Trainability Differences of Electrical Brain Metrics in EEG Neurofeedback: Implications for Modulating Language Function

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Introduction

Recent work on mechanisms of recovery of language function following adult brain injury (e.g. stroke, TBI) has focused heavily on the relevant brain networks for language. However, relatively few direct methods exist for strengthening connections between the nodes of these networks. Electroencephalographic (EEG) neurofeedback (NF) is currently a topic of growing interest, in that it has significant potential both as a clinical and experimental tool for network modulation. By feeding back real-time information on electrical activity across brain sites, participants are able to change those patterns of activity, and to affect the strength of connectivity between brain regions. Though NF has been successfully used to treat symptoms of multiple disorders (e.g. ADHD, dyslexia, traumatic brain injury), the utility of this tool to address language deficits directly has not yet been systematically explored.

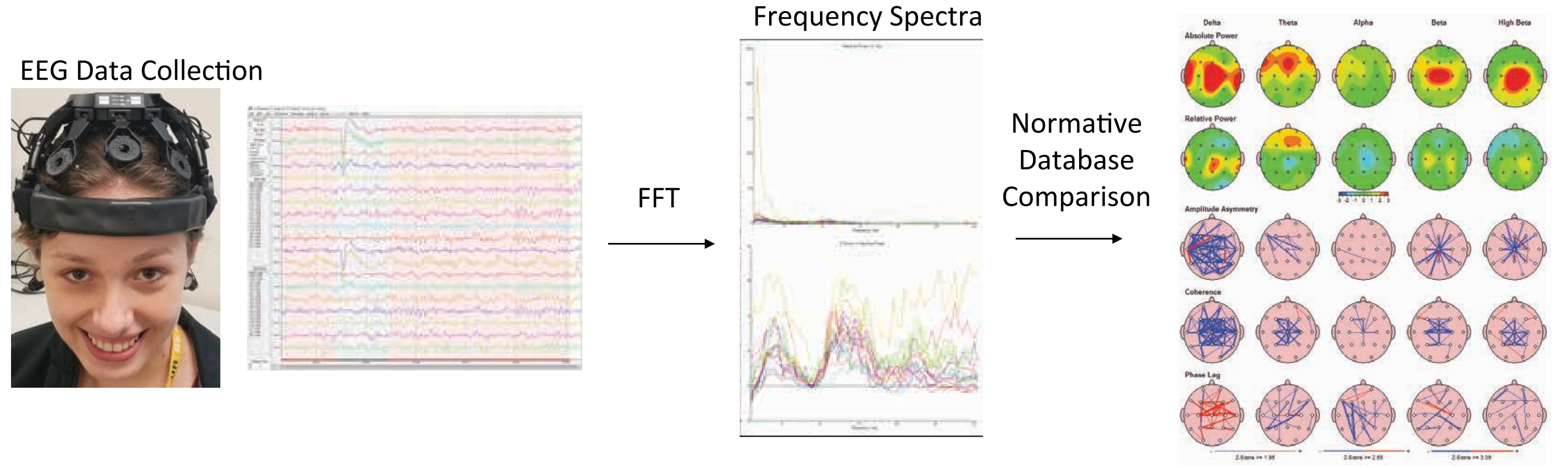
Barriers to Progress

1) Lack of standardized, evidence-based protocols for language treatment
   Though case studies have shown promising results, few studies have directly targeted language symptoms or addressed language dysfunction as a primary symptom
2) Problem of non-response and assessing treatment candidacy
   For those whom NF works well for, it can have very dramatic results, but many (estimates range from 15-60%) do not respond well, and there is not currently a way to prospectively identify these patients

The current work gives an overview of methods for EEG NF using Neuroguide software, and presents pilot data which proposes some ways to overcome these barriers to progress.

Neurofeedback Methods

Quantitative EEG Analysis (QEEG)

