Flexible and selective information sampling in multi-alternative choice

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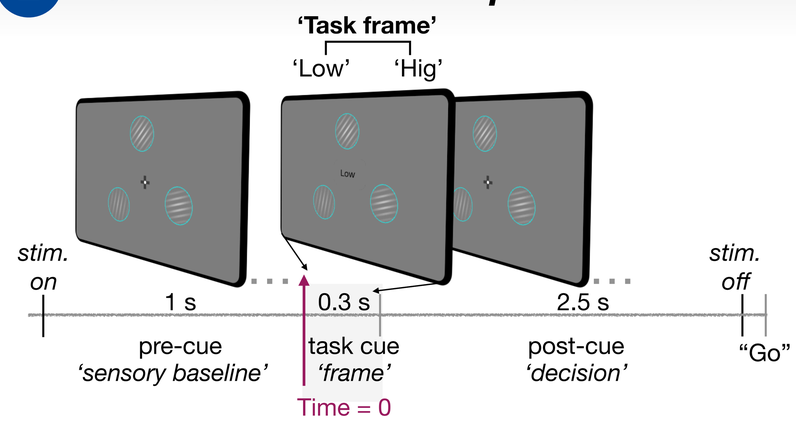
1 Background

Computational principles underlying decision over *N* > 2 alternatives?

From binary to multi-alternative choice

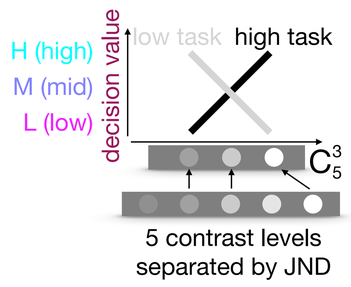
- For multi-alternative choice, the brains deploy attention flexibly and selectively.
- Behavioural economics relies on eye-tracking to study information sampling in multi-alternative decision [1].
- The role of ***covert*** attention (without eye movements) is not clear.
- ***Limitation of eye-tracking***: Knowing where people fixate says nothing about what they think (e.g., does looking at A guarantees that B is not covertly considered at the same time in a comparative manner?)

2 Behavioural task and performance

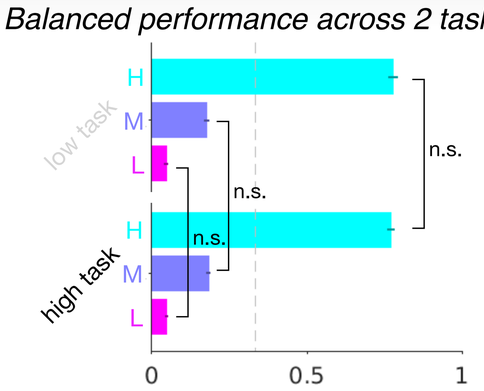


- Human participants (*N* = 20) viewed arrays made up of three Gabor patches that had distinct contrasts and orientations.
- Task (random across trials): choose the stimulus with either the ***highest*** or ***lowest*** contrast.
- Trial structure: *sensory baseline* (no task information) — *frame-cue phase* instructing the task (high/low) — *decision phase* — *Go cue* probing the choice.

