OpenScope Predictive Processing:

Human EEG spin-off

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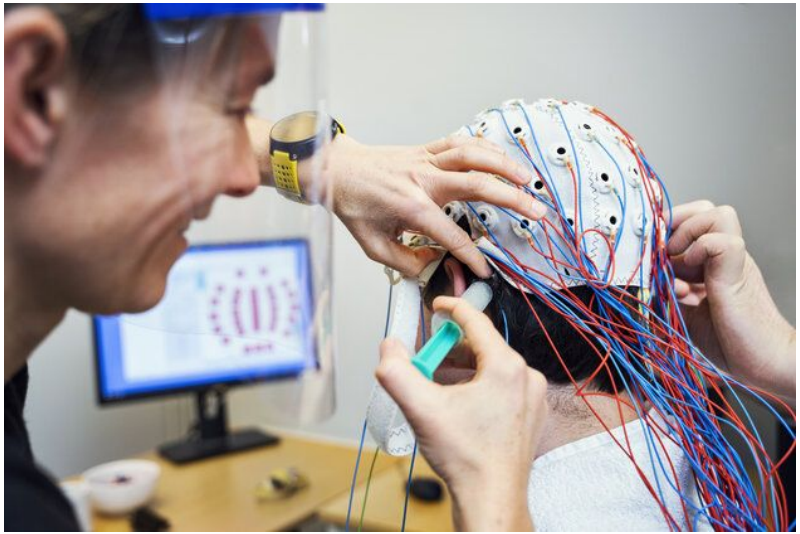
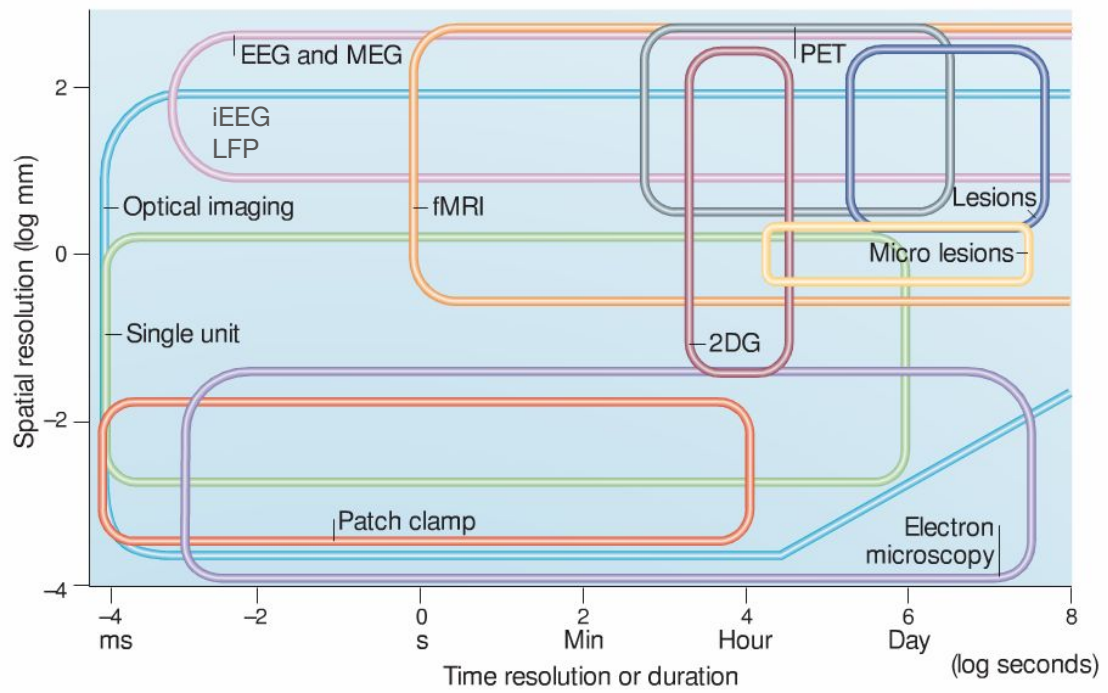


Aims

- Supplement the original OpenScope project with human data
- Run adapted versions of original paradigms with scalp EEG
- Target large sample size (N > 100) to investigate inter-individual variability
- Multi-lab collaboration to increase reproducibility and impact
- Pre-registration and open data sharing in the spirit of OpenScope

Why EEG?