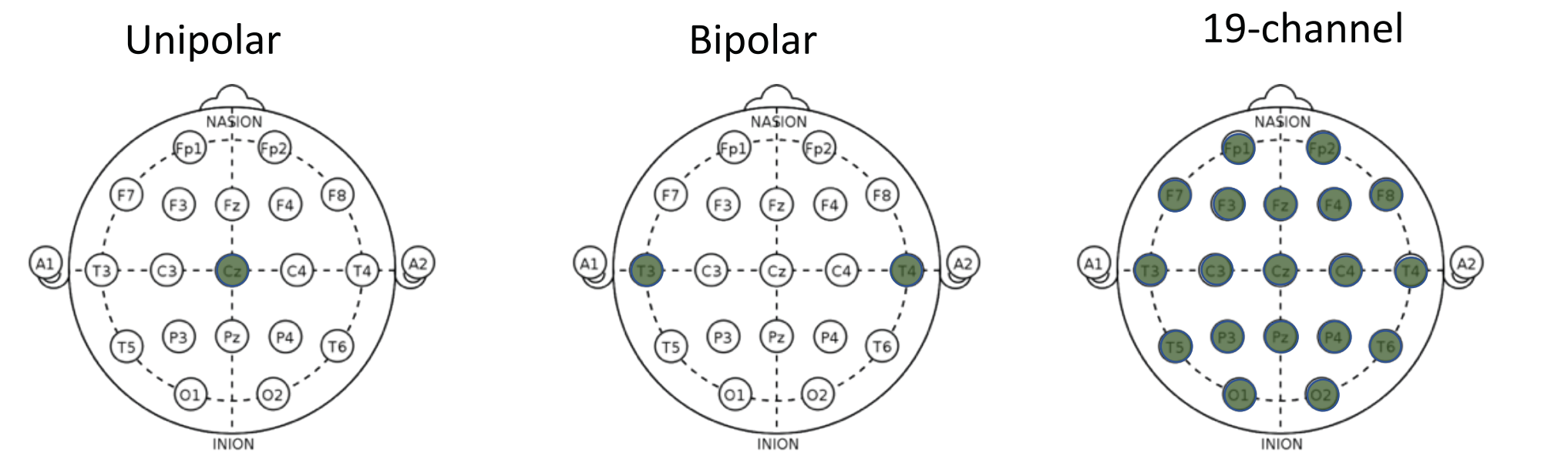


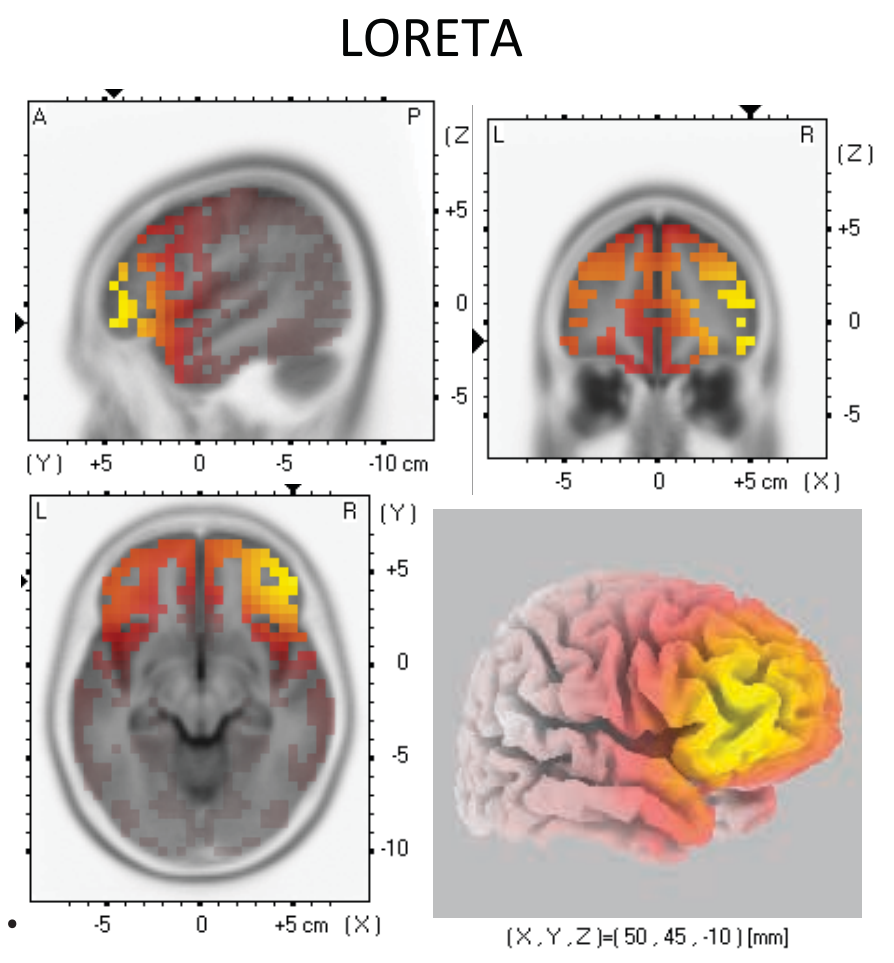
For QEEG, brain activity is recorded at rest (eyes open/closed), processed to remove artifacts (eye blinks, etc.), decomposed into various frequency bands (delta, theta, alpha, beta, high beta), and then compared to a normative database of EEG patterns. Reports are often generated based on Z-scores, which identify EEG metrics that are significantly different from normative values.

