Results and Modelling for ATC Experiment E1

Russell Boag

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Results

- Conventional statistical analyses are reported first in order to check whether our experimental manipulations had the expected effects on manifest RT and accuracy.
- Data from two particpants was excluded from the analyses; one who failed to complete all experimental blocks and one who made no PM responses at all for the entire experiment.
- We excluded trials with outlying RTs, defined as less than 0.2s or 3 times the interquartile range / 1.349 (a robust measure of standard deviation) above the mean (8.35% of responses overall). PM keypresses occurring during the control condition (which contained no PM stimuli) were also excluded.
- The following analyses compare mean accuracy and RT by stimulus type (conflict, nonconflict, PM) PM block (control, PM) and time pressure (Low, High) across 2 levels of trial load (2 vs 5 decision per trial).
- In our omnibus significance testing for accuracy effects we used generalized linear mixed models with a probit link function. In our omnibus significance testing for mean correct RTs we used general linear mixed models.
- Significance was assessed with Wald's chi-square tests, and an alpha level of 0.05 was used in all analyses. The results of our omnibus analyses are tabulated in the supplementary materials. All standard errors reported in text and displayed in graphs were calculated using the bias corrected method.

Ongoing Task (Non-PM) Trials

- Accuracy was lower for conflicts (67.1%) compared to nonconflicts (80.8%), slightly lower under PM load compared to control (control M = 74.8%, SE = 3.2%; PM M = 73.1%, SE = 3.4%), and decreased across different levels of time pressure during both low traffic load (Low TP M = 77.2%, SE = 2.7%; High TP M = 74.4%, SE = 2.7%) and high traffic load conditions (Low TP M = 75.8%, SE = 2.5%; High TP M = 68.5%, SE = 2.5%).
- Mean RT was slower for conflicts (3.00s) compared to nonconflicts (2.65s), slower during PM blocks than control blocks (control M = 2.62s, SE = 0.14s; PM M = 3.03s, SE = 0.15s), and faster across different levels of time pressure for both low traffic load (Low TP M = 3.46s, SE = 0.11s; High TP M = 2.81s, SE = 0.08s) and high traffic load conditions (Low TP M = 2.95s, SE = 0.09s; High TP M = 2.07s, SE = 0.07s).
- To summarise, the addition of PM load resulted in slower (0.4s) and slightly less accurate (1.7%) ongoing task performance, while increased time pressure led to faster but less accurate ongoing task performance.

PM Trials

- PM responses were scored correct if the participant pressed the PM-response key instead of an ongoing task (conflict/nonconflict) response key on the PM target trial.

- PM accuracy decreased across different levels of time pressure during both low traffic load (Low TP M = 80.5%, SE = 1.8%; High TP M = 72.5%, SE = 2.0%) and high traffic load conditions (Low TP M = 72.4%, SE = 1.9%; High TP M = 57.2%, SE = 2.6%).
- Mean RT for PM responses was significantly faster at higher levels of time pressure during both low traffic load (Low TP M = 1.9s, SE = 0.05s; High TP M = 1.8s, SE = 0.05s) and high traffic load conditions (Low TP M = 1.9s, SE = 0.05s; High TP M = 1.6s, SE = 0.05s).
- There were no significant differences in accuracy or RT between conflict PM targets and nonconflict PM target. This is expected since the PM cue (i.e., particular letters in an aircraft callsign) was completely non-focal, meaning the evidence used to make PM decisions was independent of evidence used to make ongoing task decisions.
- To summarise, as with the ongoing task, increased time pressure led to faster but less accurate PM performance.

Ongoing Task Responses on PM Trials compared with Non-PM Trials

- It is possible that reactive control over ongoing task decisions could lead to slower ongoing task RTs on PM trials in PM blocks, as compared with non-PM trials in PM blocks.
- To check whether reactive control was evident without the model-based analysis, we compared correct RTs on missed PM trials to correct ongoing task RTs. That is, RTs for 'conflict' responses to conflict PM targets and 'nonconflict' responses to nonconflict PM targets were compared with RTs for 'conflict' responses to non-PM conflicts and 'nonconflict' responses to non-PM nonconflicts (in the PM blocks).
- We ran a linear mixed effects model to examine the effects of stimulus type (Conflict, Nonconflict, PM (Conflict), PM (Nonconflict)) and time pressure on RTs for conflict and nonconflict responses.
- Planned comparisons revealed that conflict RTs were significantly faster on PM trials (2.97s) than on non-PM trials (3.16s). Likewise, nonconflict RTs were significantly faster on PM trials (2.62s) than on non-PM trials (2.88s).
- Stimulus type also interacted with time pressure, such that RT differences between PM and non-PM trials were larger during low time pressure and attenuated under high time pressure.
- However it should be noted that reactive control on PM trials is confounded in raw RT by statistical facilitation from the PM response. As such, the critical test of reactive control is on accumulation rates, and is presented in the modeling section below.

Model Analysis

- Brief description of PMDC model and general parameter descriptions
- Desciption of how model parameters and accumulators can vary over our experimental factors (PM block, time pressure, latent response, stimulus)
- Prior constraints on model parameters:
- 1 A parameter
- sv parameter allowed to vary by stimulus and latent response factors but not PM block or time pressure
- sv for PM false alarms (i.e., 'PM' responses to non-PM stimuli) was fixed at 0.5 as a scaling paramter
- 1 nondecision time parameter

- Due to very low numbers of PM false alarms we pooled estimates of both accumulation rate and variance (v and sv) across all stimulus, response and experiment factors to give a single PM false alarm rate and corresponding sv parameter.
- This resulted in an 89

Sampling

- Used Bayesian techniques to estimate entire probability distributions of parameters
- Hierarchical methods too computationally expensive (several months server time per fit) with our sample size and complexity of our models
- Thus opted for separate parameter estimation for each participant
- Bayesian analysis requires the reseacher specify prior beliefs about the probabilities of parameters and the form of their distrubutions
- Since these analysis techniques have not been used on a dynamic applied task this complex, we did not have strong reasons to prefer any particular set of priors over others. We therefore used the modelling results of Strickland's (2017) PM task as a guide, but otherwise specified fairly uninformative priors (Table 1). These prior values were the same over control/PM blocks and the different levels of time pressure.
- Posterior parameter distributions were estimated using the differential evolution Markov-chain Monte-Carlo (DE-MCMC) algorithm. DE-MCMC is more adept at handling the high parameter correlations such as those common to evidence accumulation models.
- The number of chains was three times the number of parameters (e.g., for an 84 parameter model there were 252 chains per parameter). Chains were thinned by 20, meaning that one iteration in every 20 was kept. Sampling continued for each participant until a small Gelman's multivariate potential scale reduction factor (<1.1) indicated convergence, stationarity, and mixing. This factor is calculated with the number of chains doubled, by considering the first and second halves of each chain as separate chains. Convergence, stationarity, and mixing were verified by visual inspection. We retained the same number of samples for each participant: each of the 252 chains was 120 iterations long, producing 30,240 samples of each parameter's posterior distribution for each participant.