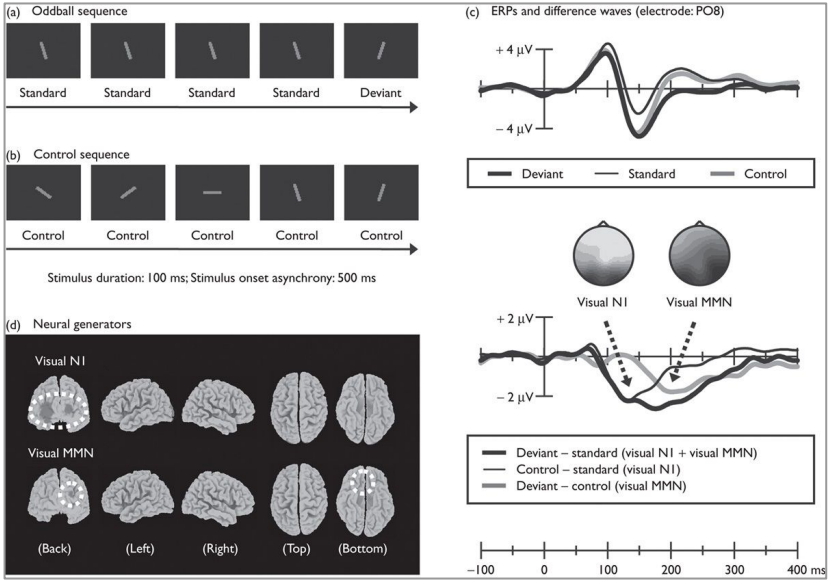
Good temporal resolution
Non-invasive
Easily accessible
Standard for MMN research

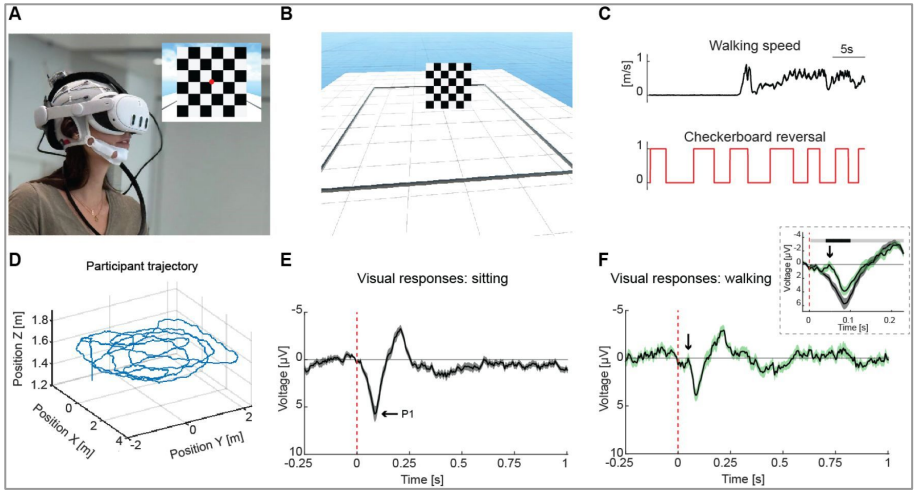


doi: 10.1038/nrn1536

Why EEG?

Ample previous work on visual (and visuomotor) mismatch responses





10.1097/WNR.0b013e32834973ba

10.7554/eLife.108941.2

Why EEG?

Previous comparative work in auditory MMN

Review Article

Do rat auditory event related potentials exhibit human mismatch negativity attributes related to predictive coding?

Jaishree Jalewa [a], Juanita Todd [a b c], Patricia T. Michie [a b c], Deborah M. Hodgson [a b c], Lauren Harms [b c d] Show more

