Walking to the beat:
How to quantify neural entrainment

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INTRODUCTION

- **Rhythmic auditory cues (RAC)** can improve **gait**[1]. Gait benefits may be modulated by the **coupling** of brain activity to RAC[2], which has never been quantified during gait.
- During finger tapping, coupling is often quantified as **EEG power** at RAC frequency[3]. However, coupling cannot be inferred from power only.
- Traditionally, the EEG signal of the electrode that shows maximal response to RAC is analyzed, introducing bias and minimizing signal-to-noise ratio. **Generalized eigendecomposition** (GED) solves these methodological concerns as it computes one time-series from all electrodes.
- GED was recently used to extract one brain component oscillating at RAC frequency during finger tapping[4]. Coupling was quantified as the **stability index** (*i.e.*, the standard deviation of instantaneous frequencies), which captures the dynamic **phase** adjustments of oscillations.
- **β-power modulation** mediates the predictions needed to synchronize our footsteps to RAC [5].

OBJECTIVES

1. Extract one neural component coupled to RAC during gait using GED.

2. Quantify coupling as power, phase consistency, stability index, and β-power modulation to find which of these variables better describes coupling of brain activity to RAC during gait.

METHODS

Participants
Open-access data of **20 young healthy adults** were analyzed[6].

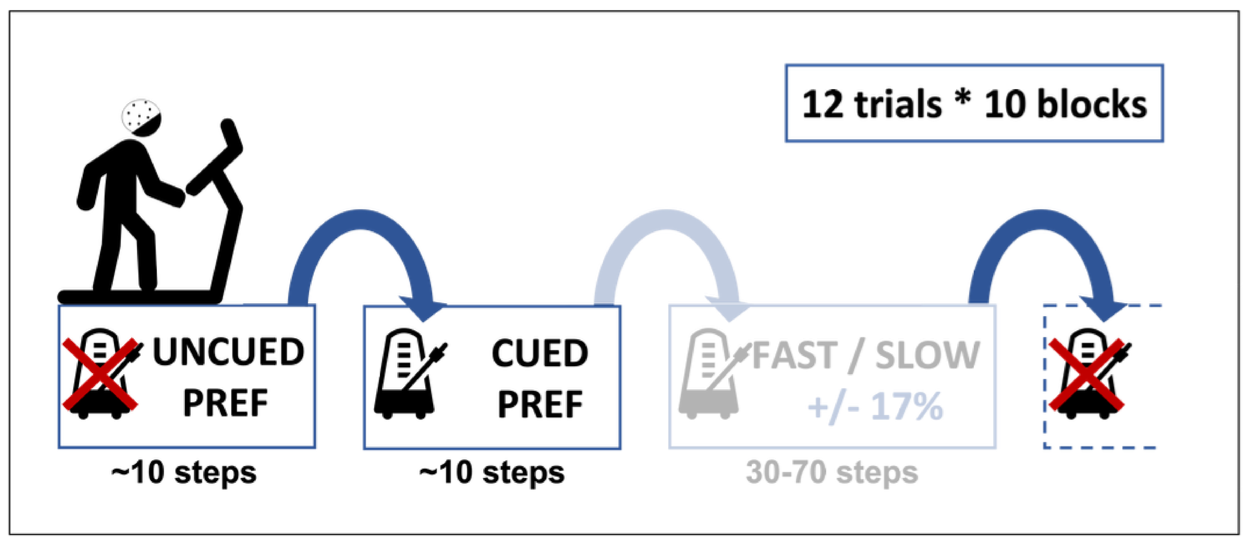

Fig. 1. Experimental protocol from Wagner et al. (2019). Only conditions Uncued Pref and Cued Pref were analyzed.

Instrumentation
EEG: 108 electrodes (EasyCap, Herrsching, Germany).
RAC: alternating high and low tones.
Foot switches: placed under the heels to detect foot strikes.