Model Parameter	Distribution	Mean	SD	Lower	Upper
A	Truncated Normal	3	1	0	10
B	Truncated Normal	2	1	0	None
v (Correct Ongoing Task Response)	Truncated Normal	1	2	0	None
v (Error Ongoing Task Response)	Truncated Normal	0	2	0	None
v (Correct PM Response)	Truncated Normal	1	2	0	None
v (PM False Alarm)	Truncated Normal	0	2	0	None
sv	Truncated Normal	0.5	1	0	None
t0	Uniform	0.3	1	0.1	1

Model Results

Model Fit

- To evaluate fit, we sampled 100 posterior predictions for each participant and then averaged over participants

- The model provided good fits to both ongoing task and PM accuracy, and gave a good account of the entire distribution of response times. The model provided a close fit to the differences in manifest RT and accuracy observed across PM and control conditions and across different levels of time pressure. The next section explains how the model fit the data in terms of model parameters.
- Figure below shows model fits to ongoing task and PM accuracy by time pressure and PM block
- Figure below shows model fits to ongoing task correct and error RT by time pressure and PM block
- Figure below shows model fits to PM RT by time pressure and PM block

Model Selection

- Model selection to assess whether we could justify contstraining model parameters over blocked experimental conditions (e.g., Control/PM Block, Time Pressure).
- We used the Deviance Information Criterion (DIC)
- DIC takes into account both goodness of fit and model complexity (number of parameters)
- Model with smallest DIC value to be prefered as most parsimonious model of the data
- Table below shows each model we compared and its corresponding DIC value
- Starting with a fully flexible 'top' model, we then built several simpler models by systematically constrained threshold and rate parameters over PM and time pressure factors. This allowed us to assess whether it was necessary to vary thresholds and/or rates to account for observed PM demand and time pressure effects.
- We compared the following four constrained models to the top model:
- A model in which rates could vary by time pressure but thresholds could not
- A model in which thresholds could vary by time pressure but rates could not
- A model in which rates could vary across PM and control blocks but thresholds could not, and
- A model in which thresholds could vary across PM and control blocks but rates could not
- In each case the simpler model was rejected in favour of the fully flexible top model, suggesting that it is necessary to allow both rate and threshold parameters to vary over PM and time pressure (i.e., both parameters are influenced by PM and time pressure manipulations and are important in explaining the observed data).
- Finally, we tested an additional model (the selected model) which allowed both rates and thresholds to vary over both PM and time pressure, but included a slight simplification from the top model. The simplification involved constraining the PM rate parameter such that it was not allowed to vary over stimulus type (i.e., PM conflicts and PM nonconflicts had the same accumulation rate). This simplification makes theoretical sense, since the evidence used to make a PM decision (i.e., particular letters in an aircraft callsign) is independent of the evidence used to make either conflict or nonconflict ongoing task decisions (i.e., speed, relative distance, and motion).
- This slightly simpler model produced the smallest DIC value and is thus selected as our preferred model.

Model	Number.of.Parameters	DIC
Top Model	89	187068
Selected Model	84	186995
Selected Model with B fixed over Time Pressure	73	188370
Selected Model with V fixed over Time Pressure	81	190690

Model	Number.of.Parameters	DIC
Selected Model with B fixed over PM Block	47	190742
Selected Model with V fixed over PM Block	74	190640

Out-of-Sample Prediction: Nonresponse Proportions

- Misspecified model in that model was fit to truncated data (due to trial response deadline)
- Model fit without information about nonresponses
- We assessed ability of the model to predict nonresponses
- Simulated out of model and matched order of stimuli and responses to actual order they were presented to each participant. Whenever the cumulative sum of RTs within a trial exceeded that trial's deadline, a nonresponse was predicted.
- We compared predicted nonresponses with observed nonresponse proportions accross the different levels of time pressure (i.e., different response deadlines)
- Figure below shows observed versus predicted nonresponse proportions
- As shown in the figure, the model's predicted nonresponse proportions closely matched the empirical nonresponse proportions
- This gives us confidence that the slight model misspecification due to fitting to truncated data is not of concern

Model Summary

Capacity Sharing (Non-PM Trial Accumulation)

- Capacity sharing theories of PM costs propose that holding PM intentions or monitoring for PM stimuli draws limited-capacity cognitive resources away from the ongoing task. As such, they predict that ongoing task evidence accumulation rates will be higher in control conditions (when more resources can be devoted to the ongoing task), and lower under PM load (when resources must be shared between the ongoing task and concurrent PM monitoring processes), which would lead to slower ongoing task RTs under PM load. Alternatively, another prediction consistent with capacity sharing is increased accumulation rates for error responses under PM load relative to rates for correct responses. This would lead to lower accuracy under PM load relative to control.
- The figure below shows accumulation rates in control and PM blocks for non-PM ongoing task stimuli (i.e., conflicts and nonconflicts that were not also PM targets). Contrary to the predictions of capacity sharing theories, accumulation rates for correct responses were higher under PM load than in the control condition for both conflict and nonconflict stimuli. It should be noted however that accumulation rates for error responses were also greater under PM load, which is not inconsistent with a capacity sharing account.
- Taken together, this pattern of large increases in correct and error accumulation rates from control to PM conditions provides convincing evidence against a capacity sharing account of PM costs in this task. As will be discussed later, these results are more indicative of an overall increase in effort or arousal/task engagement during PM blocks, which may be because the ongoing task becomes subjectively more difficult and/or engaging with the addition of the concurrent PM task relative to control blocks.

