

# Precision-weighted evidence integration predicts time-varying influence of memory on perceptual decisions



Poster

GitHub

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GitHub

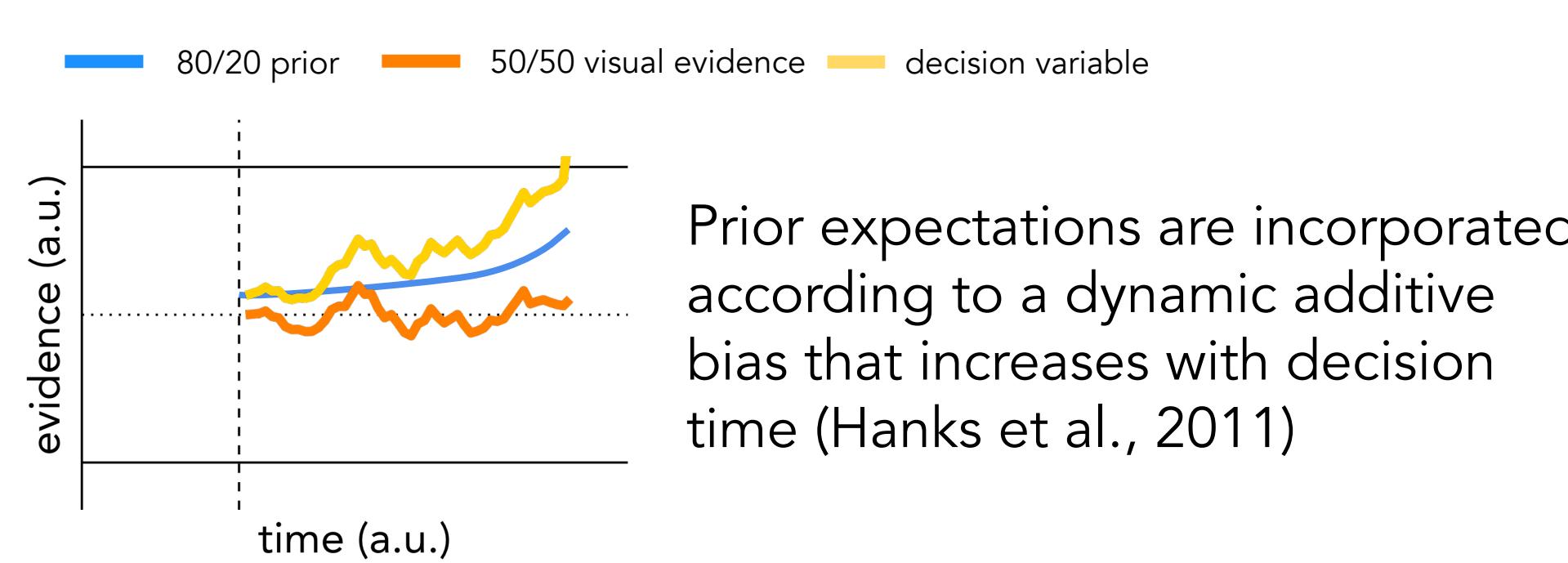
Poster

## Motivation

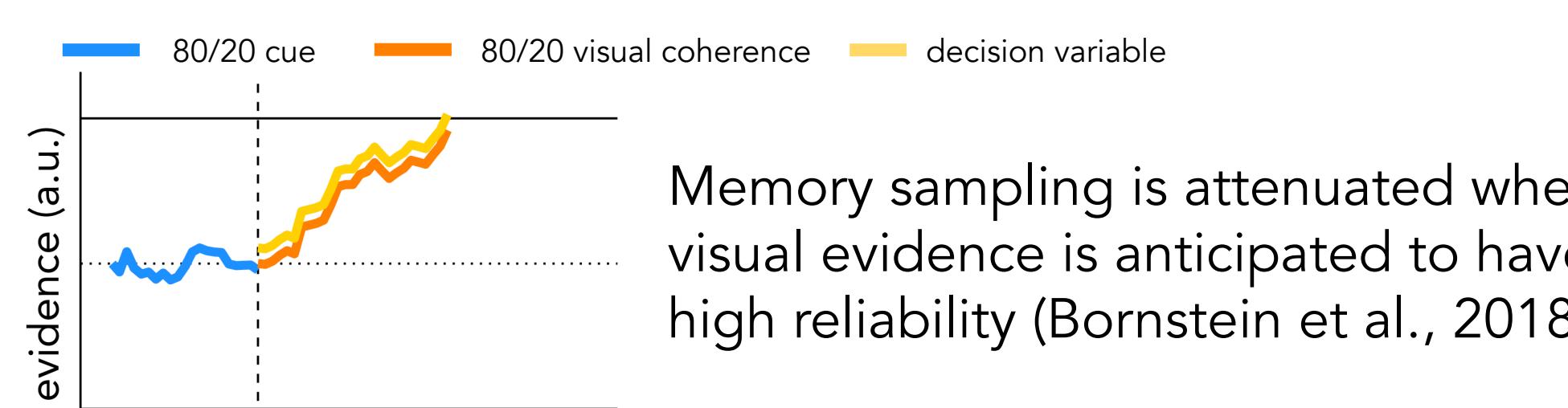
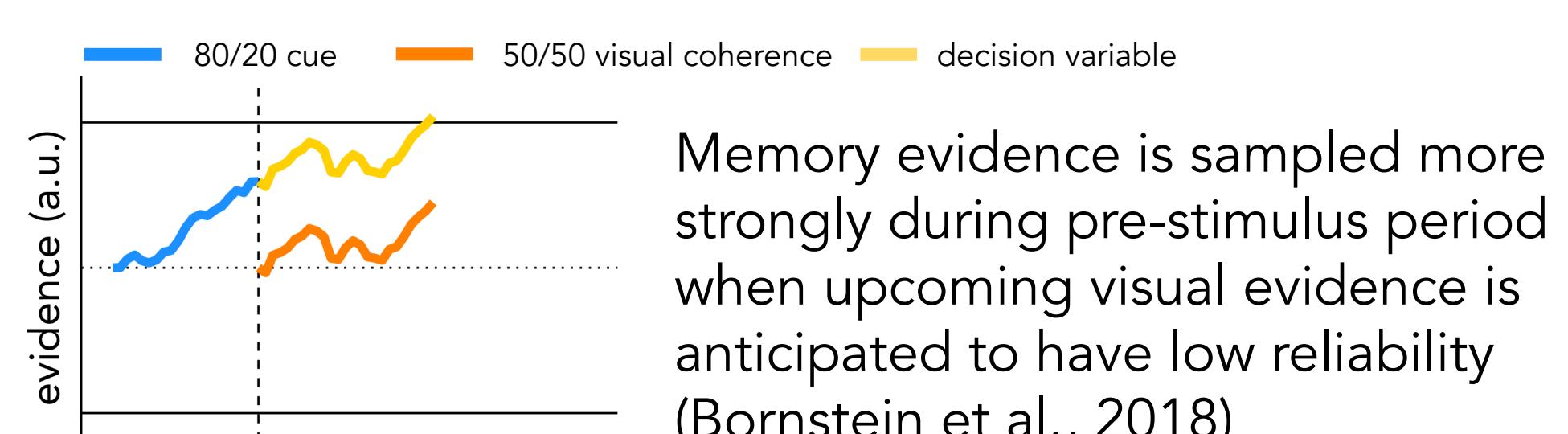
How are **expectations** integrated with **sensory evidence** during decision making under uncertainty?