Statistics
Linear mixed-effects models assessed whether power, phase consistency, stability index, and β-power modulation differed in cued and uncued conditions as follows:
Outcome measure ~ 1 + Conditions + (1 | Participants)

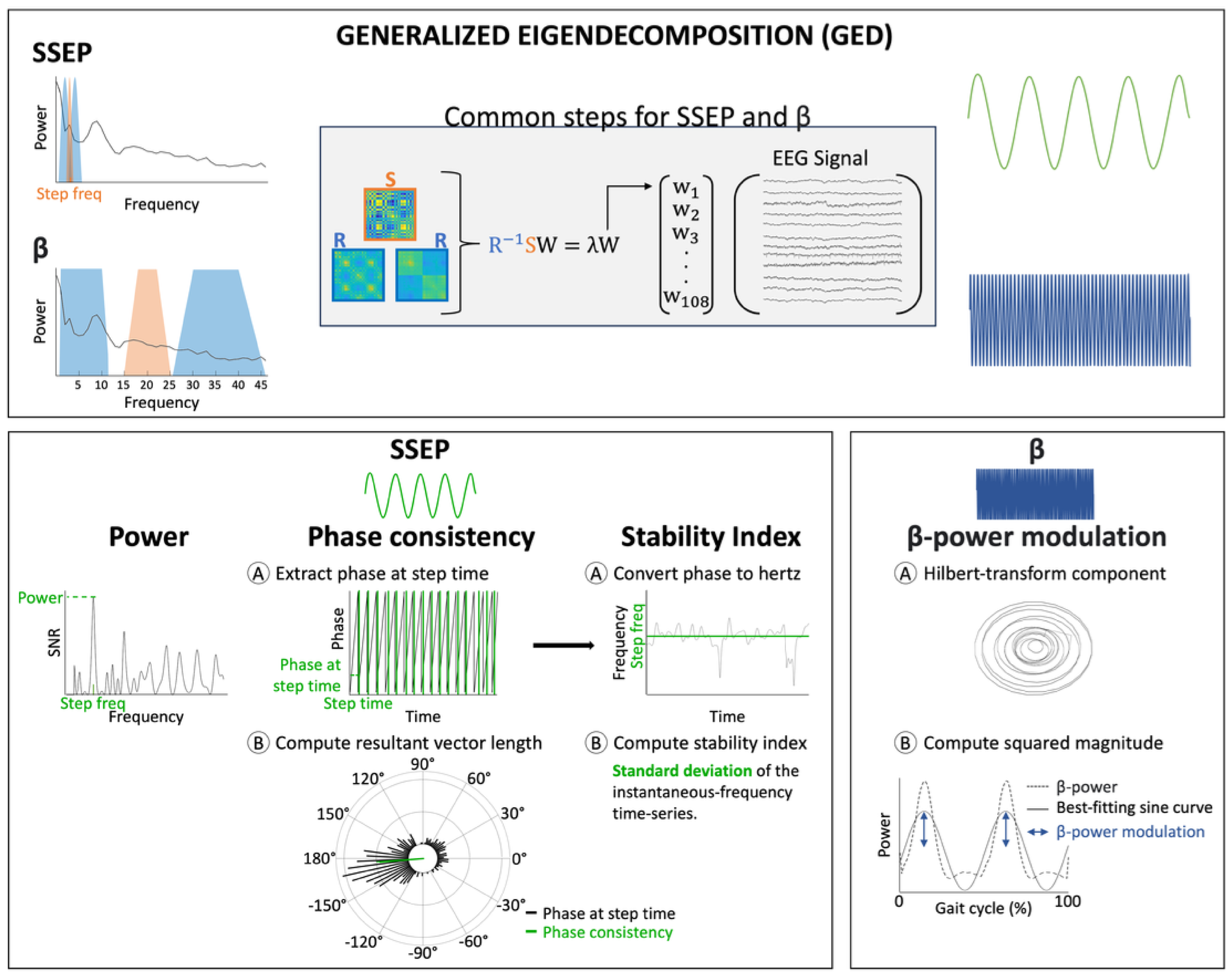

Fig. 2. EEG processing. GED creates spatial filters to extract two neural components: SSEP (coupled to the step frequency) and β (around 20 Hz). Power, phase consistency, and the stability index were computed from the SSEP time-series. β-power modulation was computed from the β component.

