior predictions from the parallel self-terminating fixed variance model for observer O4, see Figure 9 below.

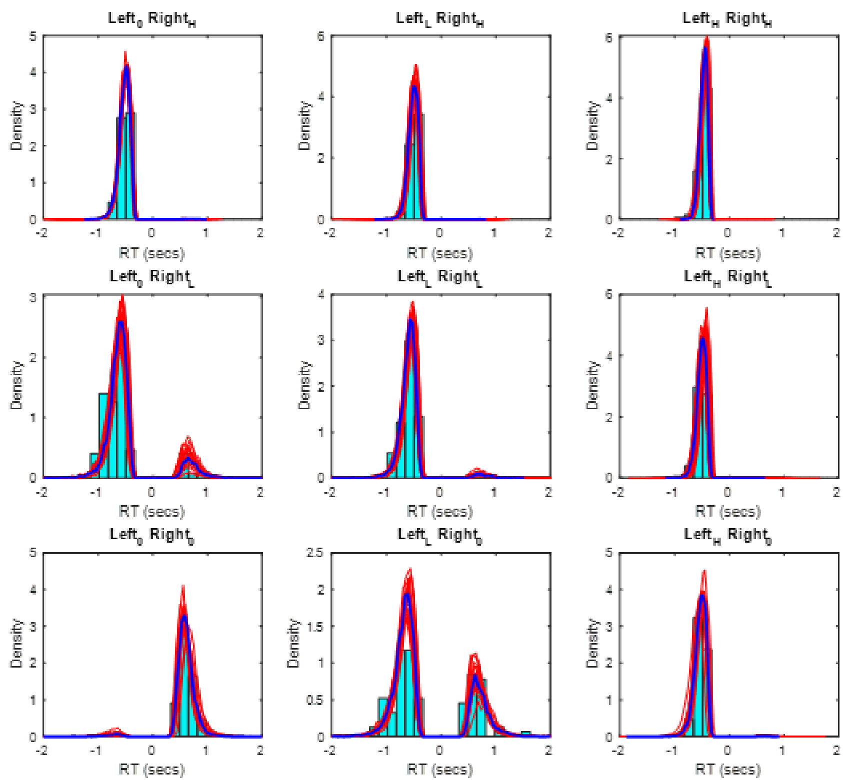

Figure 9. Posterior predictions from the parallel self-terminating fixed variance model for observer O4.

Observer O5: parallel self-terminating free variance model. For the posterior predictions from the parallel self-terminating free variance model for observer O5, see Figure 10 below.

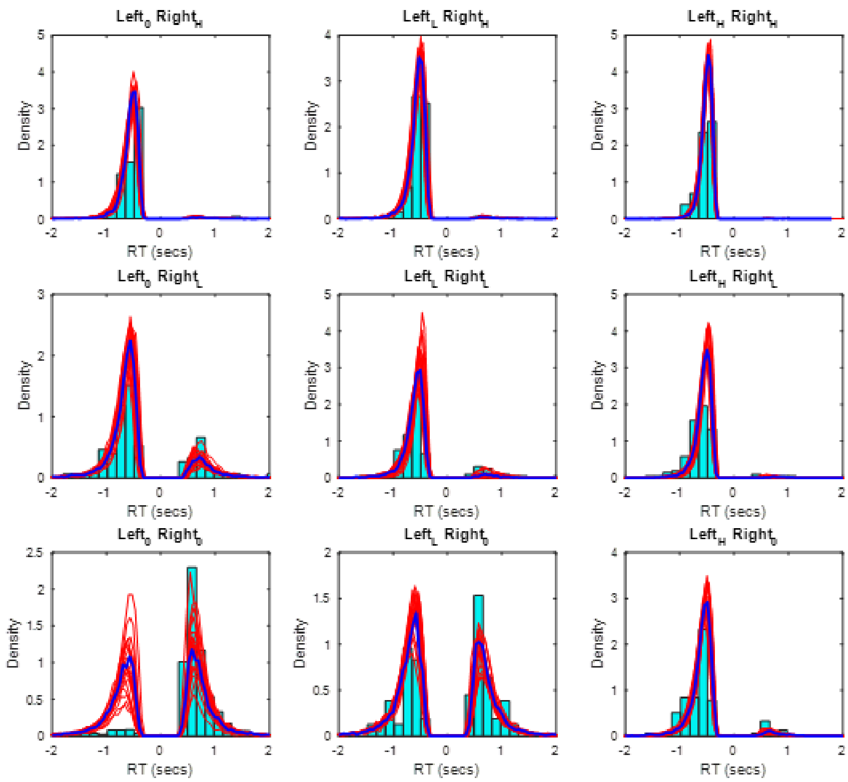

Figure 10. Posterior predictions from the parallel self-terminating free variance model for observer O5.