Two different studies found **time-varying** effects of expectations (the **prior**) on perceptual evidence accumulation:

### Late effect: slow mixing of prior over time



### Early effects: adaptive memory sampling



We propose **dynamic, relative reliability-weighted** integration as a unifying explanation.

## Precision-weighted multi-source sequential sampling model

The simulated agents treat each evidence source  $s$  as reflecting an independent probability of observing target X:

$$p(x_s) \sim Beta(\alpha_s, \beta_s)$$

where  $s = \{memory, vision\}$

At each timepoint  $t$ , evidence samples  $o$  are drawn from a Bernoulli distribution with reliability  $\theta$  and additive Gaussian noise:

$$o_{st} \sim Bernoulli(\theta) + Normal(0, 1)$$

Memory samples are drawn at  $\frac{1}{4}$  the rate of visual samples to approximate the ratio of theta oscillations ( $\sim 8$ Hz) to visual sample presentation rate (30Hz).

Each sample updates the probability of observing target X:

$$p(x_s)_t \sim \begin{cases} Beta(\alpha_{st-1} + 1, \beta_{st-1}) & \text{if } o_{st} > 0 \\ Beta(\alpha_{st-1}, \beta_{st-1} + 1) & \text{if } o_{st} < 0 \end{cases}$$

The precision of each evidence stream is computed as the inverse variance of the updated Beta distribution:

$$precision_{st} = \frac{\alpha_{st}\beta_{st}}{(\alpha_{st} + \beta_{st})^2 (\alpha_{st} + \beta_{st} + 1)}^{-1}$$

The weight placed on each sample at each timepoint is computed as the **relative precision** of each stream at that timepoint:

$$w_{mem_t} = \frac{precision_{mem_t}}{precision_{mem_t} + precision_{viz_t}}$$

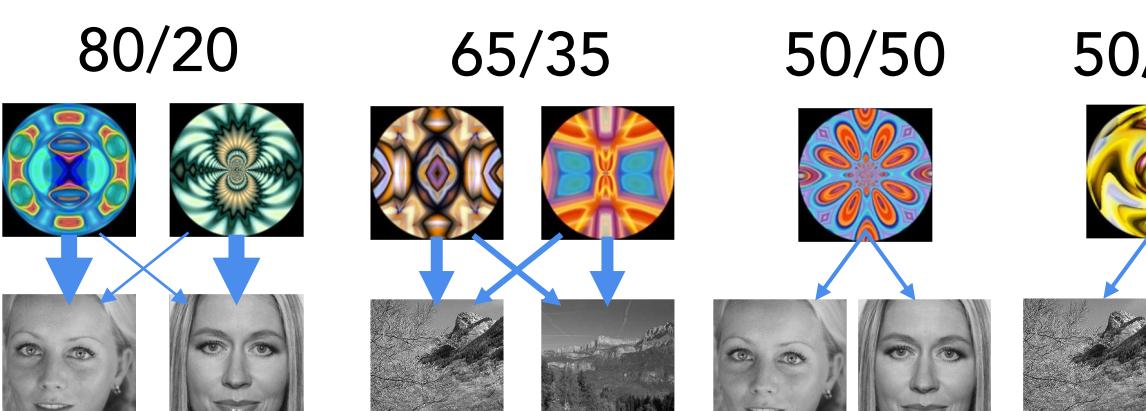
$$w_{viz_t} = \frac{precision_{viz_t}}{precision_{mem_t} + precision_{viz_t}}$$

The decision variable is a weighted sum of samples from each evidence stream:

$$DV_t = DV_{t-1} + o_{mem_t} w_{mem_t} + o_{viz_t} w_{viz_t}$$

## Task design

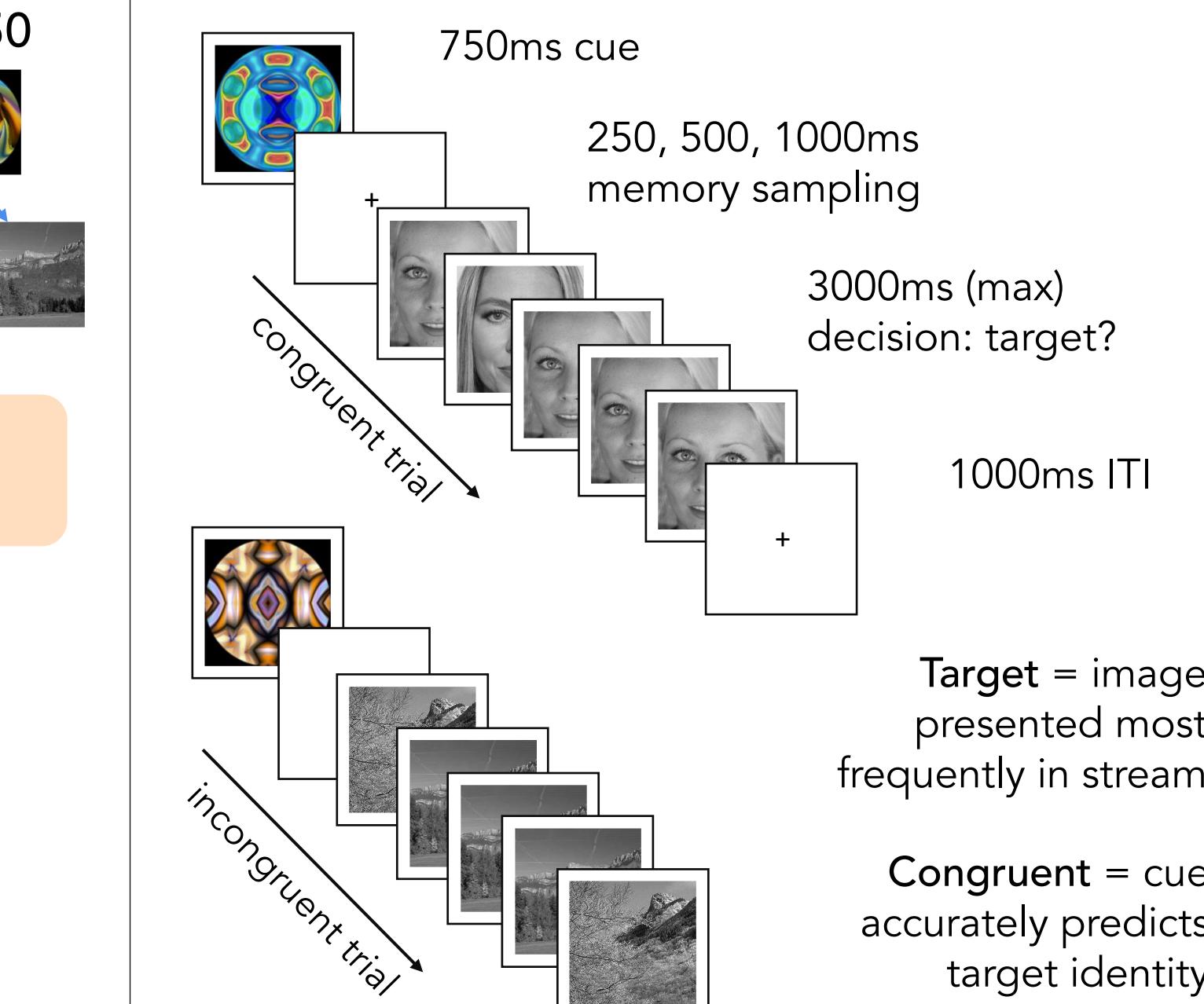
### Learned prior target probabilities



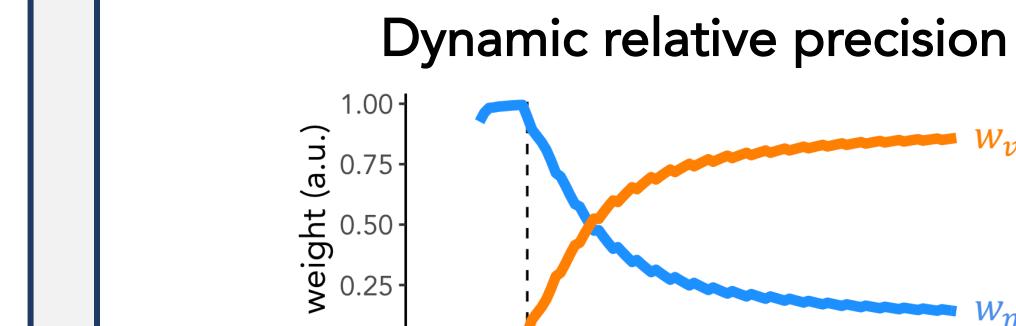
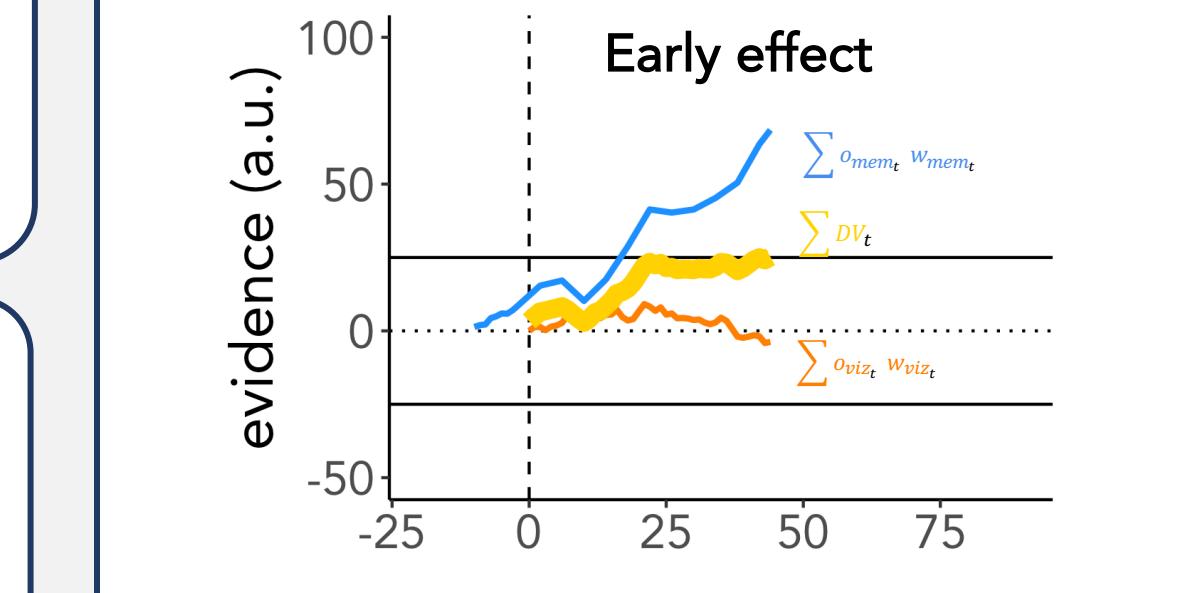
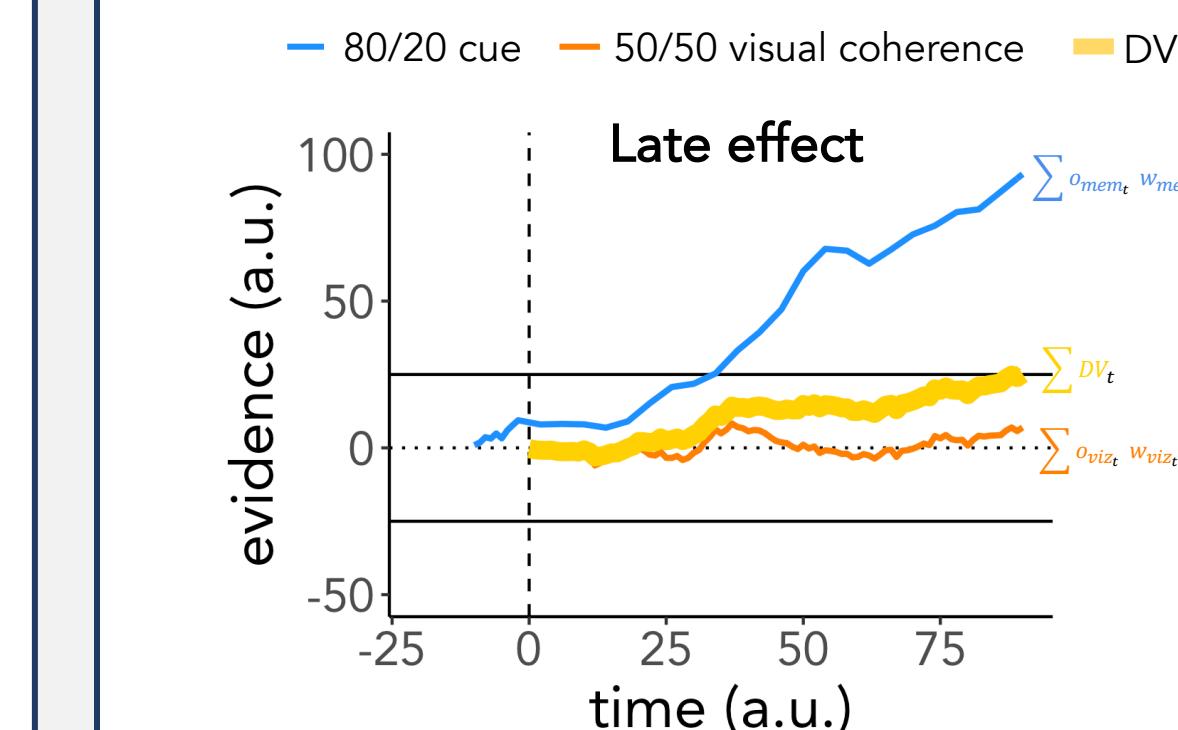
### Visual coherence: proportion of frames containing target image



