On Augmenting Working Memory through Neurostimulation

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IEEE brain

Introduction

This study examines the prospect of augmenting working memory performance through closed-loop, personalized neurostimulation.

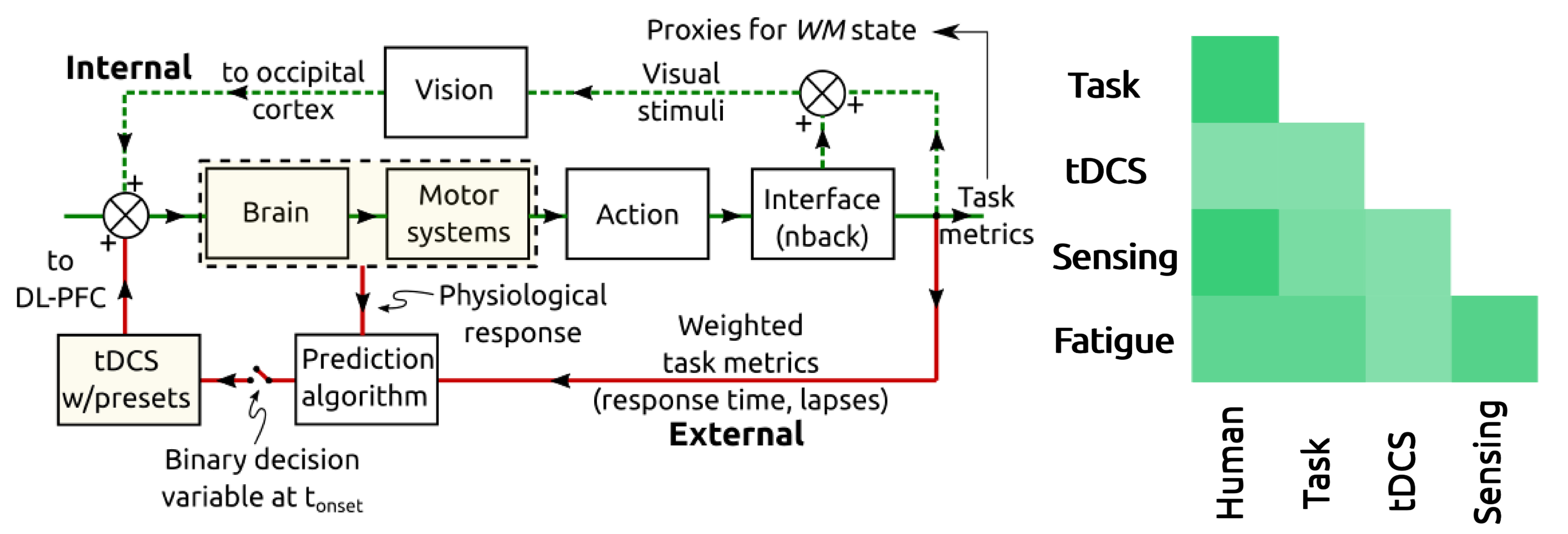

Fig. 1: **(a)** Schematic representation the proposed closed-loop framework for augmenting Working Memory (WM) with transcranial Direct Current Stimulation (tDCS), and **(b)** a metaphor for the known/ unknown interactions in this domain.

- **Rationale:** Current tDCS protocols are mostly sequential, and non-specific to user cognitive states, while relying on existing dosage standards and recommendations.
- **Hypothesis:** Closed-loop, personalized neurostimulation can improve working memory (WM) performance, while remaining accessible to the recipient if structured like a recommender system
- **Approach:** We decompose the problem into two goals for this pilot study -- **(i)** to develop a predictive framework for WM decline, and **(ii)** to evaluate tDCS efficacy in augmenting or restoring WM.

Methods and protocol

We recruited **30** participants (15 female) from the university student pool, who were cast into counterbalanced groups for **anodal**, **sham**, and **control** conditions on separate days (in progress).