Neurofeedback Session Example

Based on whatever EEG metrics are being trained, the client gets "rewards" via auditory-visual feedback when their EEG patterns are moving towards the desired values (here a Z-score of zero in Theta).

Locations for Training

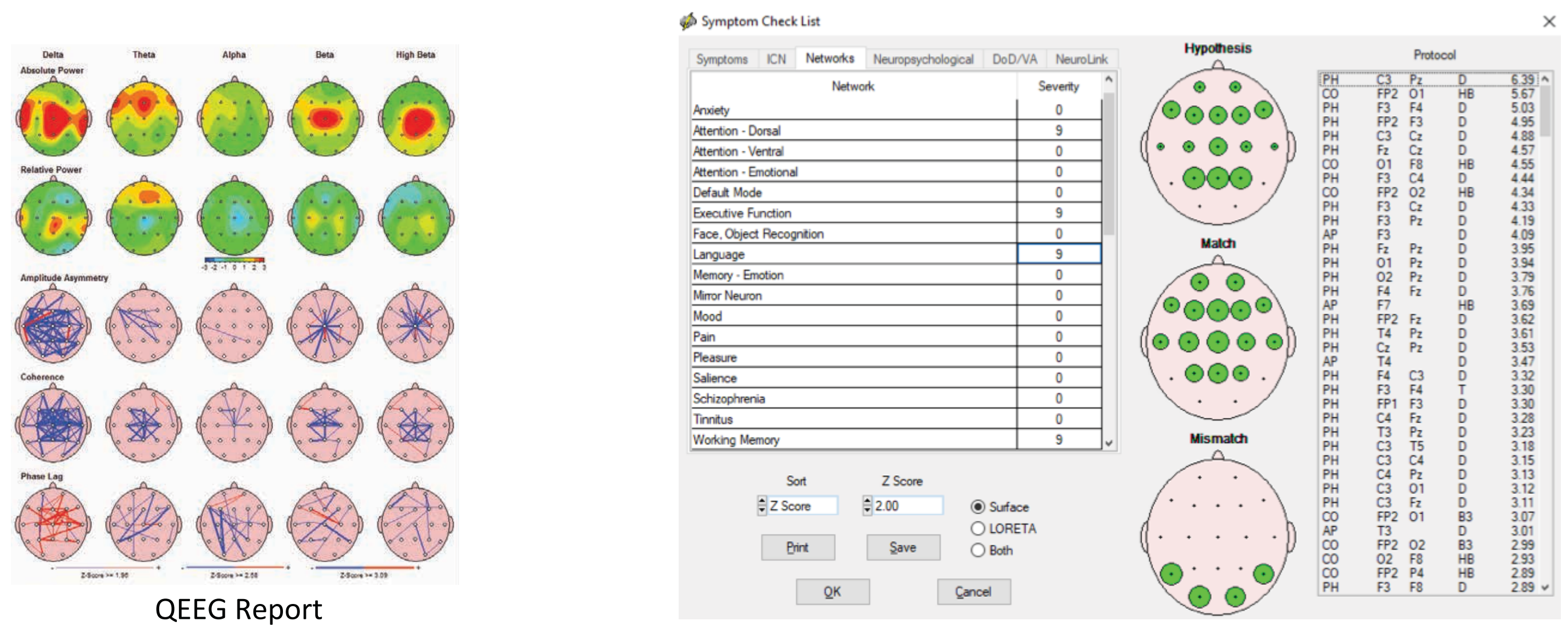




A crucial choice in neurofeedback protocol design is what EEG channels will be trained - this ranges from a single site, to comparisons of two or more sites, up to 19 (or more) channels being trained. High numbers of channels allow estimates of the underlying electrical sources (e.g. LORETA).