### Cued perceptual inference



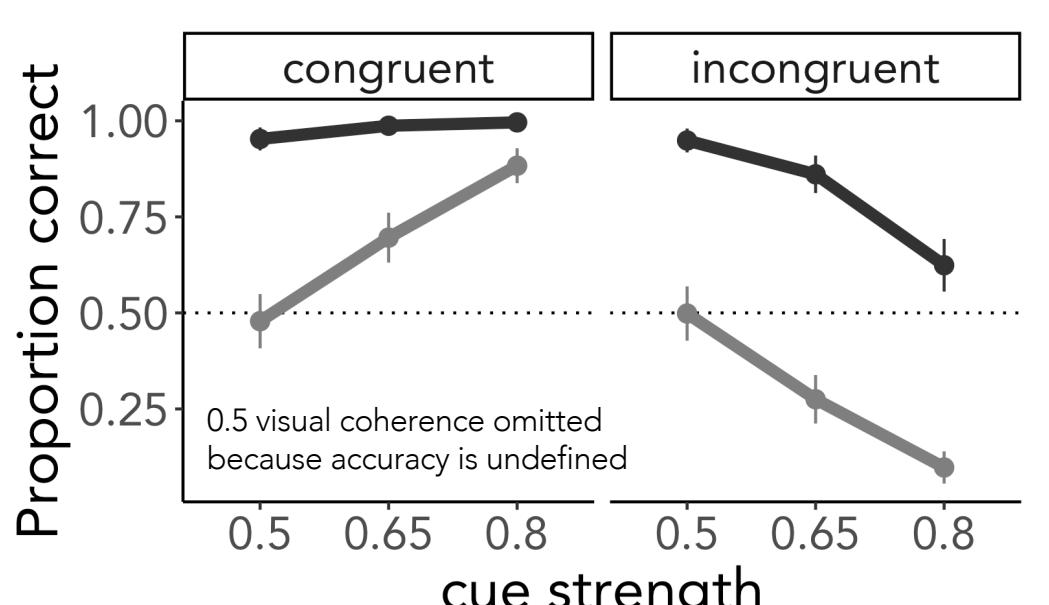
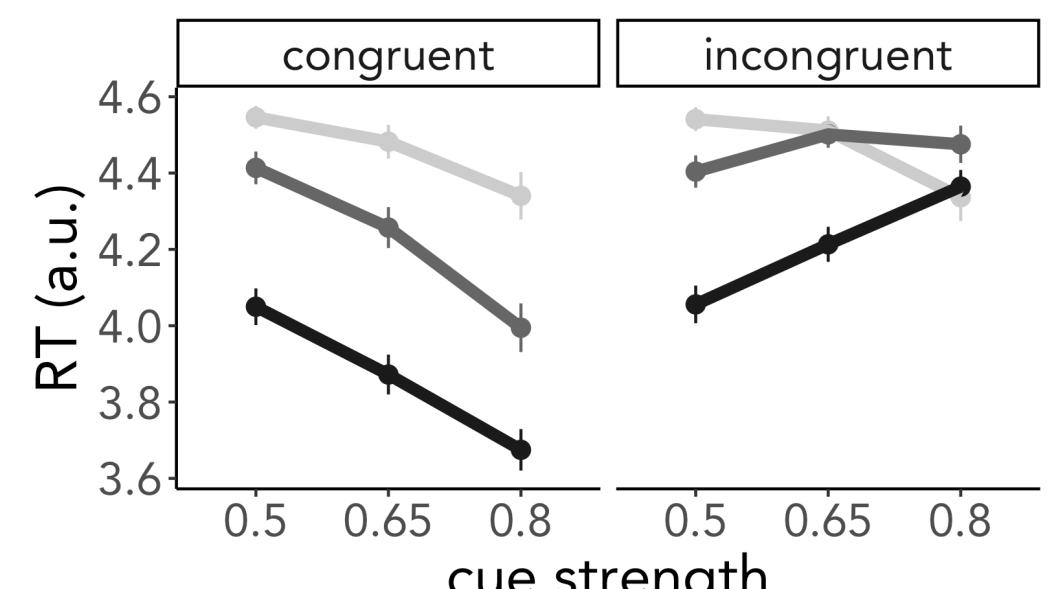
Dynamic precision weighting captures late and early effects of prior on DV