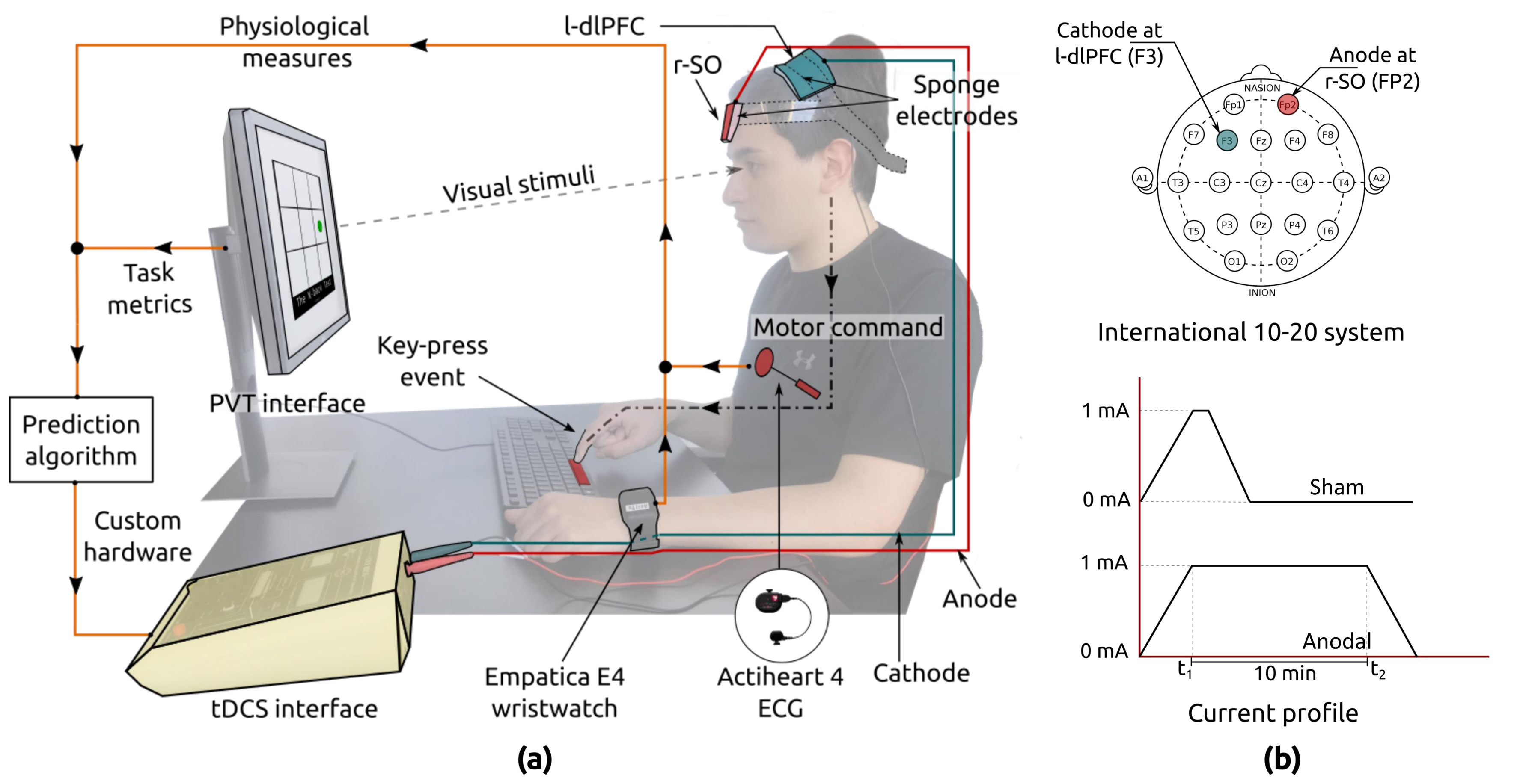

Fig. 2: **(a)** Schematic representation of the workflow when participant is engaged in the two-back test. **(b)** Anodal tDCS montage for working memory with anode over l-DLPFC, and cathode over the r-SO regions (Top), and (ii) current waveforms for anodal, and sham stimulation conditions (Bottom).