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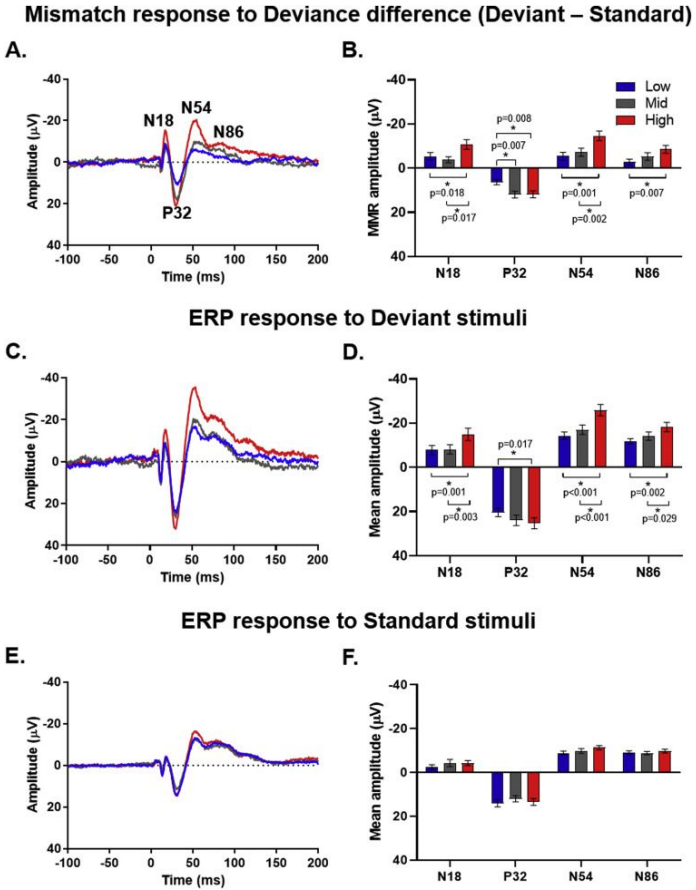
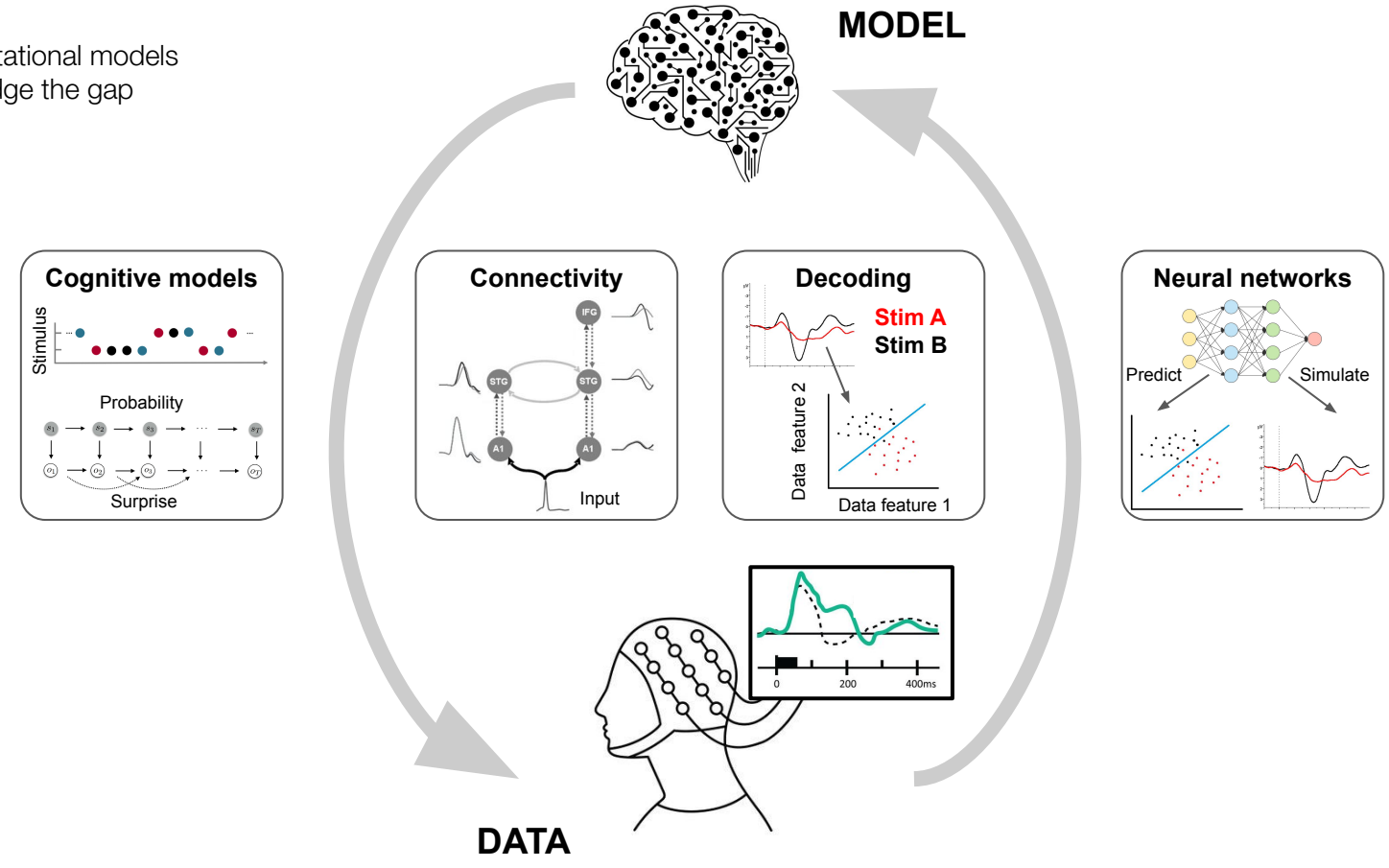