Designing Neurofeedback Protocols for Language Disorders

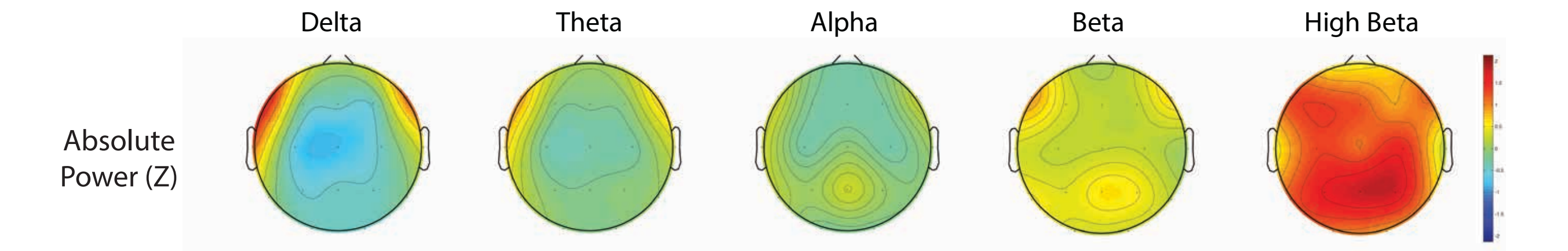
Symptom Checklist



QEEG Report

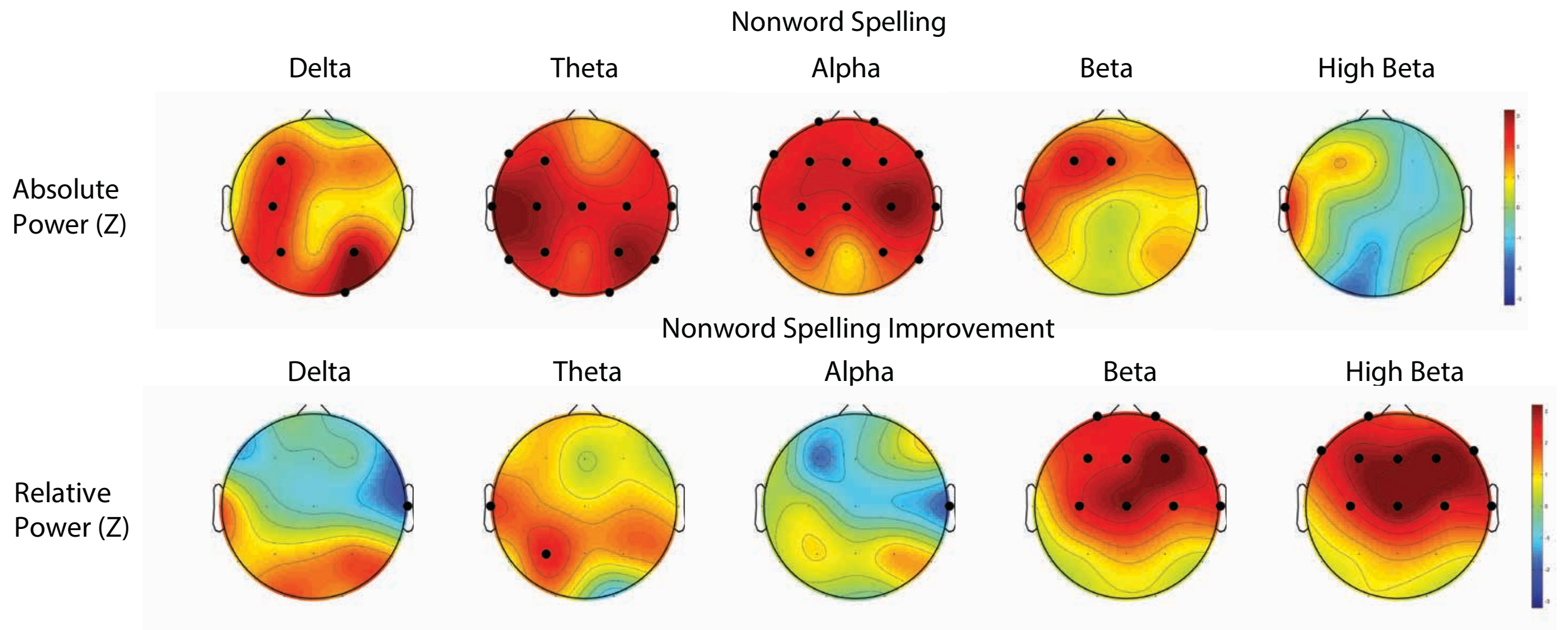
Based on regions and networks identified from the literature, a set of candidate regions can be identified that matches a patient's symptoms. These symptoms can then be compared to the deviations from normative values seen in the QEEG report, to identify EEG metrics where QEEG abnormalties match symptoms, which will then be used as targets for treatment.