Ideal observer predictions with 25 trials/cell

n=50, error bars = +/- 1 SEM

visual coherence □ 0.5 □ 0.65 □ 0.8



Stronger memory associations result in faster and more accurate decisions for congruent visual evidence, while slowing responses and impairing accuracy for incongruent visual evidence (all  $\beta > 0.04$ , all  $p < .001$ ).

## Future directions

- Collect behavioral and EEG data to test model predictions.
- Investigate how **subjective confidence** in each evidence stream modulates their integration.

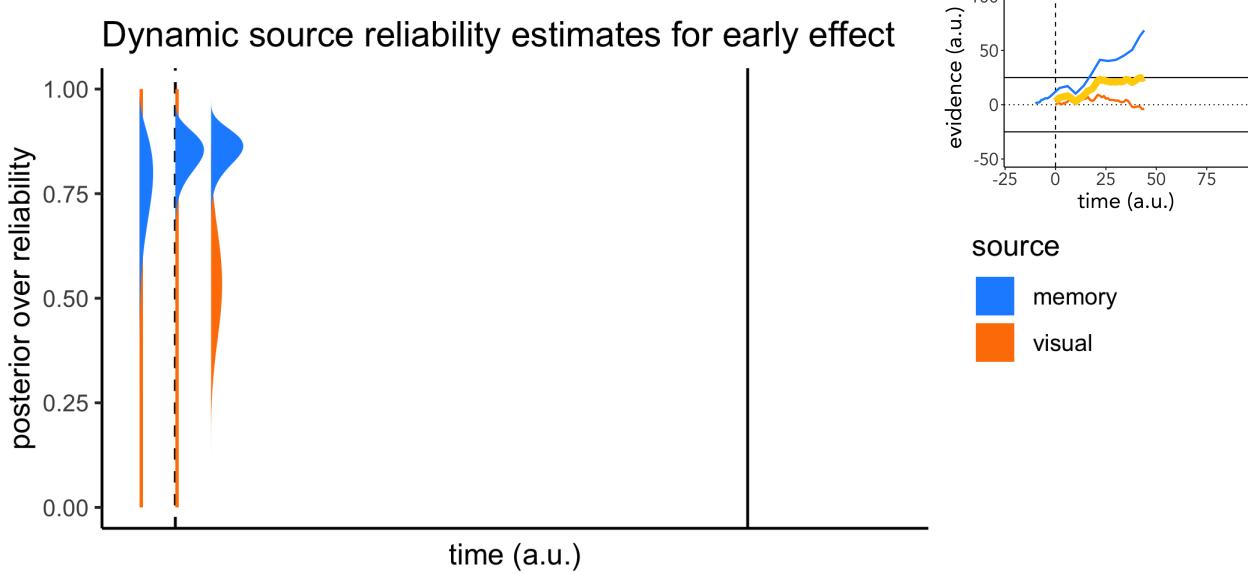
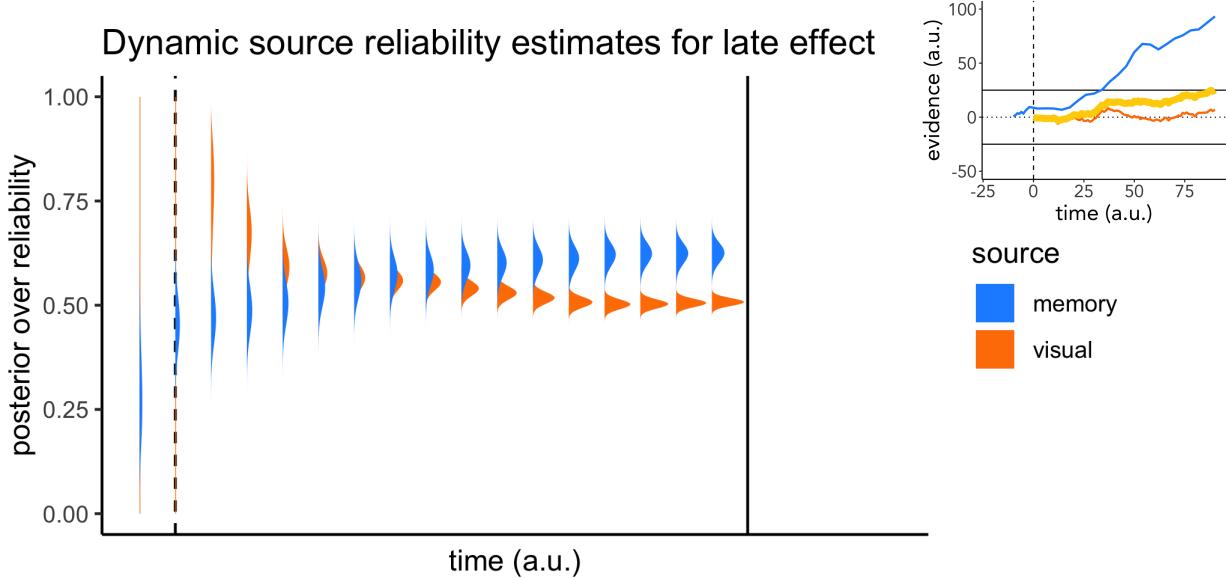
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### References:

- Hanks, T. D., Mazurek, M. E., Kiani, R., Hopp, E., & Shadlen, M. N. (2011). Elapsed decision time affects the weighting of prior probability in a perceptual decision task. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, 31(17), 6339–6352.  
Bornstein, A. M., Aly, M., Feng, S. F., Turk-Browne, N. B., Norman, K. A., & Cohen, J. D. (2018). Perceptual decisions result from the continuous accumulation of memory and sensory evidence. *In bioRxiv. bioRxiv*. https://doi.org/10.1101/186817