- Experiment protocol: **12** blocks of **5** minutes each
- PNB data: **(i)** ECG, **(ii)** fNIRS (control), and **(iii)** subjective responses

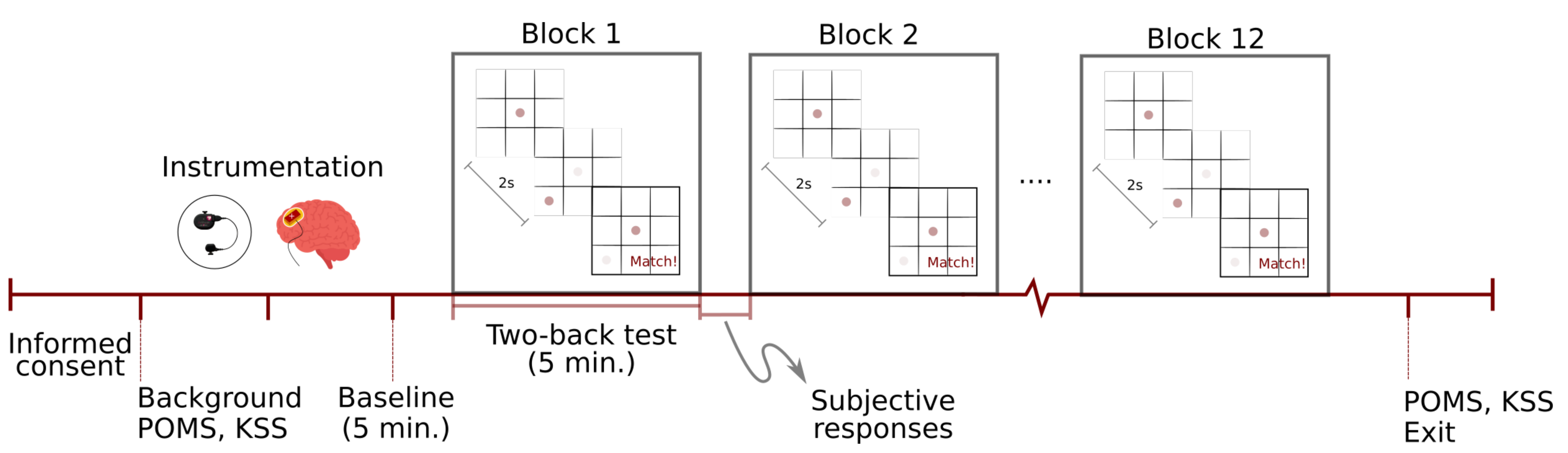

Fig. 3 Experiment timeline for the *Control*, *Sham*, and *Anodal* conditions, where participants were brought in on separate days for each experiment. Stimulation was introduced at the **onset of block 5** for both Sham, and Anodal conditions.

Biomarkers and prediction workflow

The raw ECG signal (256 Hz) and performance data (block-wise) are recorded during the experiment and subject to an exhaustive feature extraction workflow.

