Mouse-tracking Reveals Individual Differences in the Dynamics of Belief Updating Under Volatility

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Abstract

Decision-making under uncertainty can require dynamic updating of beliefs about the state of the world over time. While previous work has often used two-alternative forced choice tasks to investigate this process, here we introduce a novel mouse-tracking paradigm that tracks belief updating in real time . Participants (N=30) adapted their belief updating across environments with low and high levels of volatility in keeping with a normative model employing a non-linear form of evidence accumulation, and exhibited slow-timescale belief updating dynamics that substantially lagged those observed on a simple sensory-motor task with matched motor requirements. Interrogation of single-subject belief dynamics also revealed marked individual differences: while some participants produced a highly-resolved range of reported beliefs consistent with the normative model, others exhibited strong clustering of beliefs suggestive of a more limited set of categorical commitment states. These findings highlight the sensitivity of mouse-tracking to otherwise hidden individual differences in belief updating, showcasing a novel tool for dissecting computational and neural mechanisms of this key cognitive function

Keywords: Belief updating; mouse-tracking; normative model; volatility; attractor model

Task and Modelling

Thirty human participants completed a belief-updating task (Fig. 1) adapted from and , observing a continuous sequence of stimuli with spatial locations (polar angles) generated from one of two Gaussian distributions. Participants inferred the generative source of each stimulus, which changed over time with hazard rate H, and continually reported the direction and strength of their belief by moving a mouse cursor along a horizontal scale. All participants completed separate blocks of this task under low (H=0.05) and high (H=0.2) volatility, as well as a sensory-motor control task where they tracked a marker the location of which reflected the dynamic belief of a normative model (Glaze et al., 2015) performing blocks of the primary belief updating task. We fit this model to each participant's mouse-tracking data from the belief updating task:

$$L_n = \psi_n + LLR_n \quad (1)$$

$$\psi_n = L_{n-1} {}^{+\log\left[\frac{(1-H)}{H}+\exp(-L_{n-1})\right]}_{-\log\left[\frac{(1-H)}{H}+\exp(L_{n-1})\right]} \quad (2)$$

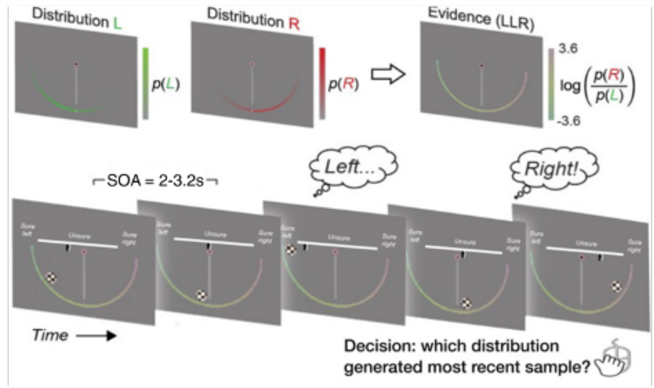

Figure 1: Perceptual decision-making task with within-trial change-points.

where L_n is the posterior belief after accumulating evidence sample n, LLR_n is the evidence (log likelihood ratio) carried by that sample and ψ_{n+1} is a non-linear, H-dependent transformation of L_n into a prior belief for the next sample. Fits included subjective H and decision noise as free parameters and allowed us to assess the extent to which participants' belief updating, as reflected in cursor movements, aligned with the (H-biased, and noisy) normative model (Fig.2)

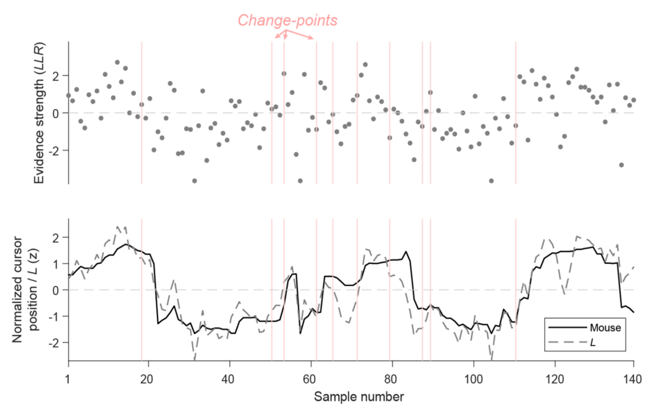

Figure 2: Stimuli (top), mouse cursor positions and model-estimated beliefs (bottom) for an example participant/block of the belief updating task (H=0.05).