Group Averaging



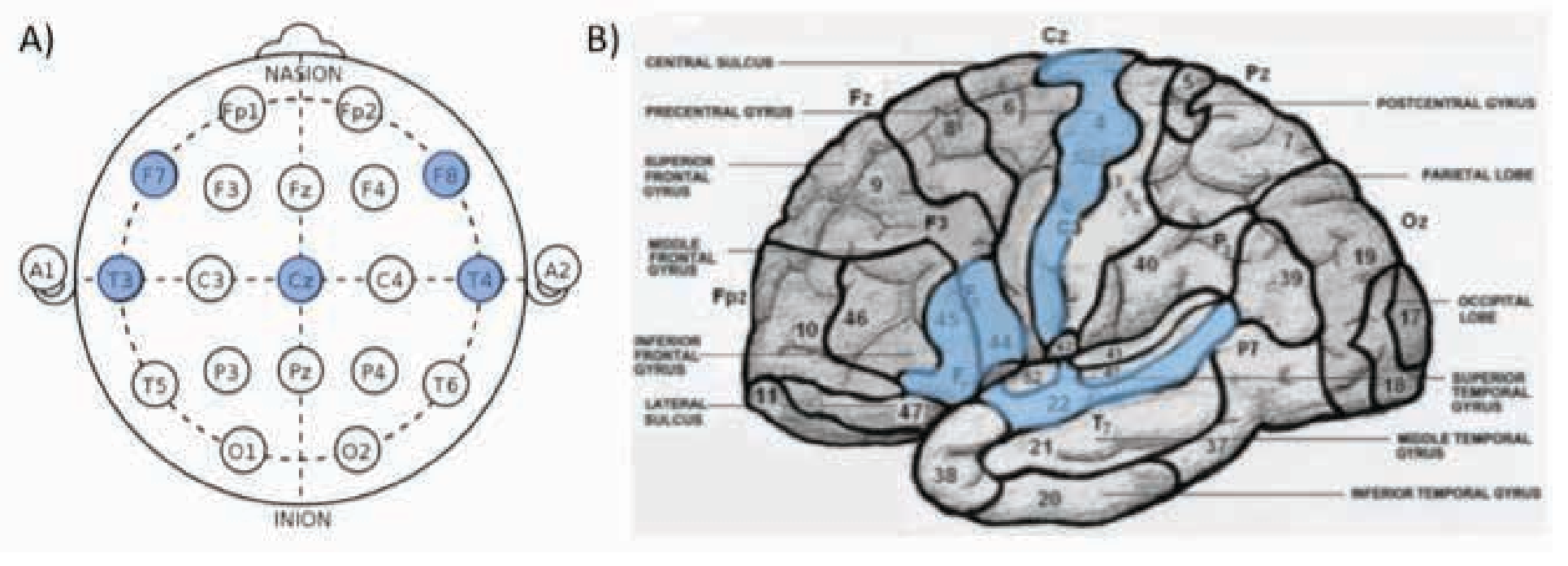
For any population, group average maps can be generated, showing common deviations for that group. Above, we show that a sample of children (n=51) with reading disorders had elevated high beta power, suggesting that a protocol reducing high beta power may be a useful treatment approach in this group.

EEG Behavior Correlations



In this same population, we correlated various behavioral measures with EEG measures to identify relationships between EEG and language performance. We saw an interesting pattern, in which better nonword spelling performance was associated with higher than normal global power in the theta and alpha bands, but children who improved the most had more relative beta and high beta power who did not improve as much, suggesting that high beta activity may in fact be adaptive. Further analyses are needed to map out these relationships in terms of designing NF protocols.

Known Language Regions



Protocols can also be generated more simply, based on regions known to be involved in language processing (e.g. Broca's, Wernicke's areas, etc.) - this can include electrode sites over these areas (A), or Brodmann areas for use in LORETA neurofeedback (B).

Prospective Efficacy Assessment

Surface Neurofeedback

Block	Site	Band	Parameter
A	All	All	Resting Eyes Open - 5 min.
1	T3	Theta	Absolute Power
2	T3-T4	Theta	Interhemi AmpAsym
3	T3-F7	Theta	Intrahemi AmpAsym
4	T3-T4	Theta	Interhemi Coherence
5	T3-F7	Theta	Intrahemi Coherence
6	T3-T4	Theta	Interhemi Phase Lag
7	T3-F7	Theta	Intrahemi Phase Lag
B	All	All	Resting Eyes Open - 5 min.