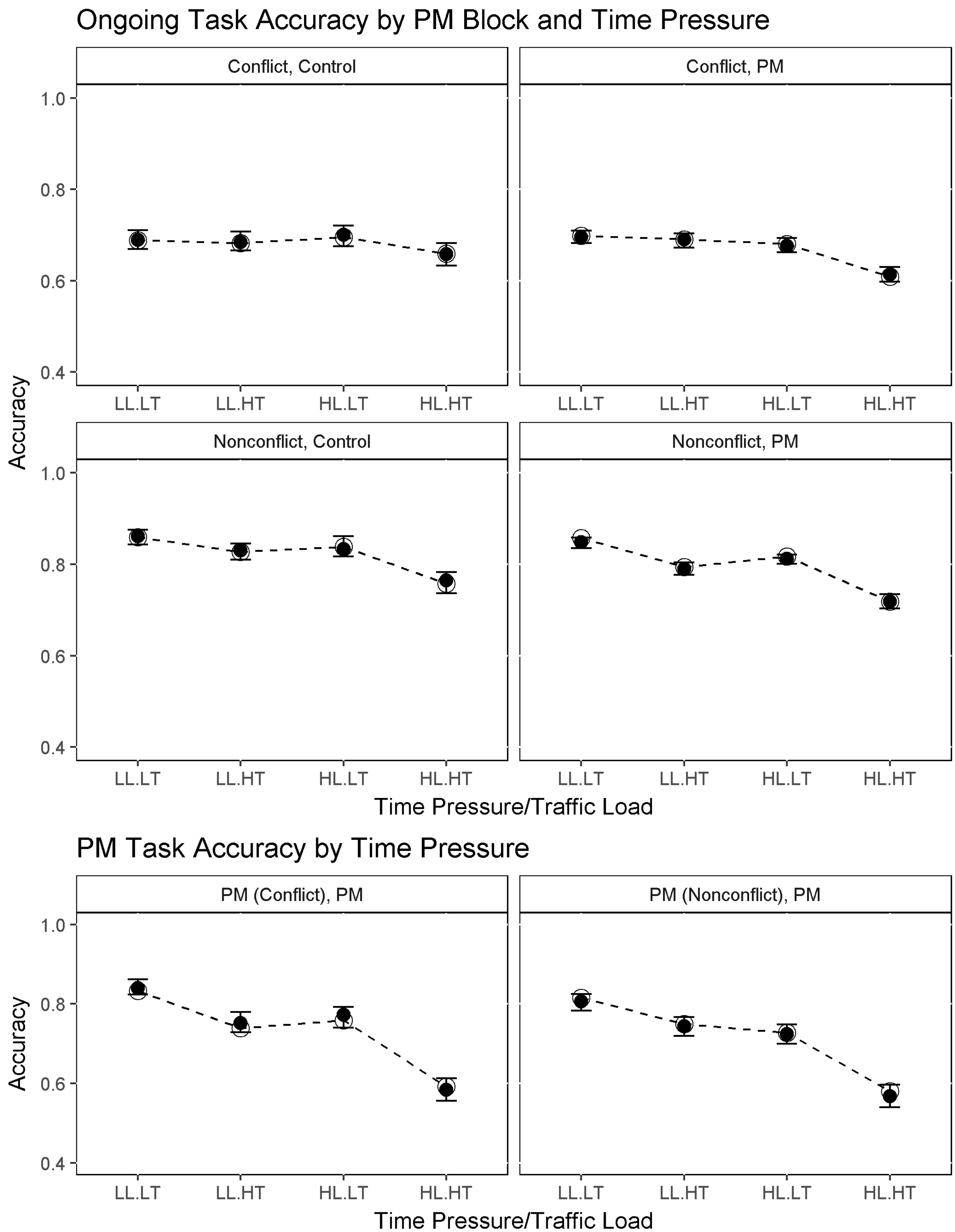


Figure 1: Figure: Model Fits: Accuracy

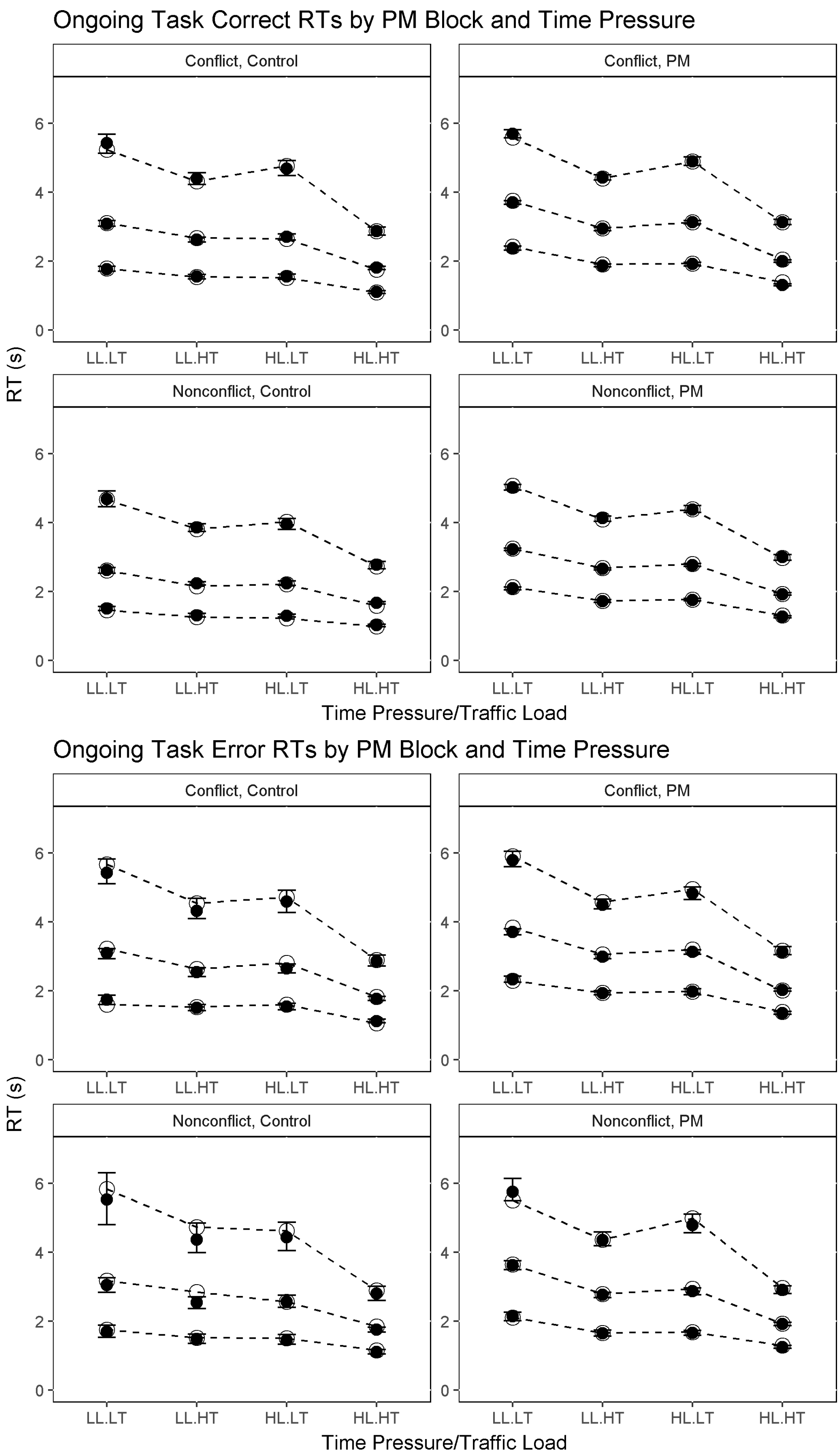


Figure 2: Figure: Model Fits: Ongoing Task RT

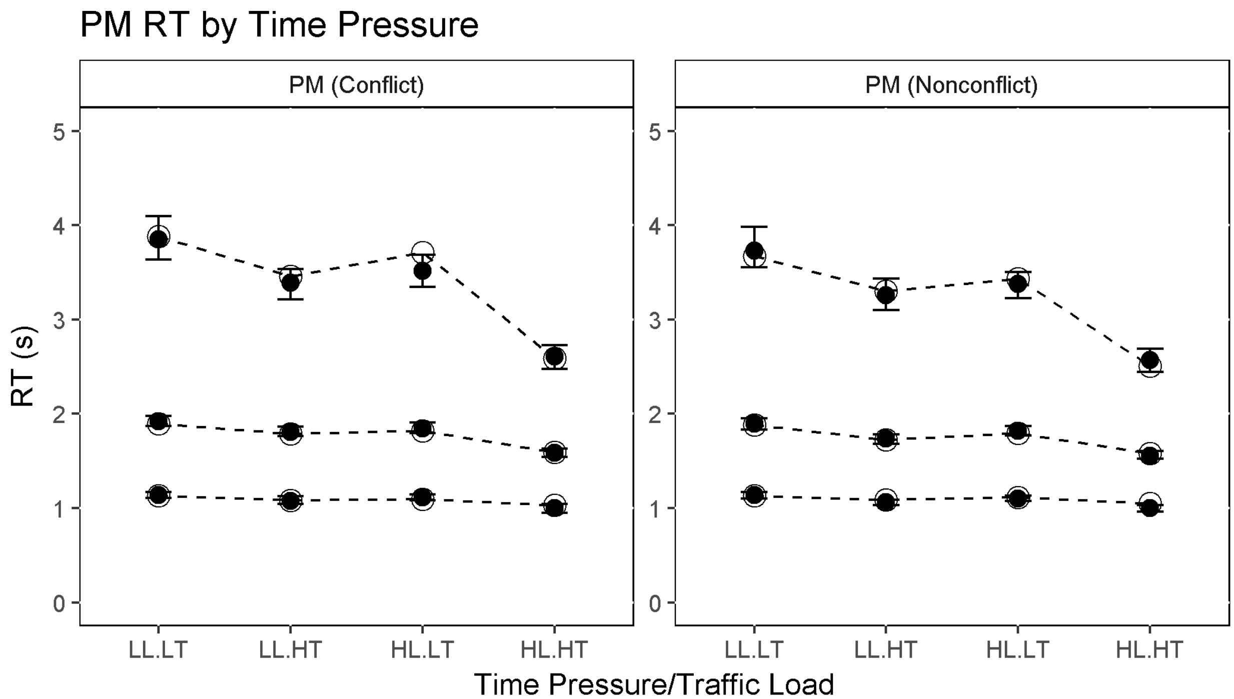