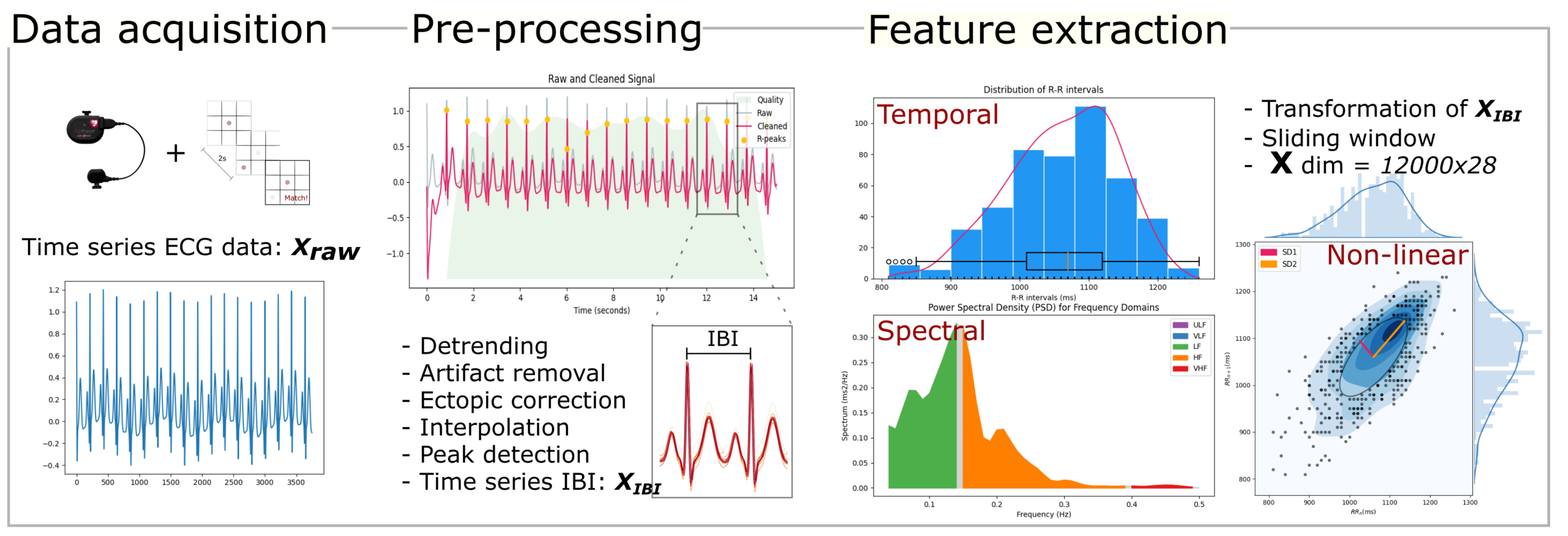

Fig. 4: Feature engineering workflow for raw ECG data involves signal acquisition, preprocessing and feature generation resulting in 28 temporal, spectral, and non-linear domain features for heart-rate variability (HR/V).

1. A sliding window is applied, epoch size: *300s* , *50%* overlap
2. HR/V features are feature-scaled across each participant
3. Task accuracy measures are a composite of lapses and errors

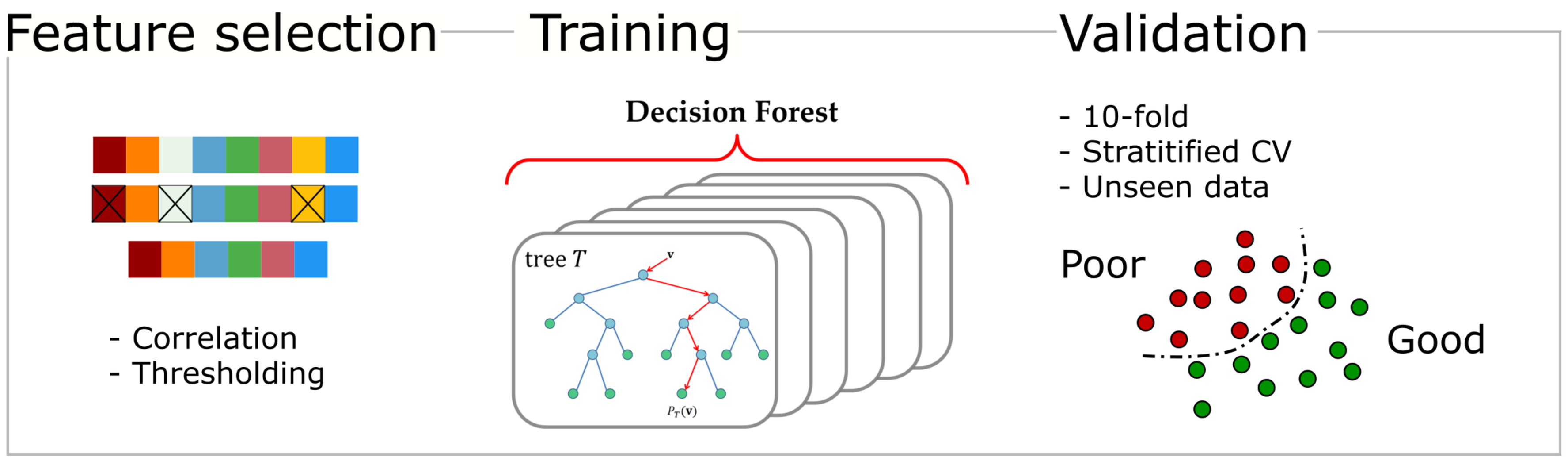

Fig. 5: The machine learning workflow used takes a supervised approach where blocks are labeled contingent on performance differences with baseline. An exhaustive ensemble learning template was built in *scikit-learn 0.23.2* with *10*-fold stratified cross-validation

The Random Forest was among the top performing models with a CV accuracy of *84.72%*. *LF_power*, and *SD1* were implicated as among the top model contributors.