RESULTS

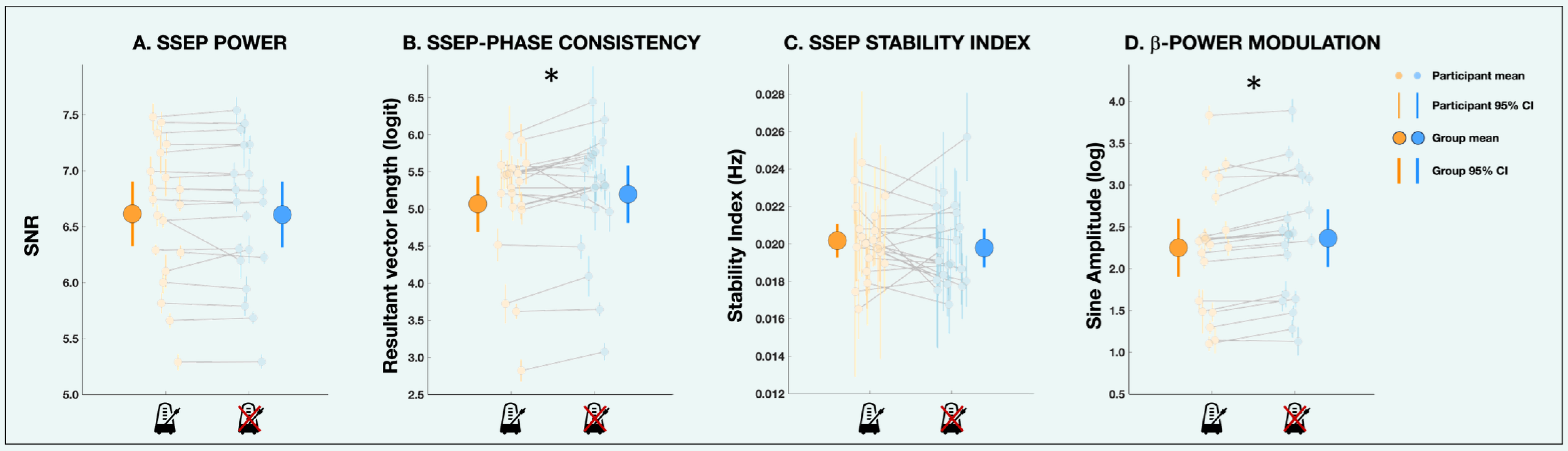

Fig. 3. Group means with 95% CI bars plotted against each participant's mean and 95% CI bar for **A.** SSEP power, **B.** phase consistency, **C.** stability index, and **D.** β-power modulation during cued (orange) and uncued (blue) conditions. *Note.* Significant main effects of *Conditions* are shown with a black asterisk.

Power: no effect (Estimate = -.001; SE = .012; t = -.082; *P* = .934).
Phase consistency: coupling more stable without cues (Estimate = .156; SE = .033; t = 4.68; *P* < .001).
Stability index: no effect (Estimate = -.0008; SE = .0007; t = -1.18; *P* = .240).
β-power modulation: Better predictions with cues (Estimate = .113; SE = .016; t = 6.91; *P* < .001).

CONCLUSION

- SSEP and β components could be extracted with GED during gait, lowering electrode-selection bias and increasing signal-to-noise ratio.
- Outcome measures computed from the SSEP component seem to reflect neural coupling to motor behaviour, instead of RAC. In fact, high power at the movement frequency is expected during uncued repetitive motor tasks [7].
- β-power modulation might better describe neural coupling to RAC as it happens at a frequency that differs from movement itself.

References
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