AND TASK

The following plots show the posterior predictions from the best-fitting model for each observer from the AND task.

Observer A1: coactive-max fixed variance model. For the posterior predictions from the coactive-max fixed variance model for observer A1, see Figure 11 below.

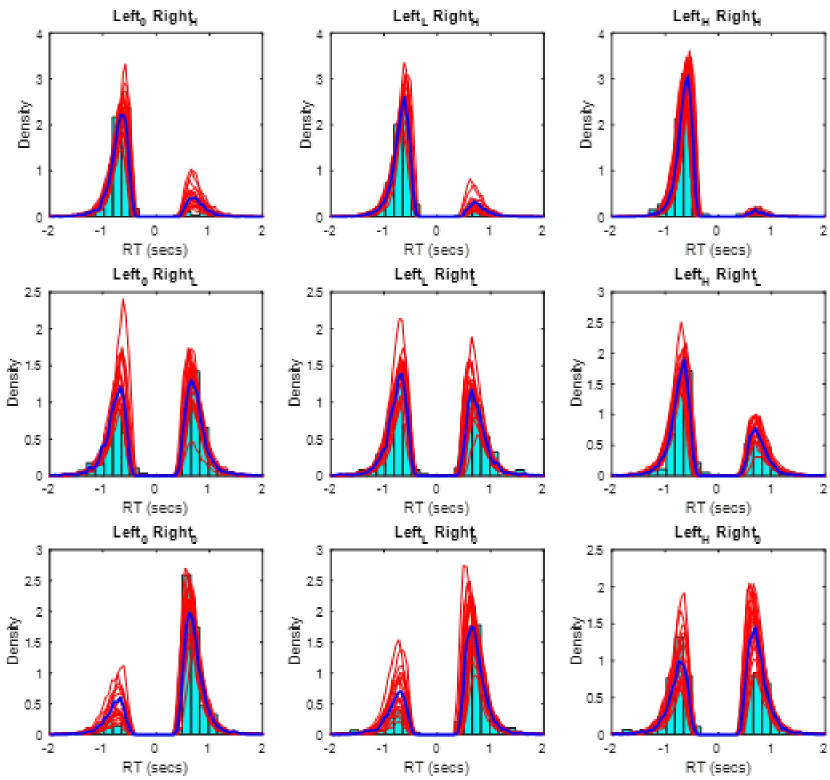

Figure 11. Posterior predictions from the coactive-max fixed variance model for observer A1.

Observer A2: serial self-terminating free variance model. For the posterior predictions from the serial self-terminating free variance model for observer A2, see Figure 12 below.