Figure 3: Figure: Model Fits: PM RT

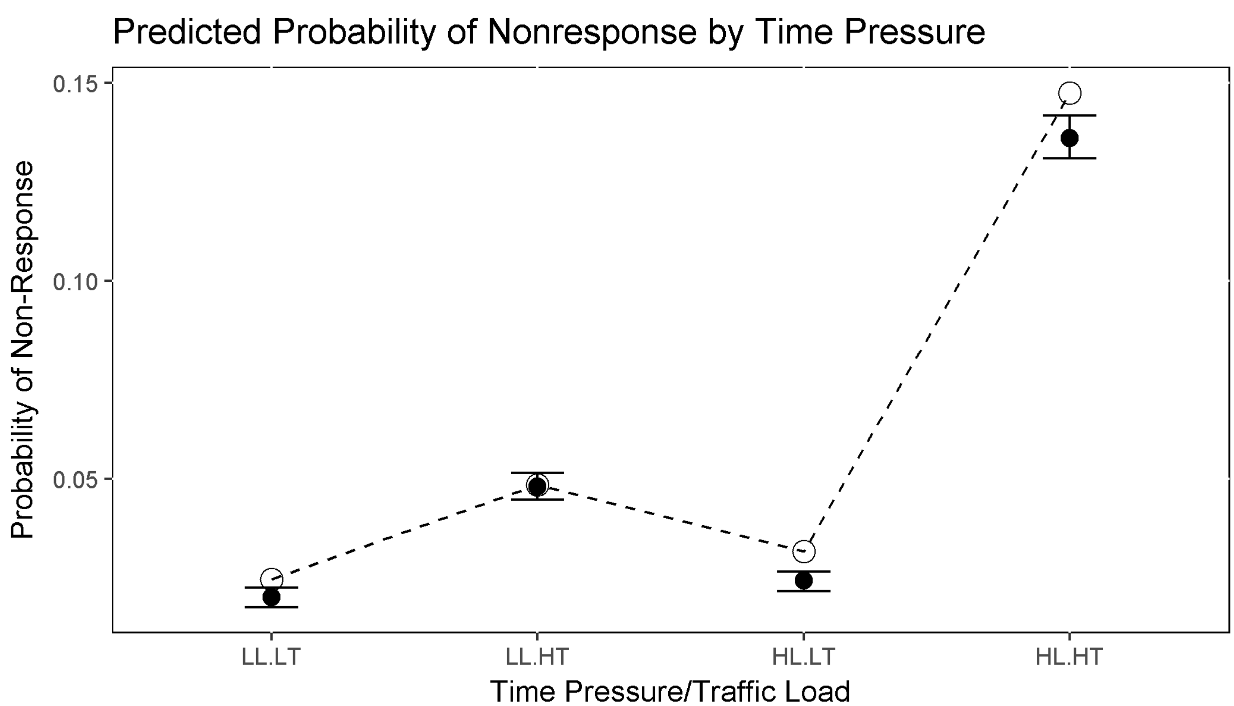


Figure 4: Figure: Model Fits: Nonresponse Proportions

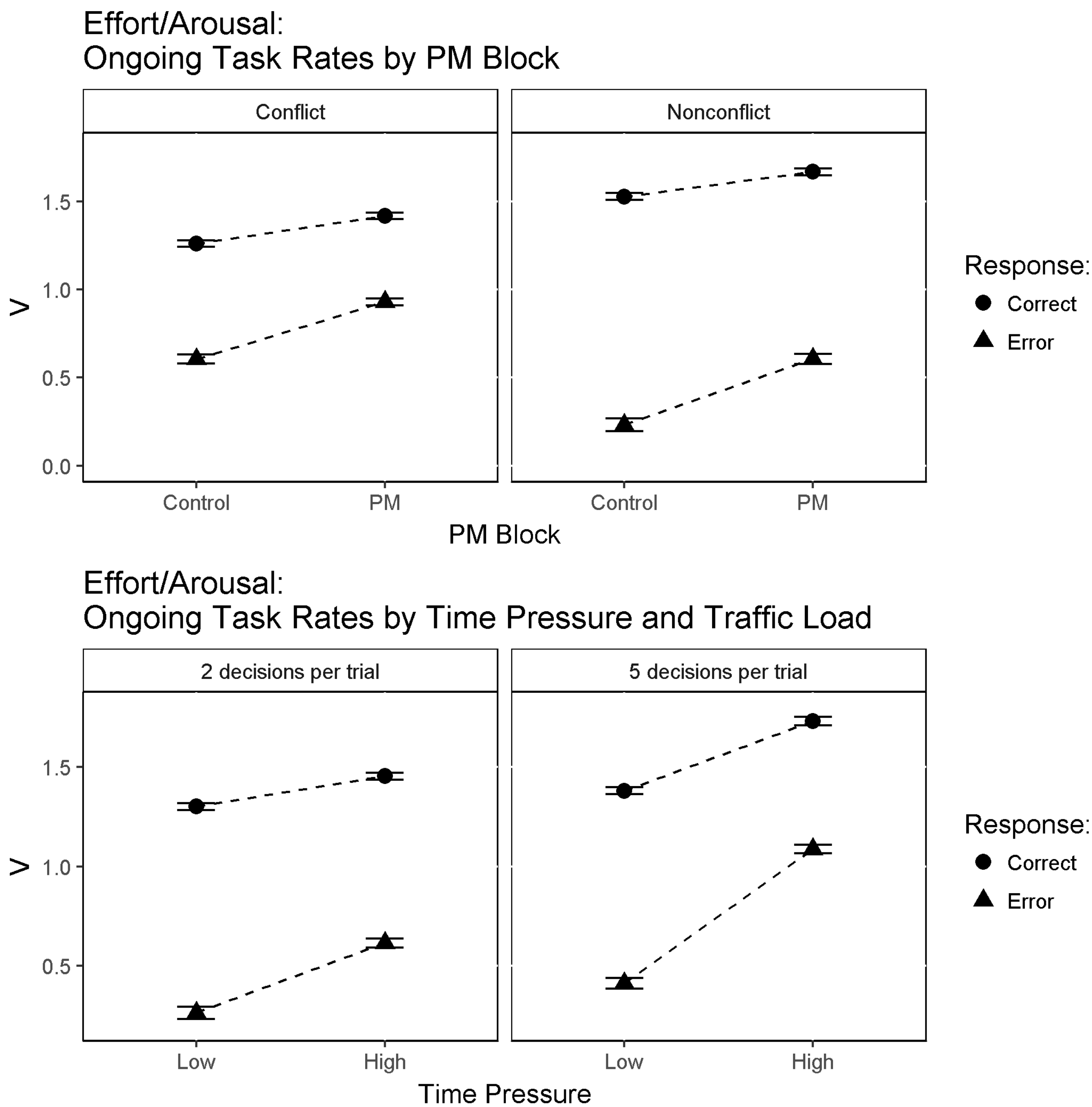


Figure 5: Figure: Effort/Arousal

Proactive Control (Thresholds)