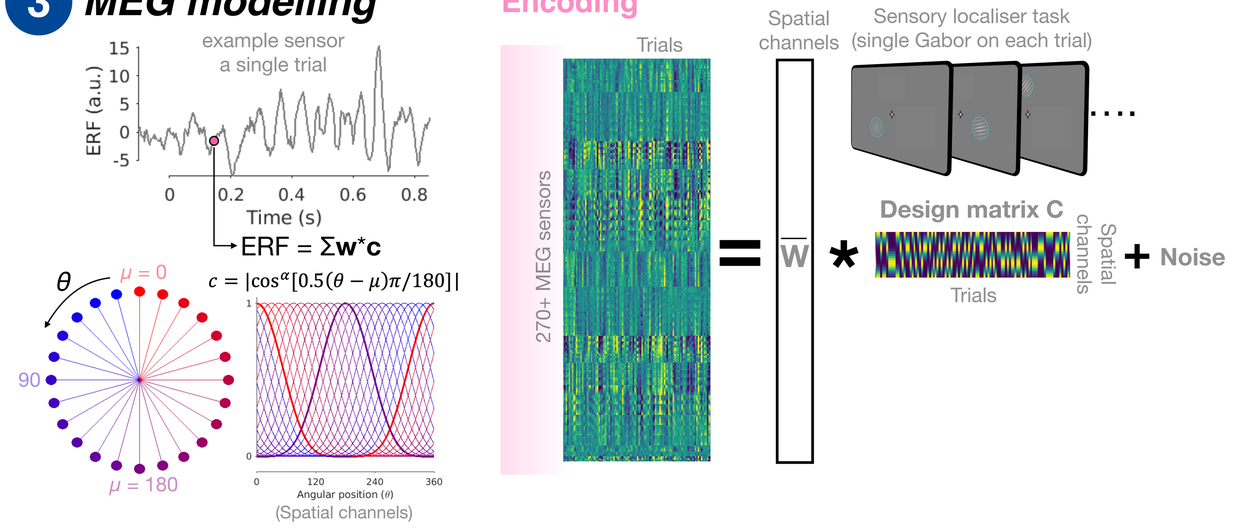
Orthogonalisation of decision value by task



Balanced performance across 2 tasks

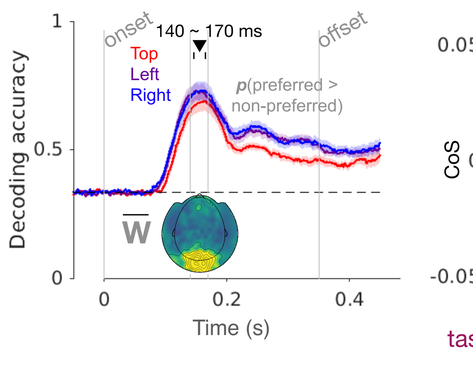


3 MEG modelling

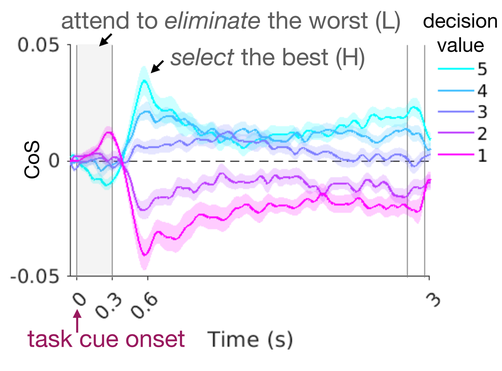


4 Results: Neural gain and information sampling

Decoding performance within sensory localiser (cross-validated)

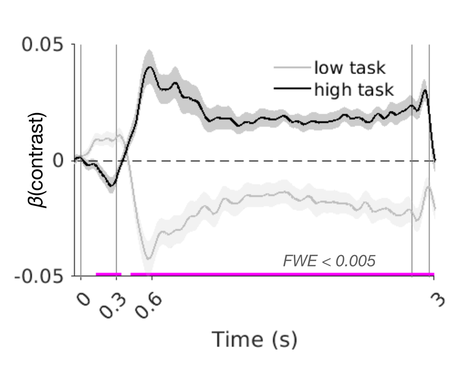


Neural gain tracks decision value (main choice task)