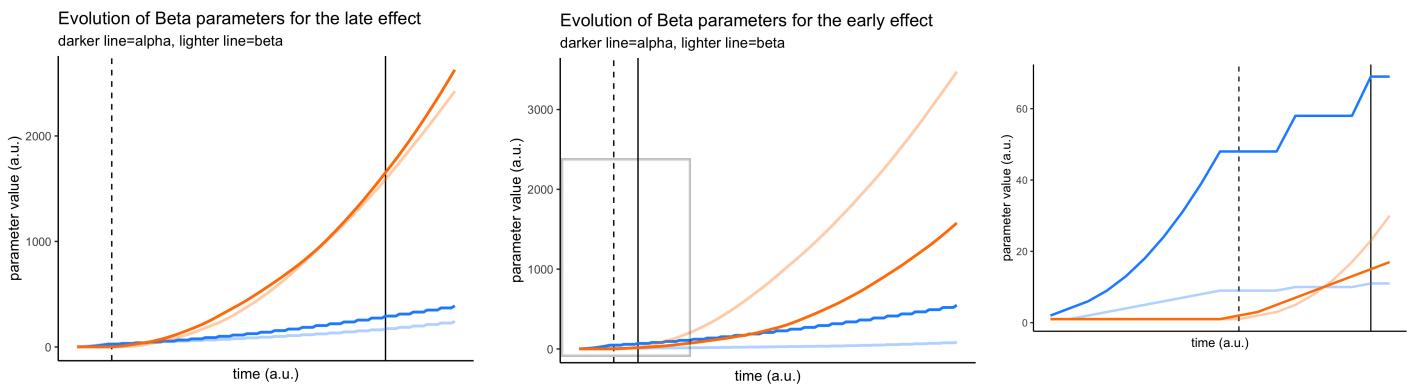
# Supplemental materials

Posterior distributions over source reliability estimated over the course of sampling in a single trial



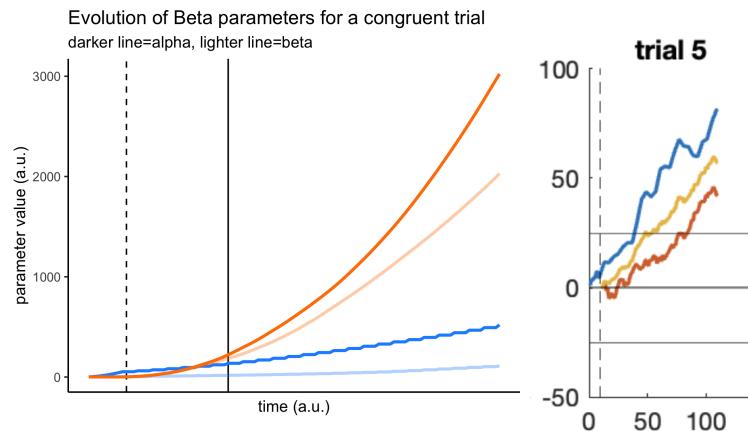
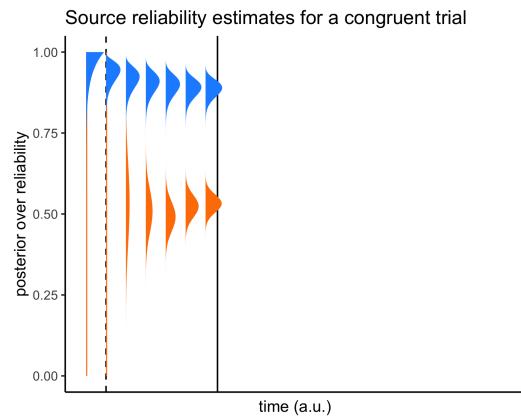
# Supplemental materials

## Evolution of alpha & beta parameters over the course of sampling in a single trial

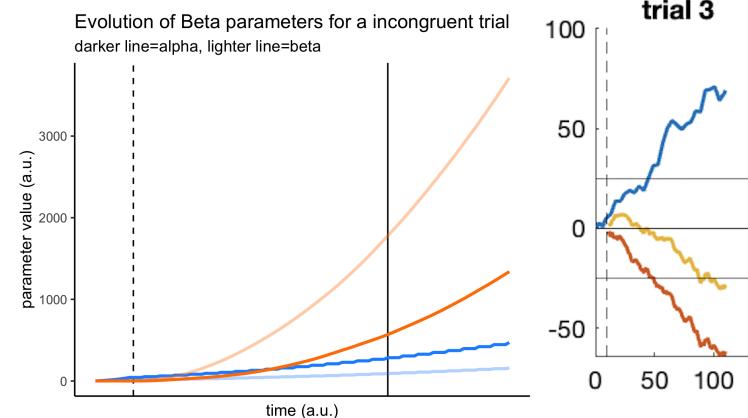
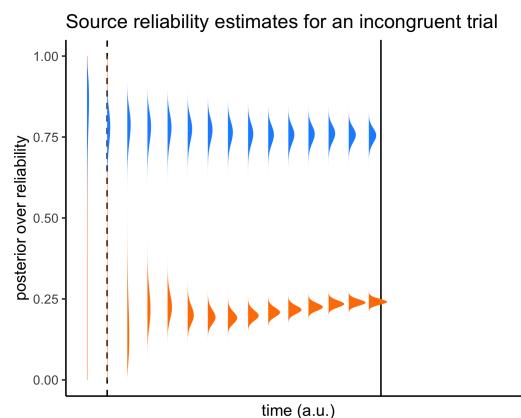