Proactive Control under PM Demand

- Proactive control over ongoing task decisions predicts higher conflict and nonconflict response thresholds under PM load compared to during control blocks.
- Z-score effect sizes and p-values for threshold comparisons are shown in the table below.
- The figure below shows conflict and nonconflict response thresholds in the control and PM blocks.
- Ongoing task thresholds where much higher in PM than control blocks
- This is consistent with strategic delay theories on PM costs where responses to the ongoing task are deliberately delayed in order to avoid preempting PM targets.

Proactive Control under Time Pressure

- Spiel about speed-accuracy trade-off and adjusting threshold to increase speed at expense of accuracy
- The lower panels of the figure below also show ongoing task and PM response thresholds under low and high time pressure for both low trial load (2 decisions per trial) and high trial load (5 decisions per trial)
- In both cases thresholds decreased under high time pressure relative to low time pressure
- Consistent with much choice-RT modelling of the speed-accuracy trade-off
- Consistent with proactive control of decision processes whereby thresholds are strategically lowered in order to facilitate fast responding (at the expense of accuracy)

Reactive Inhibition (PM vs. Non-PM Trial Accumulation)

- A prediction of PMDC theory is that ongoing task (conflict/nonconflict) evidence accumulation rates will be lower on PM trials due to ‘reactive’ inhibitory control of the decision process by the PM stimulus detector.
- The figure below shows accumulation rates for ongoing task responses to non-PM conflict/nonconflict stimuli compared to PM conflict/nonconflict stimuli (i.e., ongoing task stimuli that also contained a PM target).
- Consistent with the predictions of PMDC’s reactive inhibition mechanism, rates for ongoing task accumulators where much lower for stimuli containing a PM cue compared to when the same stimuli did not contain a PM cue.
- This supports the idea that when the PM detector detects a PM target, the accumulation process for the competing ongoing task response is supressed or inhibited.
- The reactive inhibition of ongoing task responses was slightly stronger for the incorrect ongoing response accumulators
- These findings are consistent with the idea that response accumulators compete with each other based on their inputs; in the presence of a PM stimulus, evidence accumulation processes for conflict and nonconflict are inhibited relative to when a PM stimulus is absent.
- (Maybe include some stuff about the connection between this finding and research on PM lures (stimuli that share some but not all of the features of a PM target))