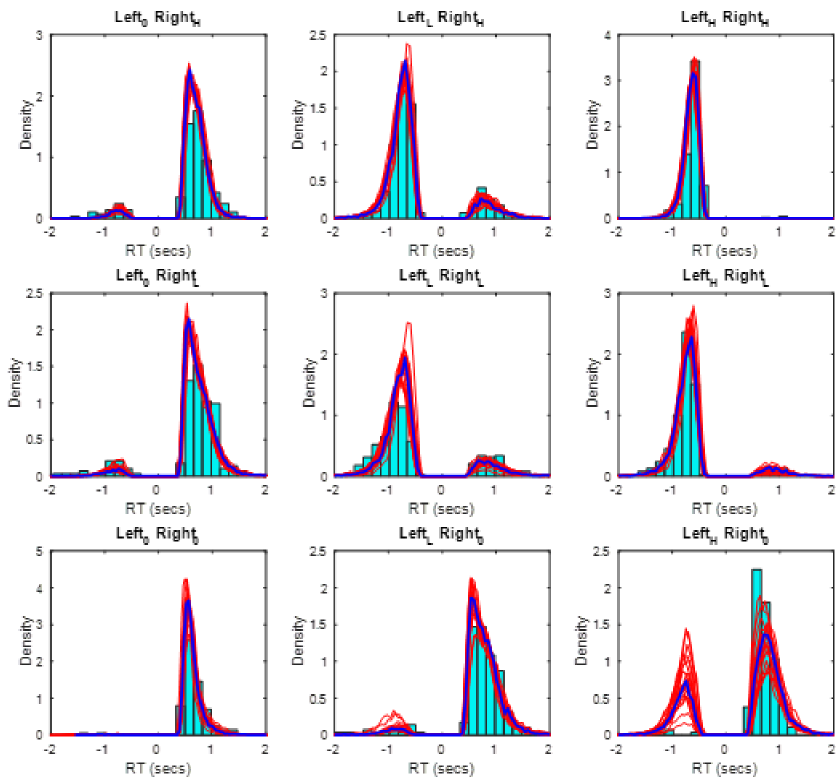

Figure 12. Posterior predictions from the serial self-terminating free variance model for observer A2.

Observer A3: serial self-terminating fixed variance model. For the posterior predictions from the serial self-terminating fixed variance model for observer A3, see Figure 13 below.

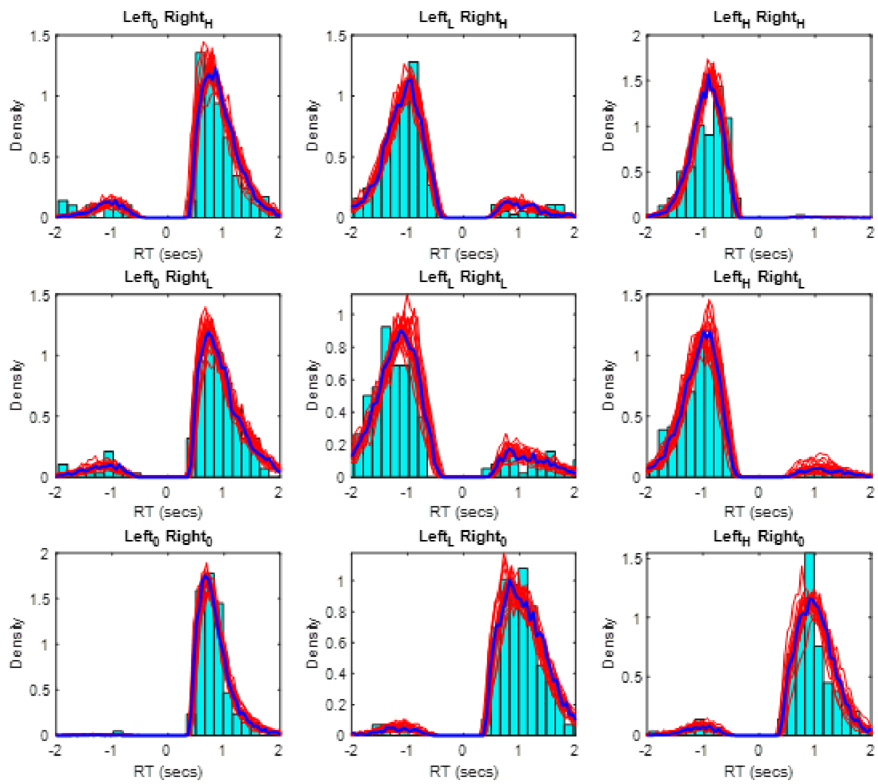

Figure 13. Posterior predictions from the serial self-terminating fixed variance model for observer A3.

Observer A4: serial self-terminating fixed variance model. For the posterior predictions from the serial self-terminating fixed variance model for observer A4, see Figure 14 below.