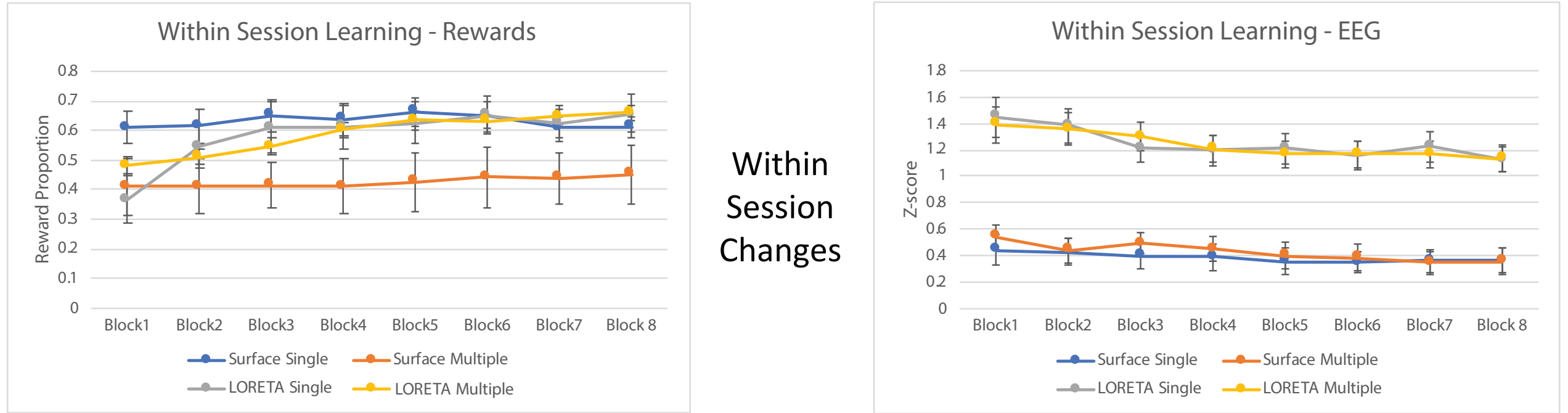
LORETA Neurofeedback

Block	Site	Band	Parameter
A	All	All	Resting Eyes Open - 5 min.
1	L_BA22	Theta	Absolute Power
2	L_BA22 - R_BA22	Theta	Interhemi Coherence
3	L_BA22 - L_BA44	Theta	Intrahemi Coherence
4	L_BA22 - R_BA22	Theta	Interhemi Phase Lag
5	L_BA22 - L_BA44	Theta	Intrahemi Phase Lag
B	All	All	Resting Eyes Open - 5 min.

Each metric was trained for 3 (surface) or 5 (LORETA) minutes toward a Z-score of zero, with a threshold of Z=+-2.0.

Even given a small set of a predefined language regions, there are many different EEG metrics which can be targeted for neurofeedback. We conducted a pilot study (n=9, 18 sessions total) looking at modulating common EEG measures (power, coherence, phase) both within and across hemispheres, to estimate the relative difficulty of (and associated success with) training these measures. We compared both surface (Ax1, Ax2) and LORETA (Ax3, Ax4) methods, and present results of these assessments before and after several sessions of extended training (8 & 6 sessions for scalp/LORETA).

We found strong variation in difficulty of modulating EEG metrics, with several metrics at ceiling (interhemispheric phase lag & amplitude asymmetry for surface, interhemispheric phase lag for LORETA), and others more difficult (intrahemispheric phase lag for surface, absolute power for LORETA). Resting EEG strongly predicted NF performance for surface training, but less so for LORETA, and patterns for EEG values during training were similar to, but not identical with, patterns for reward feedback.



We found that LORETA training seemed to show higher rates of within session learning, both for number of rewards, and for EEG metrics. For reward proportion, surface training of multiple metrics was much harder than single metrics, but this was not the case for LORETA. Z-scores for EEG metrics were generally higher for LORETA than for surface training.

Conclusions

As expected, we demonstrated high variability in training success across metrics, and that difficulty varied largely based on neurofeedback type (surface vs LORETA). We found few changes across assessment sessions, arguing against a general, non-specific effect of neurofeedback on resting EEG patterns. We demonstrated the ability to successfully train multiple metrics at a time and to show within-session brain changes, especially for LORETA NF. More work is needed to see how these results will generalize to the application of NF to adult brain-injury.

Acknowledgements

We are grateful to all the members of the Baylor Applied Communicative Neuroscience Laboratory for their assistance with data collection and analysis.