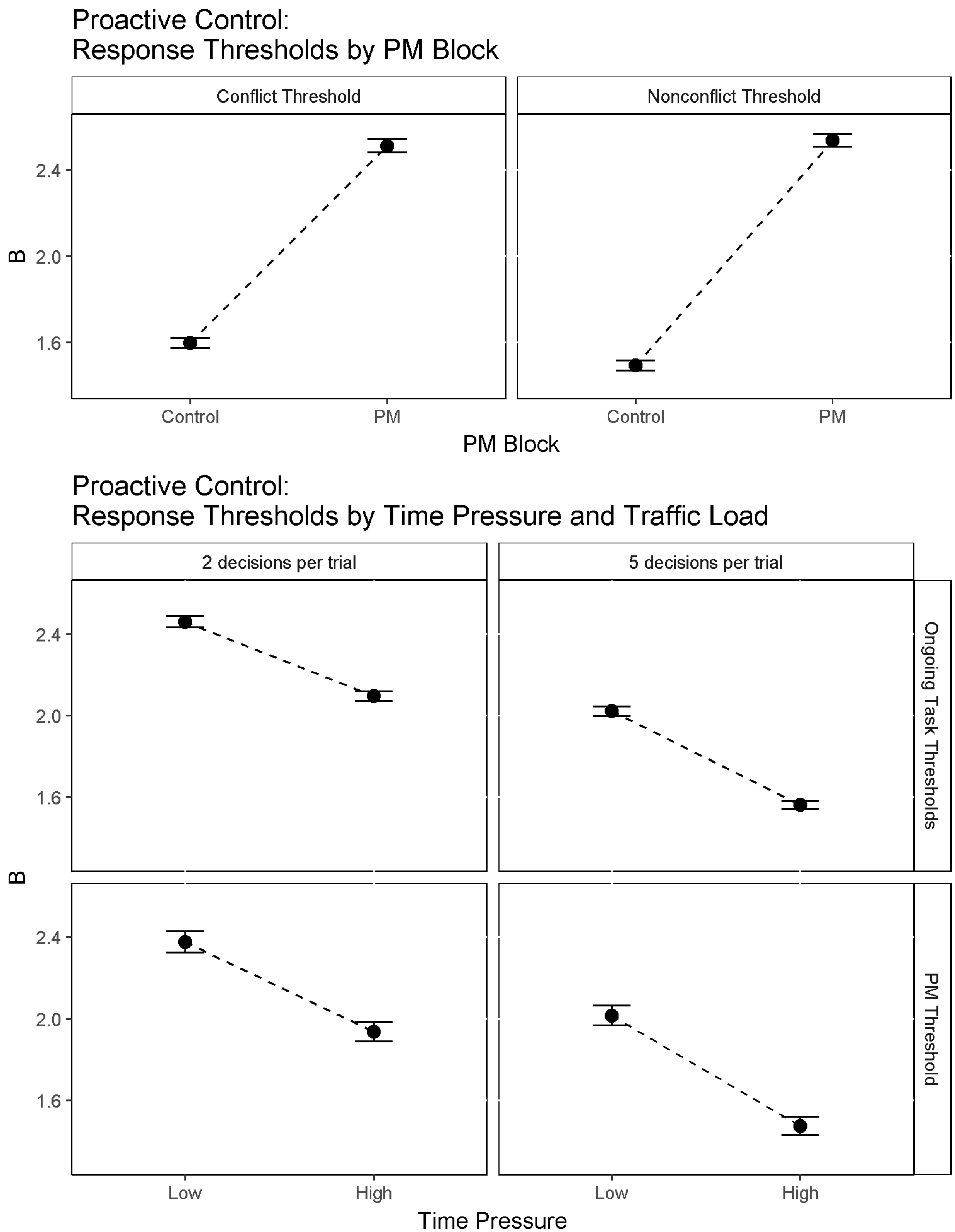


Figure 6: Figure: Proactive Control

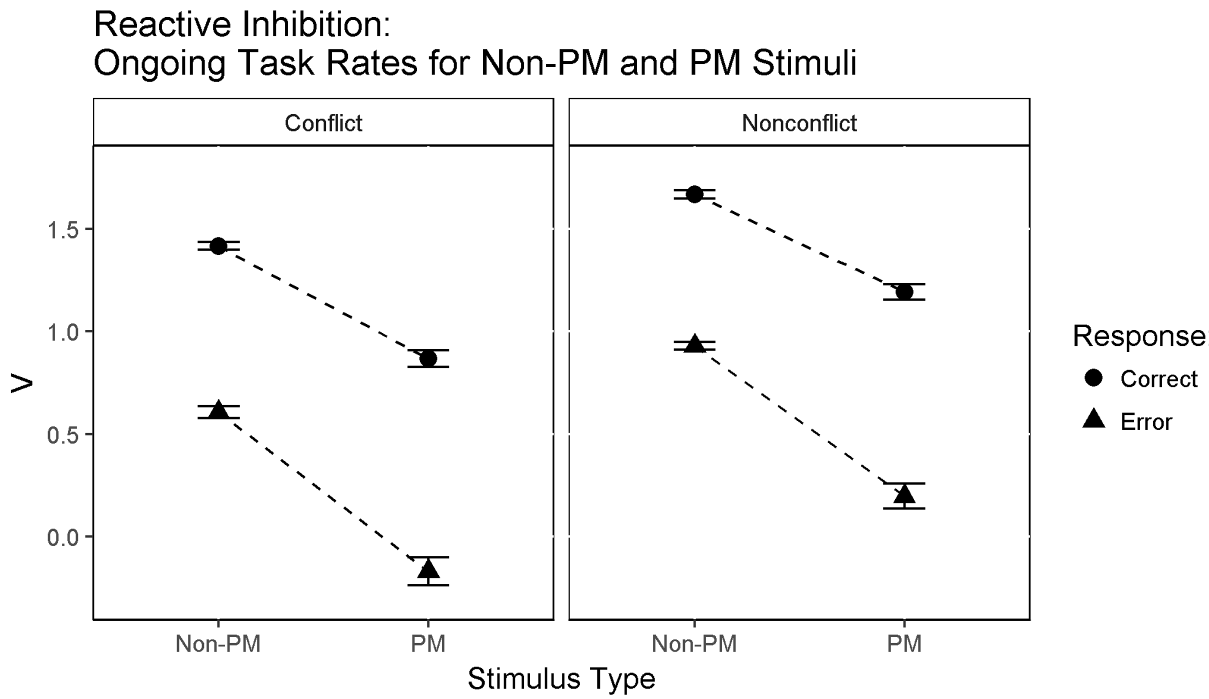


Figure 7: Figure: Reactive Inhibition

Effort/Arousal (Accumulation Increases with PM Load and Time Pressure)

- As mentioned previously, in contrast with the predictions of capacity-sharing theories of PM costs, we found that evidence accumulation rates actually increased with the addition of PM load.
- The figure below also shows correct and error accumulation rates across the different levels of time pressure for both low trial load (2 decisions per trial) and high trial load (5 decisions per trial) conditions.
- As with the increases seen from control to PM blocks, both correct and error accumulation rates were higher under higher time pressure relative to low time pressure.
- Since rates for both correct and error responses increase, this effect is also suggestive of an overall increase in arousal/task engagement or the overall effort being invested in completing the task.
- Possible that the task becomes more difficult or engaging under high time pressure leading participants to deploy more resources
- Alternatively participants could be 'satisficing', that is, in the relatively easy control and low time pressure conditions participants may believe that they can disengage from the task somewhat, expending fewer cognitive resources while maintaining a satisfactory level of task performance.

Model Exploration

- Given the complexity of our model, it is difficult to discern the overall contribution given parameters have on overall RT and/or accuracy. In this section we attempt to tease out the individual contribution to RT and accuracy provided by certain parameters and mechanisms in the model. It is our aim to give a clearer picture of the relative importance of key parameters in accounting for the observed effects.
- In order to evaluate a given parameter's contribution to the model, we first replace that parameter with the average either across control/PM blocks or across time pressure levels (e.g., replacing control

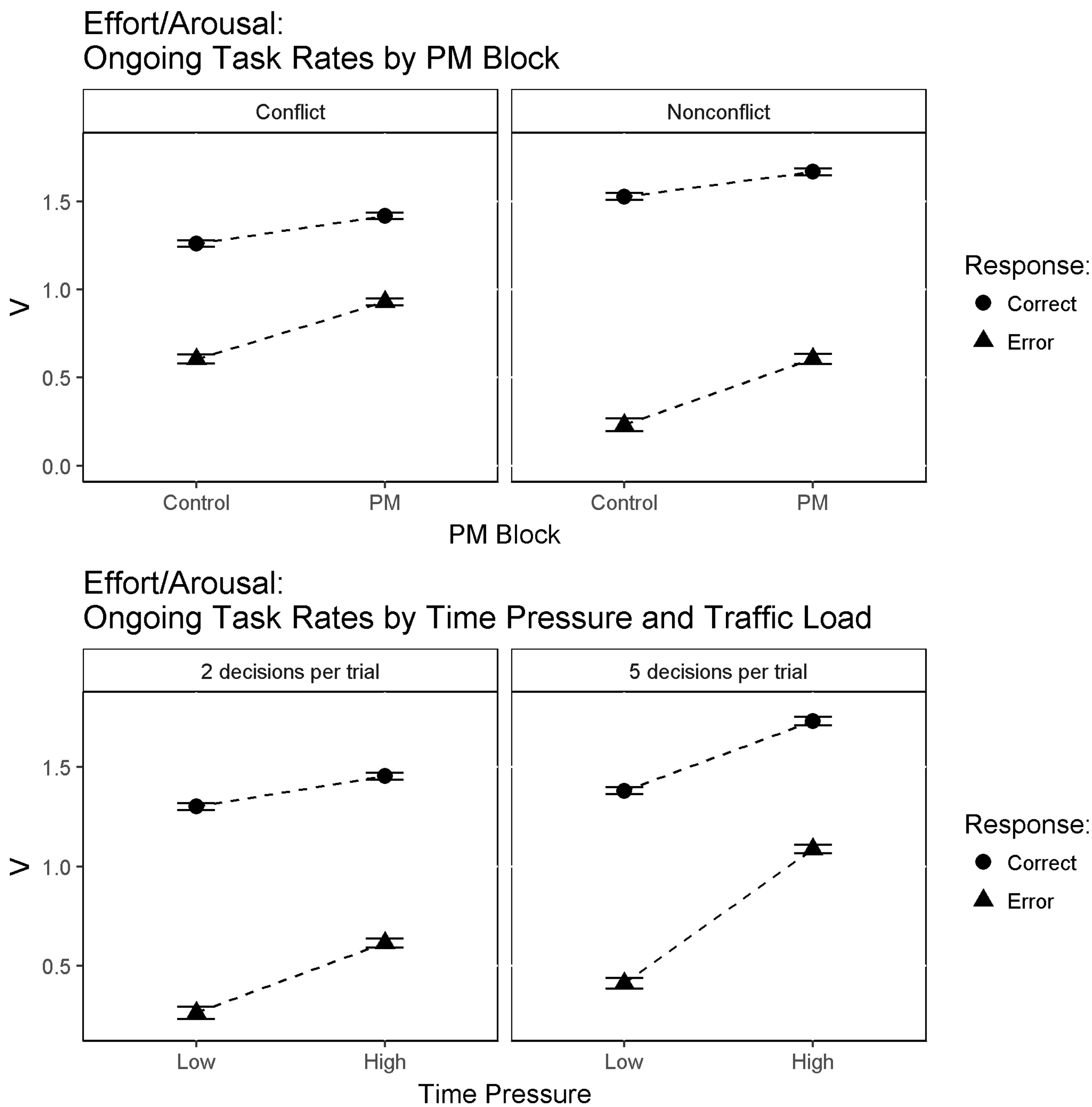


Figure 8: Figure: Effort/Arousal

and PM ongoing task thresholds with the average of the two).