10.1016/j.heares.2020.107992

Why EEG?

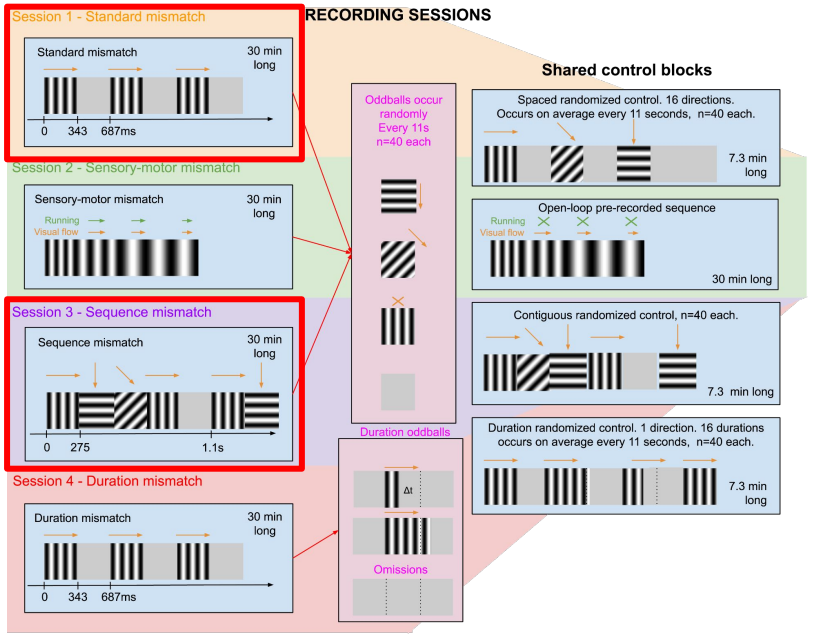
Computational models
can bridge the gap



Gütlin, McDermott, Grundei, Auksztulewicz (2024)
Clin EEG Neurosci

Overall plan

Late 2025	Decide on a subset of conditions
Early 2026	Adapt paradigm settings
Ongoing	Collect pilot data
Ongoing	Recruit labs
Summer 2026	Pre-register (OSF) and share code (Github)
Fall/winter 2026	Collect and store data (BIDS)
Spring 2027	Share data with OpenScope + participating labs
Fall/winter 2027	Share data with broader public



Adapted design

Consent, questionnaires, preparation: ~45’

EEG: ~110’ incl. breaks excl. preparation

Staircase Detection	Staircase Discrimination	Rest Eyes open	Standard oddball (Breaks every ~5’)	Rest Eyes open	Spaced control (Breaks every ~5’)	Rest Eyes closed	Sequential oddball (Breaks every ~5’)	Rest Eyes closed	Contiguous control (Breaks every ~5’)
~5’	~5’	1’	17’	1’	13’	1’	26’	1’	20’

Main	Randomized blocks and trials (60 trials per deviant per condition)	Aim: Compare vMMN between standard/oddball and sequence
Staircase	Fixed order. Details: Iemi et al., 10.1523/JNEUROSCI.1432-16.2016	Aim: Analysis of individual diffs in excitability ~ MMN
Rest	Randomized order (2x eyes open, 2x eyes closed)	Aim: Quantify individual alpha frequency ~ excitability