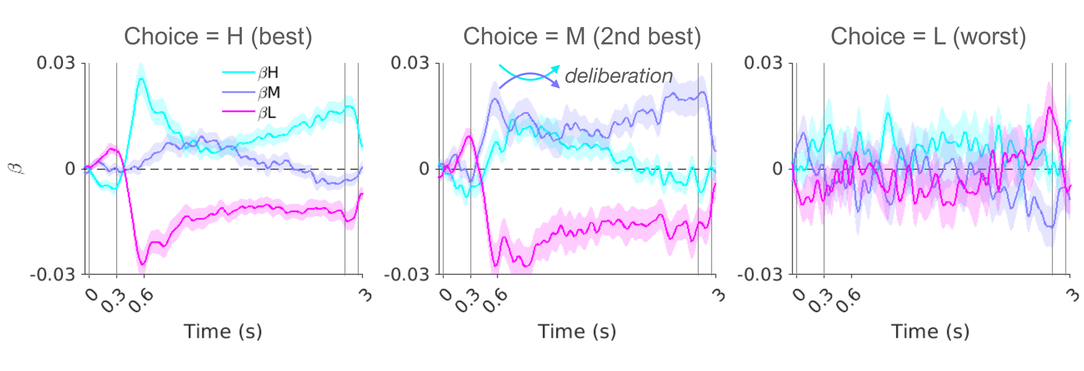
Neural gain reflects task frame

$$\begin{bmatrix}\text{Top}\\ \text{Left}\\ \text{Right}\end{bmatrix} = \beta 0 + \boldsymbol{\beta 1} \begin{bmatrix}\text{single-trial IEM proj.}\\ \text{Tc}\\ \text{Lc}\\ \text{Rc}\end{bmatrix}_{\text{nominal contrast}}$$

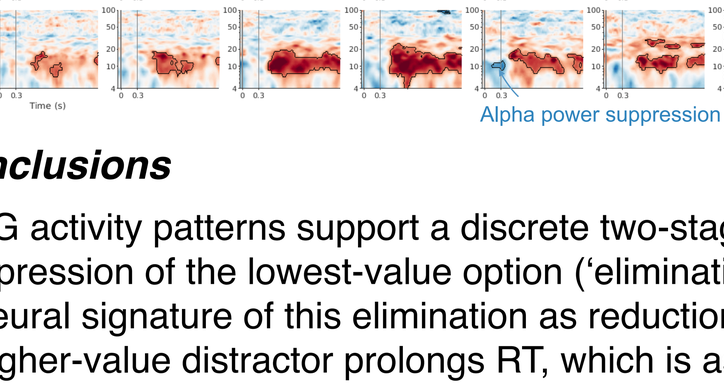


Reverse correlation: Behavioural relevance of early elimination phase

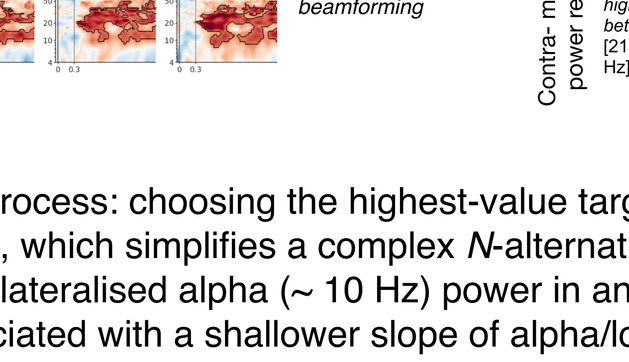
$$\begin{bmatrix}\text{sort options by value}\\ H\\ M\\ L\end{bmatrix} = \beta 0 + \beta H \begin{bmatrix}\text{single-trial IEM proj.}\\ 1\\ 0\\ 0\end{bmatrix} + \beta M \begin{bmatrix}\text{'Exceedance': Attention to an option > to others}\\ 0\\ 1\\ 0\end{bmatrix} + \beta L \begin{bmatrix}\\ 0\\ 0\\ 1\end{bmatrix}$$