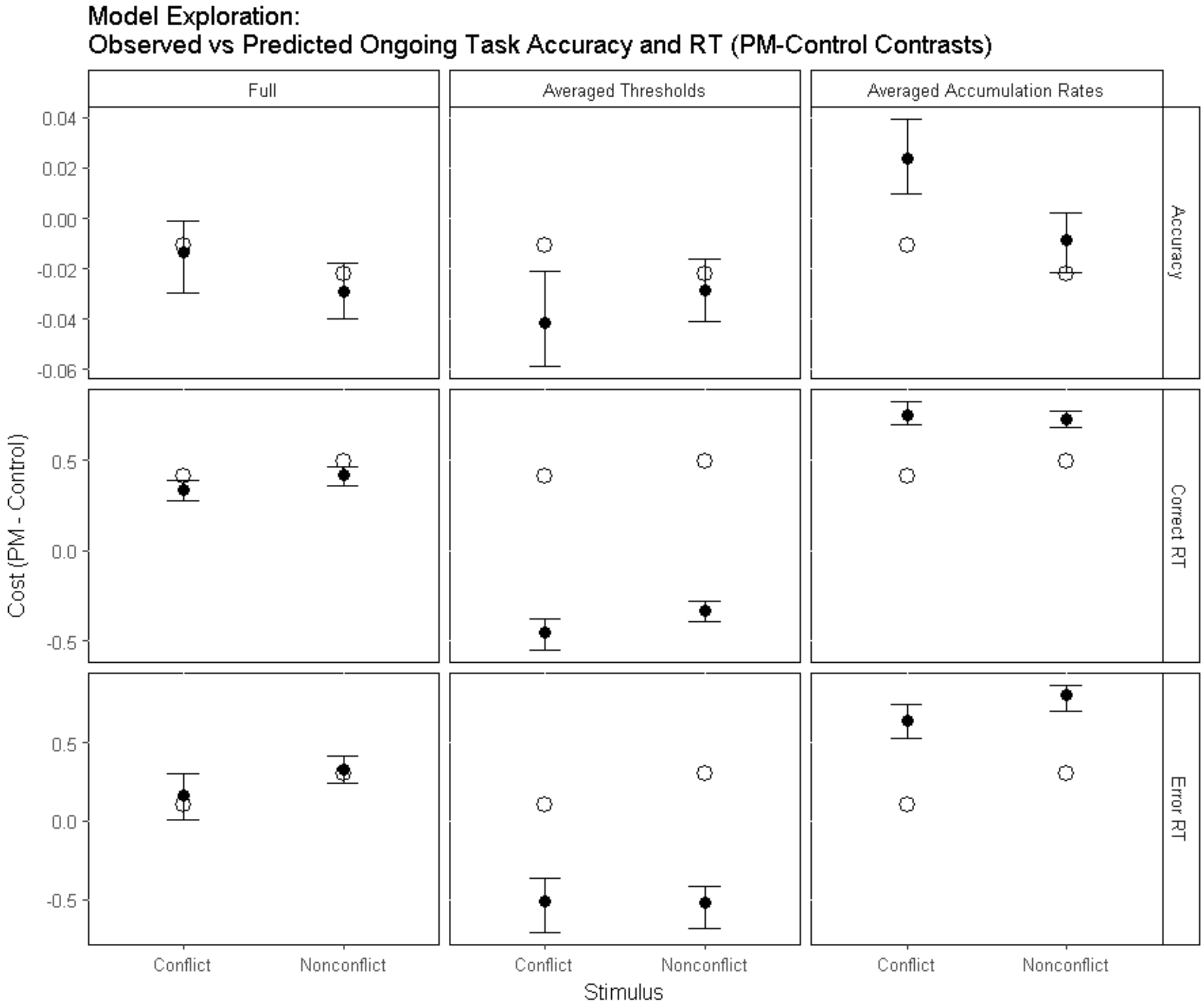


Figure 9: Figure: Model Exploration PM Contrasts

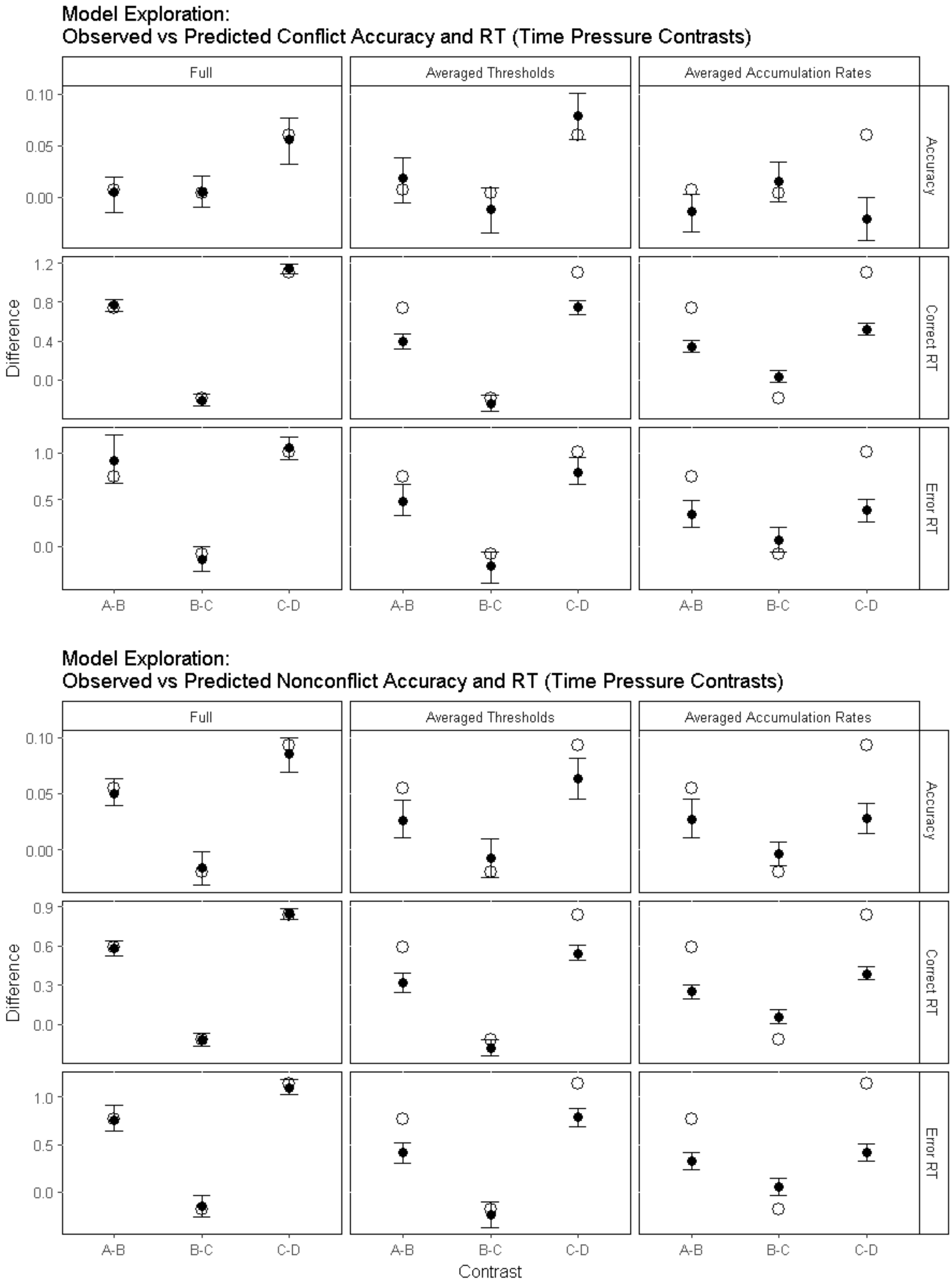
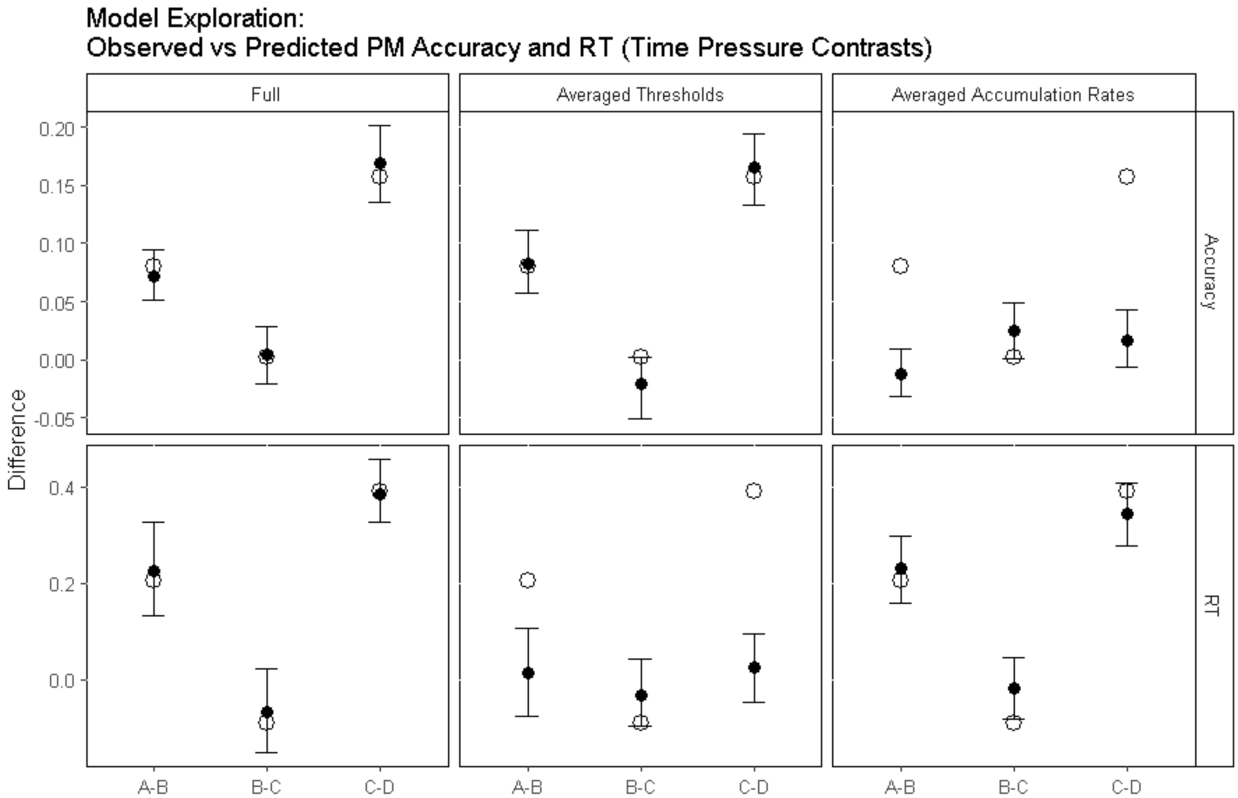