Standard oddball

Standards

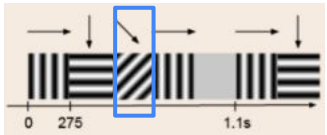
Deviants (n=60, p=0.065 each)

Spaced control

Randomized
16 orientations + Halt + Omission

Matched (n=60, p=0.065 each)

Sequential oddball



Standards in 3rd position

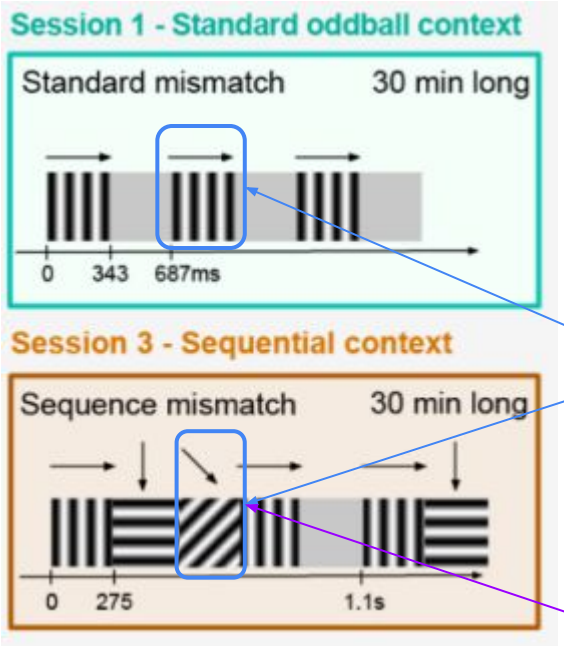
Deviants (n=60, p=0.065 each)

Contiguous control

Randomized
16 orientations + Halt + Omission

Matched (n=60, p=0.065 each)

Adapted design



Deviant orientation randomized across participants
Deviants pseudorandomized within blocks
(at least one standard between two deviants)

Right now the preprint only matches average timing of these deviants (every 11s), but not orientation, stimulus probability, or deviant probability.

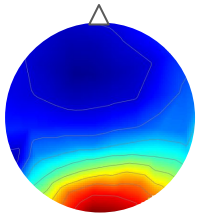
We adopted a different logic - matching orientation and deviant probability, but not average timing or stimulus probability.

"Sequential context" has structure ABXD where X can be a standard or a deviant, and deviants have a certain probability

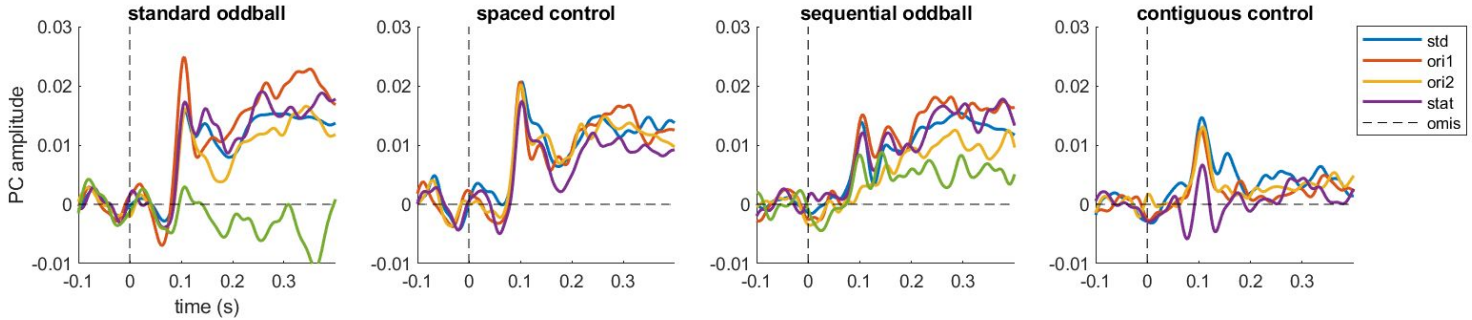
We matched the structure of contiguous control to the same ABXD, where ABD is the same across conditions and X(deviant) has the same probability

Pilot data

N=6, 64 active electrodes, BrainProducts



PC1, 77%



Analysis plan #1

I. What kind of information is encoded by mismatch responses?

EEG equivalents

Analysis #1: For each neuron and each mismatch stimulus, construct [...] the **event-triggered average**

Typical mass-univariate ERP analysis

Analysis #2: Compare the mismatch response in the novel vs. control conditions.