Observations with tDCS

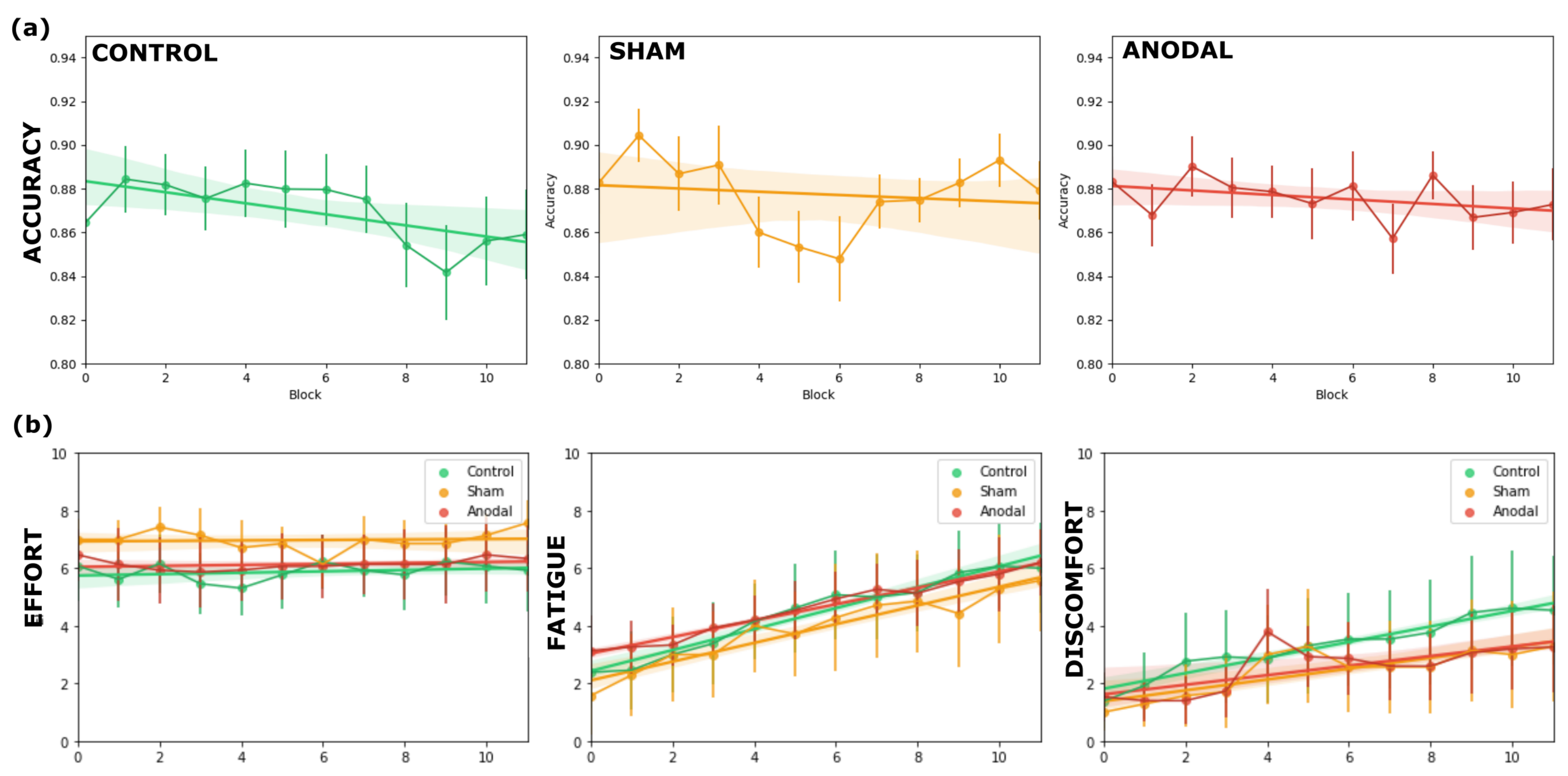

Fig. 6: **(a)** Performance across three stimulation conditions. Marked decrease during the *Control* condition in performance accuracy. *Sham* shows more variability in performance compared to *Anodal*. **(b)** Subjective response trends across the three conditions – Effort, Fatigue, and Discomfort.

Current efforts

Geared towards the completion of data collection, with focus on – **1.** differentiating between the effects of tDCS and familiarization; **2.** robustness and online predictive power of HR/V; **3.** algorithmic sensitivity to group or individual differences; and **4**. the role of cognitive indices.