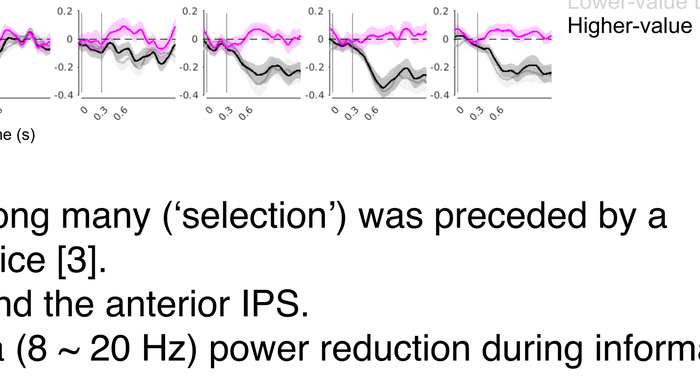
Pupil size reflects task-driven attention re-allocation



Elimination is not evident in eye position



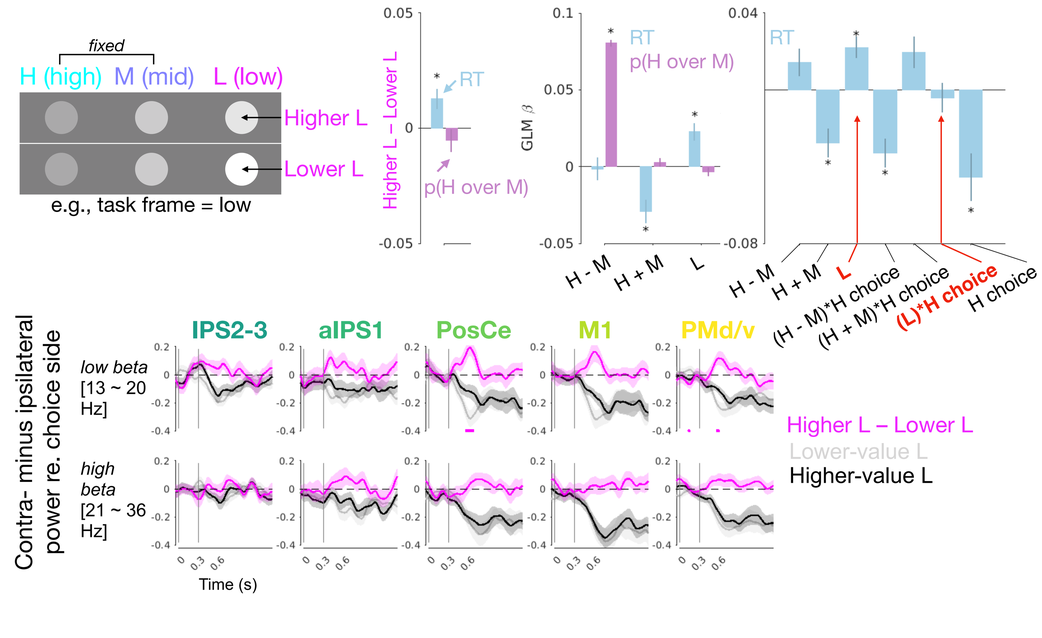
Elimination occurs regardless of current/previous task



5 Results: Time-frequency representation

Anterior IPS alpha power lateralisation reflects covert early elimination

Distractor value affects RT but not relative choice accuracy [2]



6 Conclusions

- MEG activity patterns support a discrete two-stage process: choosing the highest-value target among many ('selection') was preceded by a suppression of the lowest-value option ('elimination'), which simplifies a complex *N*-alternative choice [3].
- A neural signature of this elimination as reduction of lateralised alpha (~ 10 Hz) power in and around the anterior IPS.
- A higher-value distractor prolongs RT, which is associated with a shallower slope of alpha/low-beta (8 ~ 20 Hz) power reduction during information sampling in the motor cortex.

1. Krajbich & Rangel (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. ***PNAS, 108***(33), 13852-13857.
2. Gluth et al. (2020). Value-based attention but not divisive normalization influences decisions with multiple alternatives. ***Nature Human Behaviour, 4***(6), 634-645.
3. Tversky, A. (1972). Elimination by aspects: A theory of choice. ***Psychological Review, 79***(4), 281–299.

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