Figure 10: Figure: Model Exploration TP Contrasts Ongoing



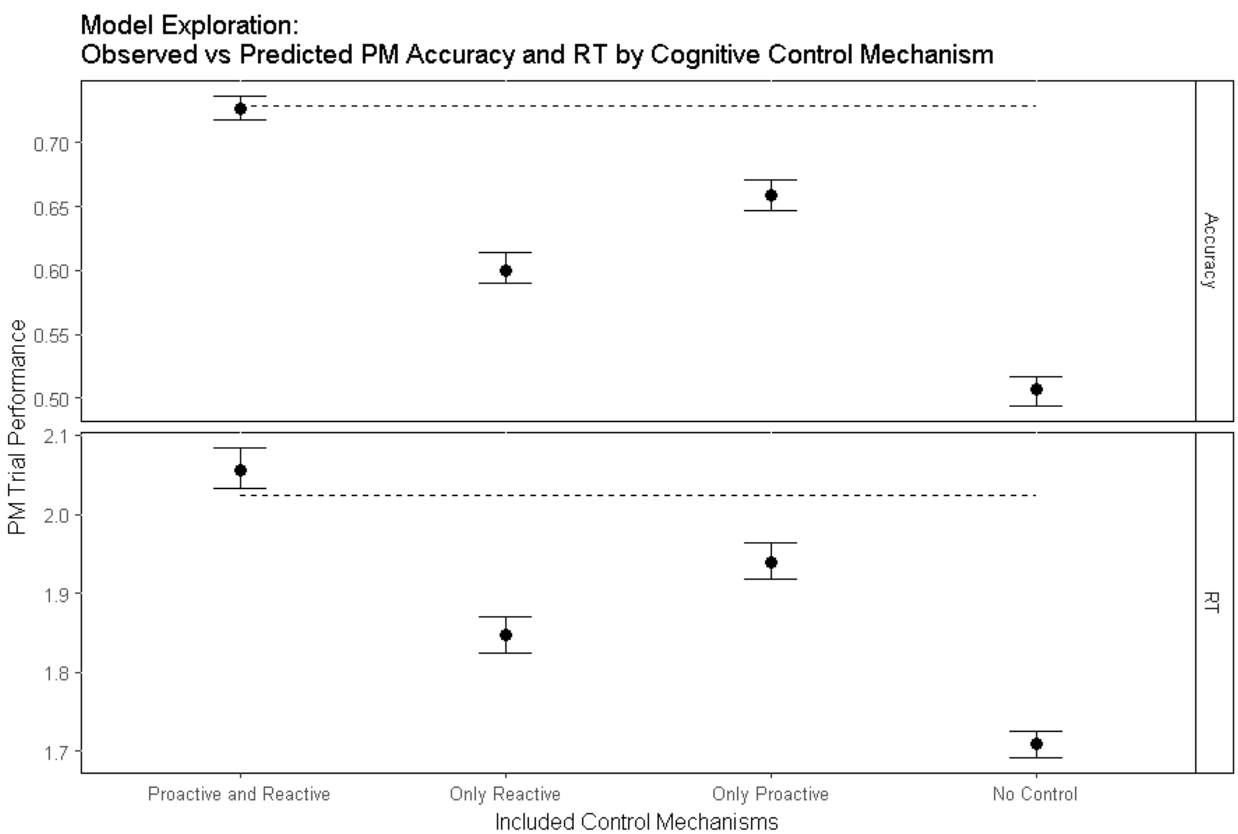


Figure 11: Figure: Model Exploration TP Contrasts PM and Control Mechanisms