- Scatter plot of responses in the two conditions and carry out a **linear fit**

Single-trial GLM

Analysis #3: Compare responses to **different mismatch** stimuli in the novel condition

Typical mass-univariate ERP analysis

Analysis #4: Calculate **decoding performance** / information encoded for mismatch stimuli and novelty per se

- e.g. compare decoding performance of novelty per se vs. performance for **individual stimuli**

Multivariate analysis (decoding / RSA)

II. Distinguish between two categories of prediction made by neurons

Analysis #3: Emergence of Prediction Signals in Single Neurons and Neural Populations

- Predictive coding vs. static **tuning** — Population tuning curves / variance partitioning
- **Predictive activity** — Prestimulus decoding
- **Latent** component dynamics — PCA / state space analysis
- Neural **dimensionality** reduction — RSA + dimensionality estimation

Analysis plan #1

III. Mismatch responses across different types of predictions

EEG equivalents

Analysis #3: Compare responses for the ***same* neurons** between the oddball (session 1) and sequence (session 3) mismatches

Mixed-effects modelling (EEG sensor or source as a random effect)

Analysis #6: Test various prediction models across session types.

- Quantify learning effects as a function of **region and layer**. Measure the response amplitude before and after repeated presentations of the same stimulus within a recording session.

  Dynamic causal models

- Analyze changes in neural responses within a recording session (e.g., occurring over periods of **seconds to minutes**) to detect patterns likely to reflect short-term memory processes.

  Single-trial GLM

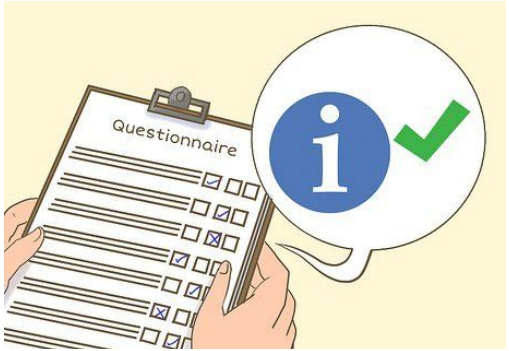
- Train **deep learning** models using self-supervised learning (e.g., to predict future activity from past activity) to extract latent feature representations of the neural data. Analyze the accuracy of stimulus decoders trained on the representations extracted from different areas and using different temporal windows.

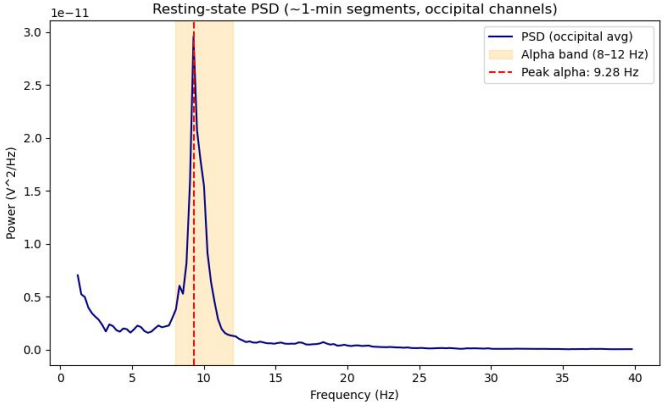
  DNNs fit to EEG data

- Use **information theory** criteria and **cross-validation** techniques to compare the goodness-of-fit of different models. Validate models using separate test datasets, including ones obtained from different laboratories

  Same as for rodent data

Additional measurements (excitability)





Trait excitability

Adult Temperament Questionnaire (Evans & Rothbart, 2007)

- Orienting sensitivity subscale
- Effortful control subscale

Neural excitability

Resting state EEG:

- Peak alpha frequency
- 1/f slope

Proxy (and modeling basis) for E/I balance

Behavioral excitability

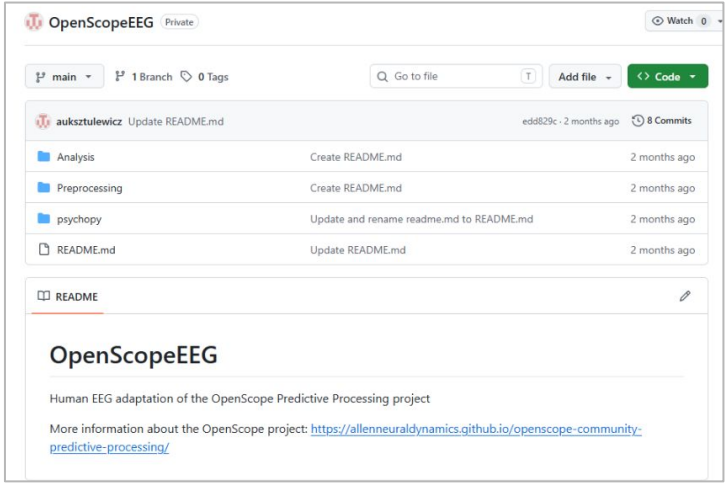
Psychophysics:

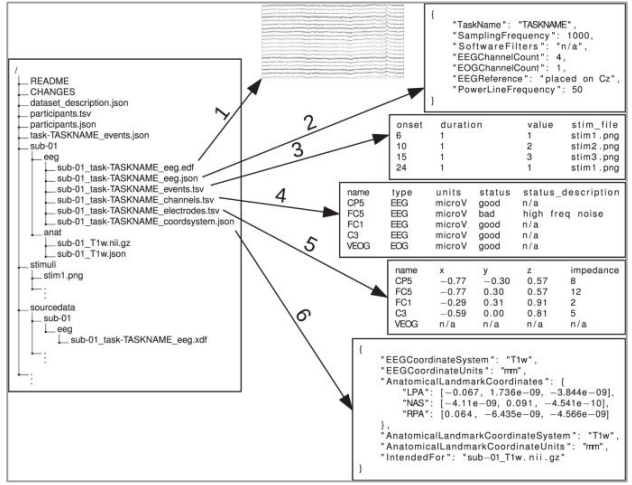
- Detection threshold
- Orientation discrim. threshold

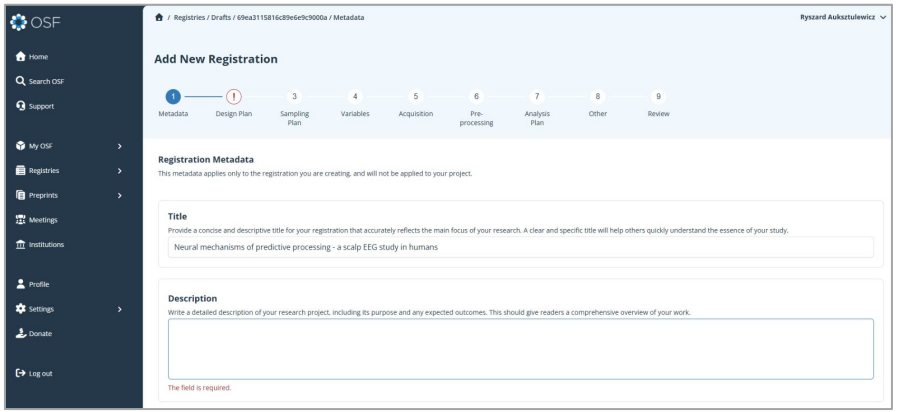
Excitability can be estimated from SDT

10.1523/JNEUROSCI.1479-24.2025
10.1523/JNEUROSCI.1432-16.2016

Logistics







3-4 EEG labs confirmed
1-2 more targeted
64-channel active EEG system required

Want to participate?
Let us know!

Feedback

1. In the updated design, the animal studies now has two control blocks - one before and one after the oddball. The rationale is to look at adaptation during the oddball and how this carries over to the subsequent control.

   -> If we don't want to increase recording duration, we could split each block into two and pseudorandomize the order.

   See updated figures here
   https://docs.google.com/document/d/1A4aj5E1jsv-XihPt2_6K0TKMnwvtiMAFau3qJUcOV-I/edit?tab=t.0#heading=h.ob2prtvh2zsk

2. The animal study actually uses the same orientation as a standard (no randomization across animals). The reason is that different orientations (vertical vs. horizontal) evoke different levels of inhibition, so differences in amplitude are not necessarily a disadvantage.

   -> We could fix it rather than randomizing orientation across participants.

3. Coordinate with Andre Bastos to make sure that stimuli can at least be easily compared to the macaque study

   -> Ryszard will discuss it with Andre hopefully next week