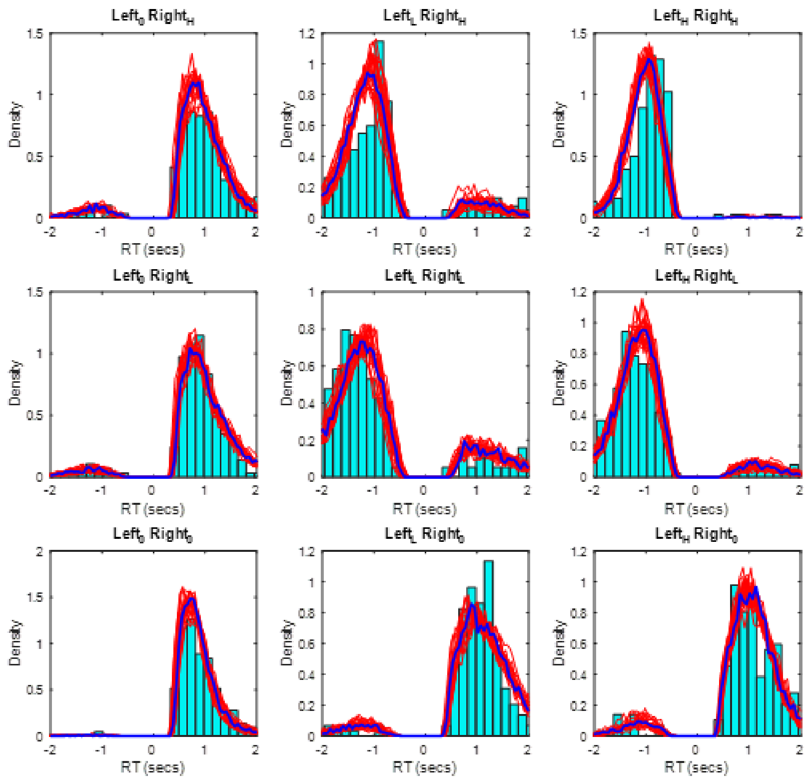

Figure 14. Posterior predictions from the serial self-terminating fixed variance model for observer A4.

Observer A5: coactive-max fixed variance model. For the posterior predictions from the coactive-max fixed variance model for observer A5, see Figure 15 below.

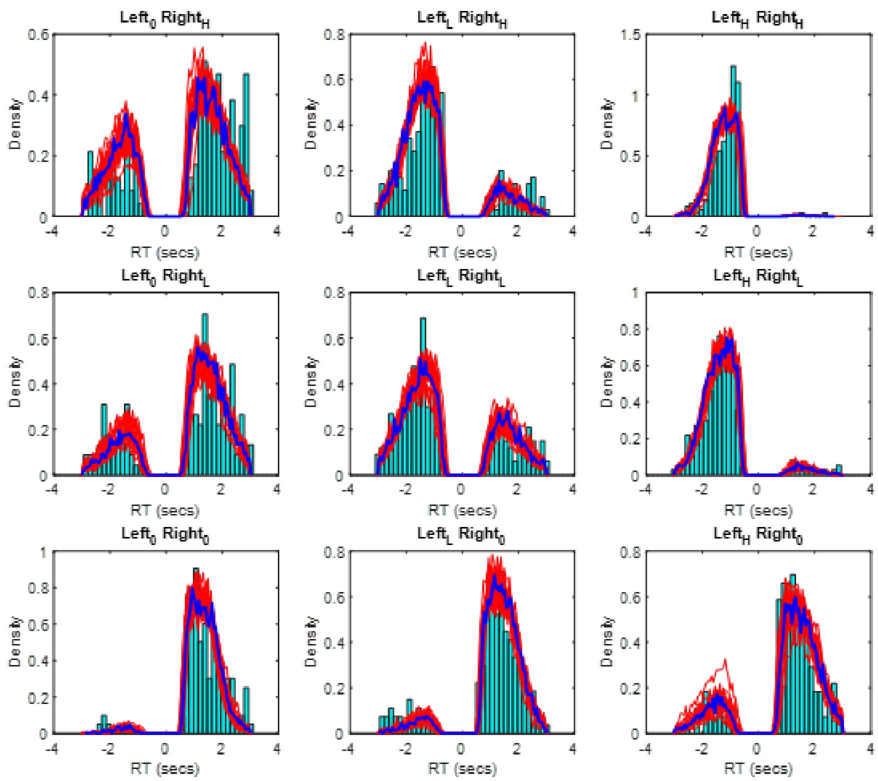

Figure 15. Posterior predictions from the coactive-max fixed variance model for observer A5.

References

Fifić, M., Little, D. R., & Nosofsky, R. (2010). Logical-rule models of classification response times: A synthesis of mental-architecture, random-walk, and decision-bound approaches. *Psychological Review*, *117*, 309-348.

Little, D. R., Eidels, A., Fific, M., & Wang, T. (2015). Understanding the influence of distractors on workload capacity. *Journal of Mathematical Psychology*, *68*, 25-36.

Little, D. R., Eidels, A., Fific, M., & Wang, T. (2018). How do information processing systems deal with conflicting information? differential predictions for serial, parallel and coactive processing models. *Computational Brain & Behavior*, *1*, 1-21.

Raab, D. (1962). Statistical facilitation of simple reaction time. *Transaction of the New York Academy of Science*, *43*, 574-590.