## Posterior plots & parameter evolution for 0.8 cue, 0.65 coh

congruent

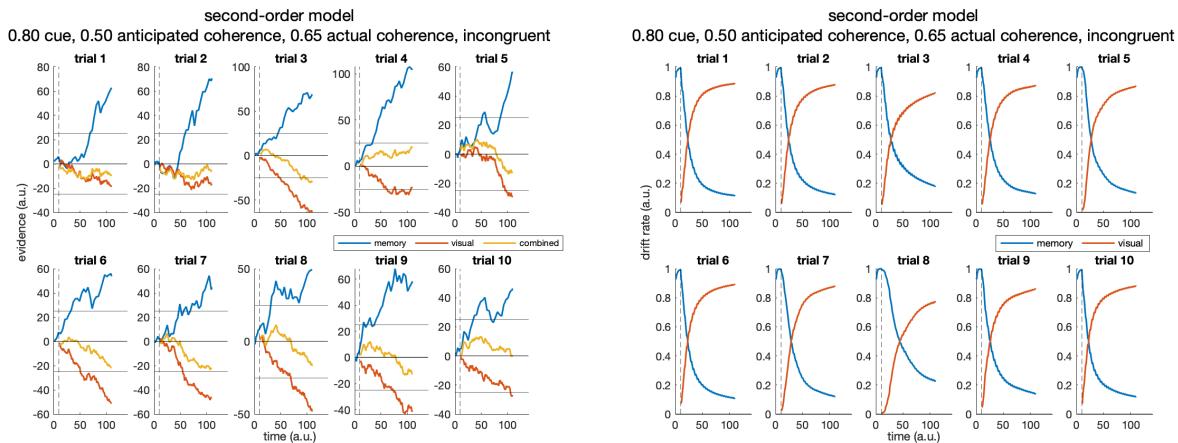


incongruent



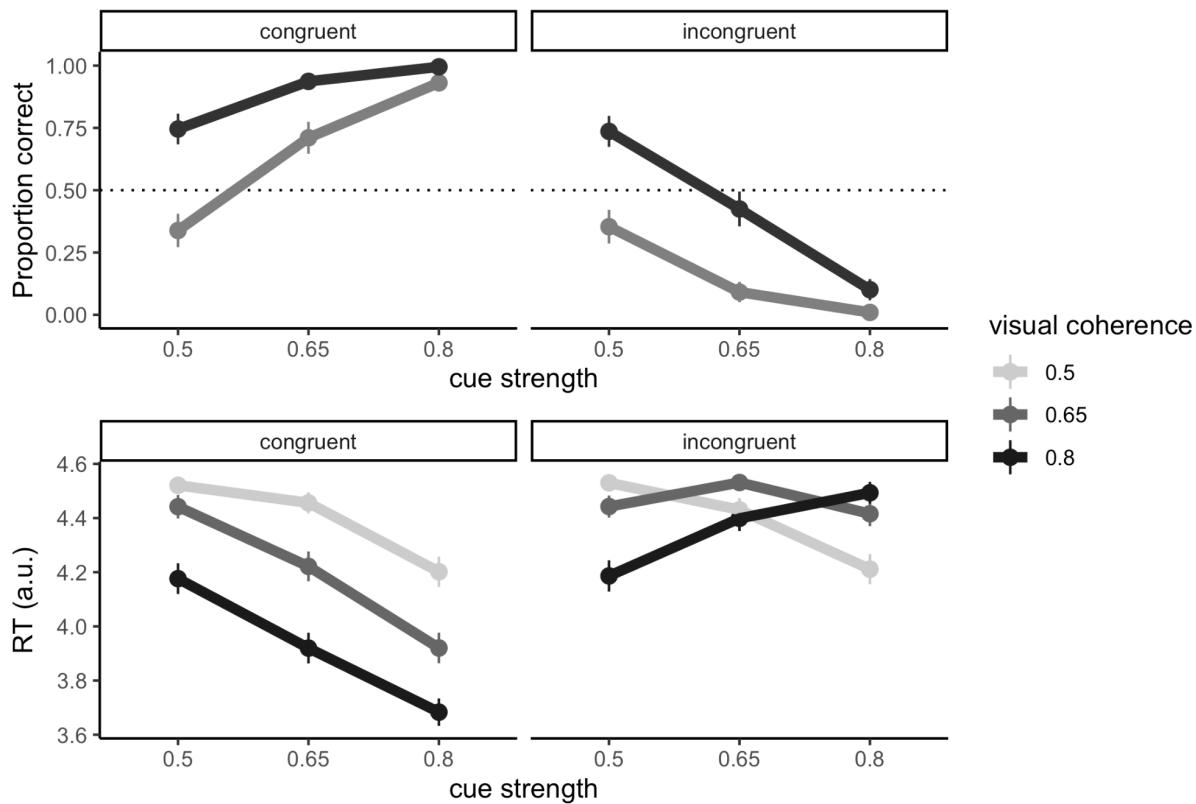
# Supplemental materials

## Example incongruent trials



First-order model: precision computed as inverse Shannon entropy of each evidence stream at each timestep

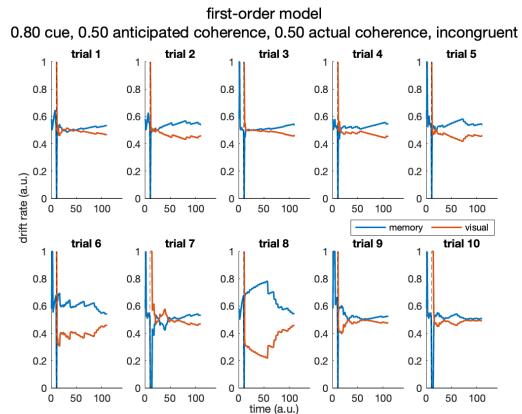
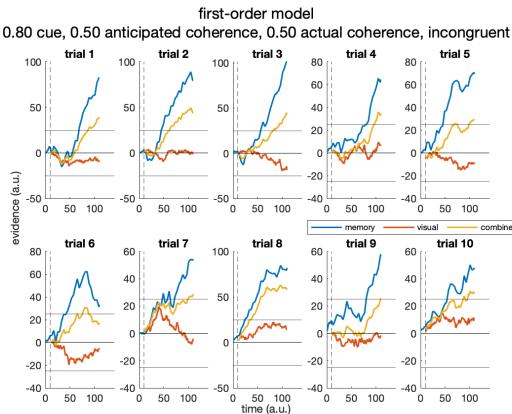
### First order model predictions