Adaptation to Volatility

Participants adapted their belief updating across volatility levels in line with the normative model, as reflected in both the fitted subjective H parameters (mean=0.043 ± s.e.m.=0.008

at low volatility compared to 0.075 ± 0.01 at high volatility; p¡0.001), and the measured cursor updates. We assessed the latter by fitting a regression model to cursor positions 1.95 s after sample onset (when updates were usually complete), separately for each level of volatility:

$$Cursor_n = \beta_0 + \beta_1 \cdot L_{n-1} + \beta_2 \cdot LLR_n + \beta_3 \cdot LLR_{n-1} \cdot CPP_{n-1} \quad (3)$$

where CPP corresponds to the change-point probability (a form of surprise) associated with each sample and the LLR·CPP interaction term approximates the effect of the non-linear transformation on belief updating in the normative model (c.f. Murphy et al., 2021). The estimated influence of previous-sample belief on the updated cursor position ($\beta 1$) was stronger under low compared to high volatility conditions, whereas the converse was true for the influence of new evidence (β 2; Fig. 3) - reflecting an adaptive, volatility-dependent weighting of prior relative to new evidence consistent with the normative model (dashed lines). Modulations of evidence weighting by CPP ($\beta 3$) were present in both conditions and, consistent with previous work on 2AFC versions of our task , were significantly larger than expected from fits of the normative model ($p < .001$).

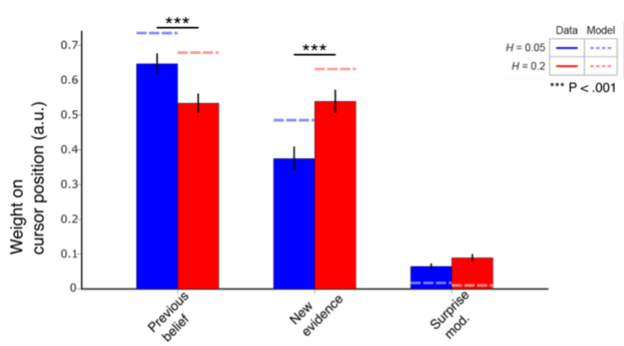

Figure 3: Coefficients from regression model predicting mouse cursor position. Bars are from human participants; dashed lines are predictions from normative model fits (without noise).

Belief Updating Dynamics

We segmented the horizontal cursor position time-series from 0-2 s around onset of each sample n, computed time-resolved single-trial Pearson correlations between cursor position and model-estimated posterior belief Ln, and fit an exponential function to the normalized (min-to-zero, max-to-1) trajectories of correlation coefficients $r_{norm,t}$:

$$\widehat{r_{norm,t}} = \begin{cases} 0 \text{ if } t < t_{on} \\ 1 - e^{\frac{t-t_{on}}{\tau}} \text{ if } t \geq t_{on} \end{cases} \quad (4)$$

where $t_o n$ and τ are the onset time and timescale, respectively, of cursor position updates in response to a new evidence sample (or marker movement, in the case of the sensory-motor task). There was a marked increase in cursor update τ and, to a lesser extent, ton during belief updating compared to sensory-motor tracking (Fig. 4). The between-task differences in these measures specifically capture belief updating dynamics controlling for sensory and motor processes and were subject to substantial individual differences in our data.

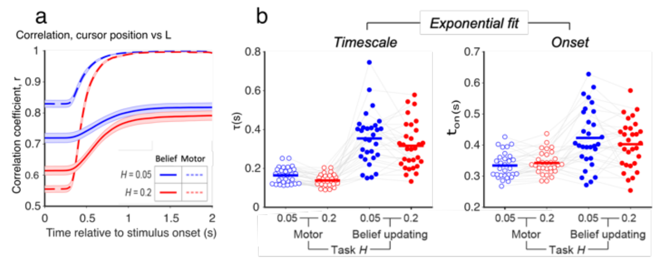

Figure 4: Time-resolved correlations of cursor position with posterior belief (a) and timescale and onset parameters from exponential fits to the trajectories (b).

Belief Clustering

We also observed that single participants tended to use the belief scale highly consistently across volatility conditions, but that there were substantial differences across individuals. Some participants (examples 1, 3 in Fig. 5) showed a highly resolved range of beliefs that were broadly consistent with the distribution of beliefs from the normative model. Others (examples 2, 4, 5) demonstrated strong clustering of cursor positions beyond model predictions, consistent with more categorical states of commitment. We posit that this behaviour may be consistent with a simple form of neural attractor model capable of reproducing approximately normative decision-making on this task (Murphy et al. 2021).

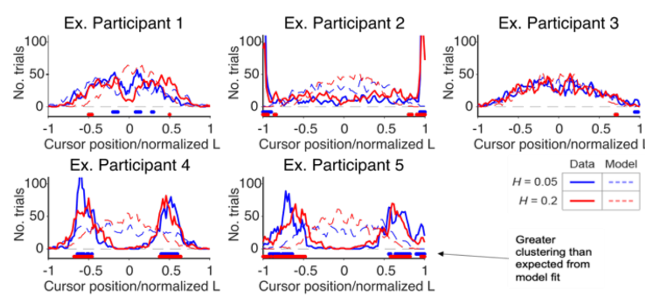

Figure 5: Histograms of observed cursor positions from example participants, overlaid on histograms of posterior beliefs from model fits. Significance markers indicate locations of significant clustering in data relative to model.

Acknowledgements

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