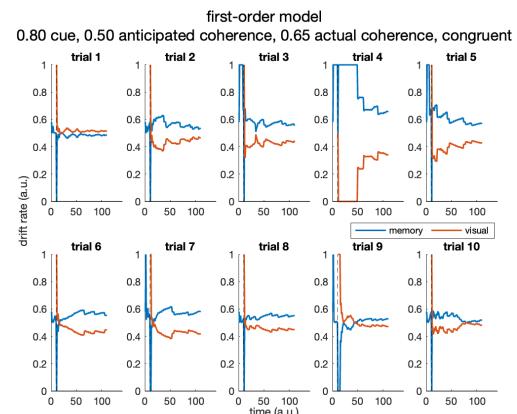
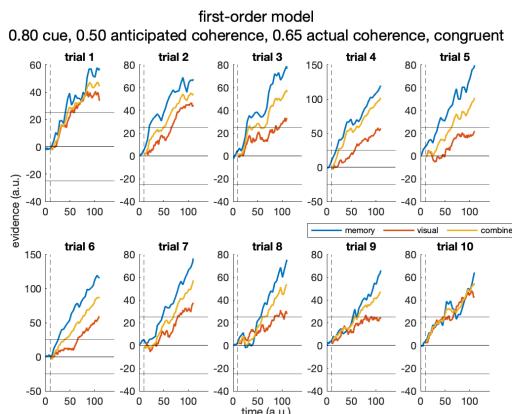
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## Example traces & drifts

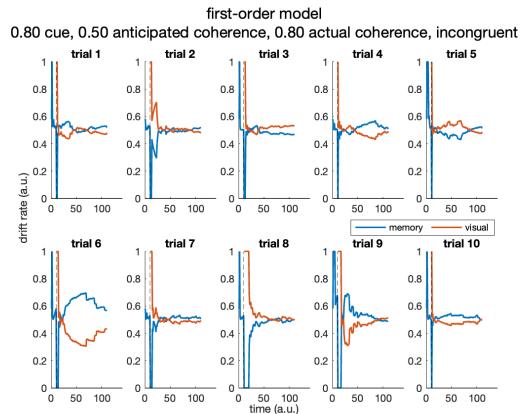
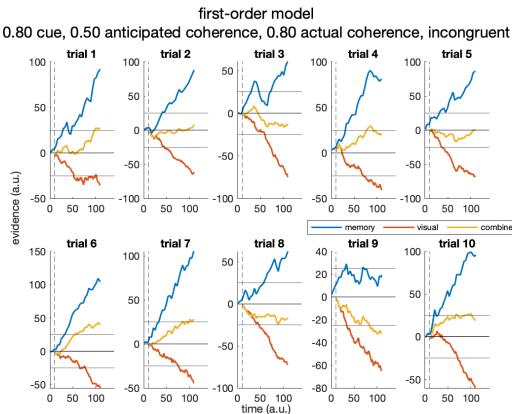
### 0.8 cue, 0.5 coh (parallel to second-order plots on poster)



### 0.8 cue, 0.65 coh, congruent



### 0.8 cue, 0.8 coh, incongruent



# Supplemental materials

## Design slides

### Response training & cue learning

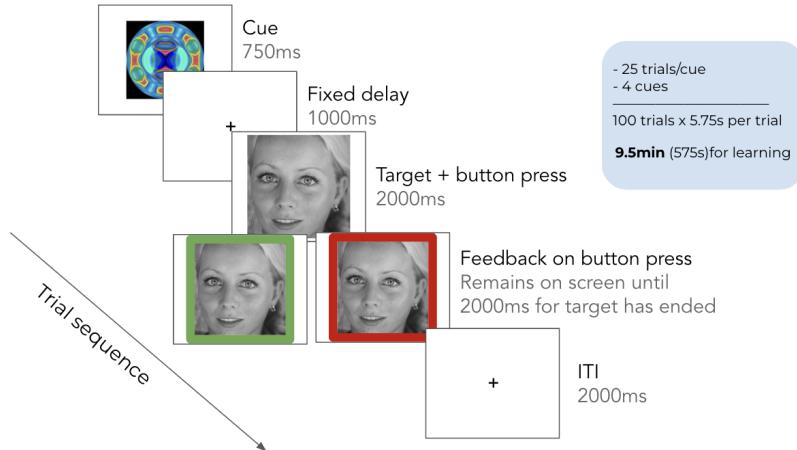
#### Response training



1      2      3      4

1. Targets are shown sequentially (twice) and participants make a self-paced key press
2. Targets are shuffled and participants have 2000ms to make a button press. If they are correct, they get visual feedback (green border around photo). If they are not, the photo remains on screen until the correct button is pressed (at which point the green feedback is given). Each photo is presented 10 times.
  - a. If participants get the same photo wrong  $\geq 2$  times, they have to start the whole training phase over

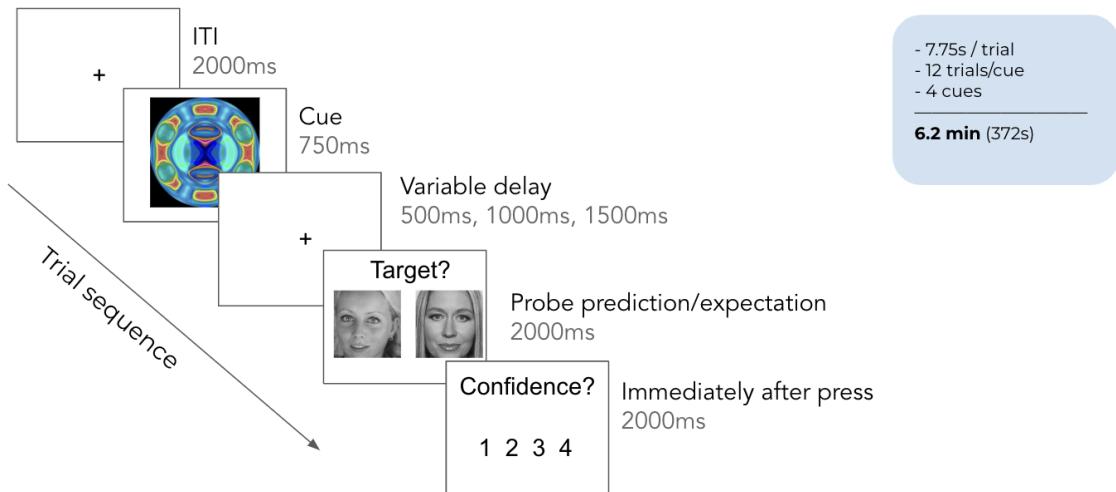
#### Sequence learning



# Supplemental materials

## Unimodal confidence trials

### Cued inference: memory confidence probe trial



### Cued inference: visual confidence probe trial

