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INTRODUCTION

- Event-related potentials (ERPs) average time-locked data taken from multiple electroencephalogram (EEG) trials, thereby allowing analysis of a specific electrophysiology process within a certain time window. [1]
- Despite their high temporal resolution, ERPs offer poor spatial resolution which leads to difficulties in localizing latent neural generators, an issue commonly known as the "inverse problem." [2]
- Dipole source localization analysis (DSLA) yields solutions for the inverse problem and can supplement ERP findings with anatomical details. [3]
- DSLA may result in underqualified data when studying a large area of the brain, or with an unpredictable number of active regions occurring at different times. [4,5]

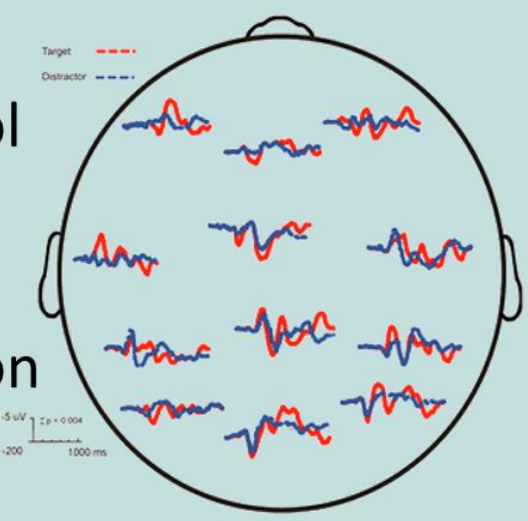
OBJECTIVES

- Determine a practical procedure which may permit to narrow down DSLA within the most relevant time windows and test their validity through simulation.
- Use this novel procedure, called *dynamically-guided dipole source localization analysis*, to appropriate pre-existing tools for the purpose of accurately examining and analyzing the neurofunction of distinct demographic groups despite limited MRI data and normalized templates.

MATERIALS AND METHODS

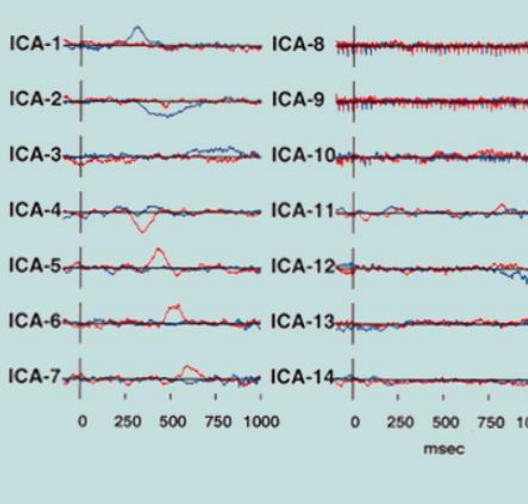
Step 1 – ERPs from EEGs:

Reprocessed ERP data collected from preschool children (n=26, mean age=4.12) performing a visual sustained attention task with target and distractor stimuli.



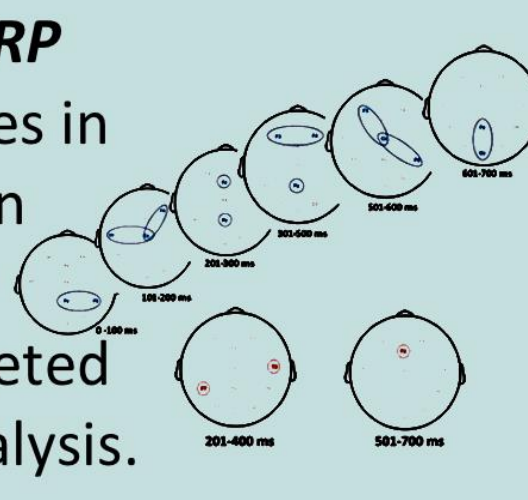
Step 2 – Independent Components Analysis:

ERP components were identified using the EEGLAB FASTICA algorithm.



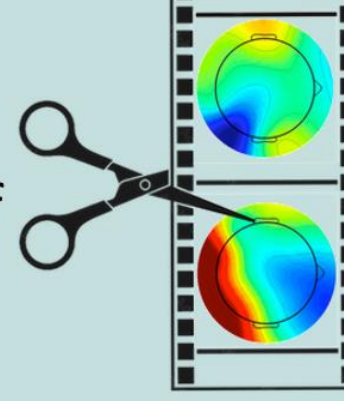
Step 3 – Identify Max ERP Activity Path:

Differences in ERP waveforms between target and distractor conditions were interpreted via ERP activity path analysis.



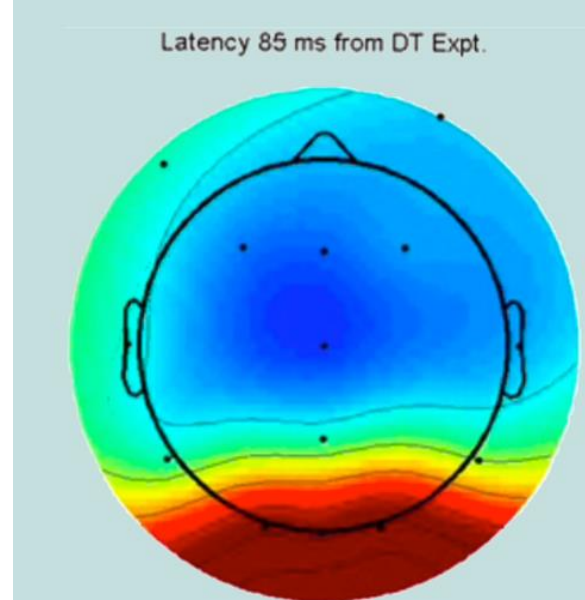
Step 4 – Topographical Maps, Movie Review & Snipping:

Topographic maps were created to represent epochs of averaged ERPs and assembled as movie clips.



Step 5 – Topographical Maps, Standstill:

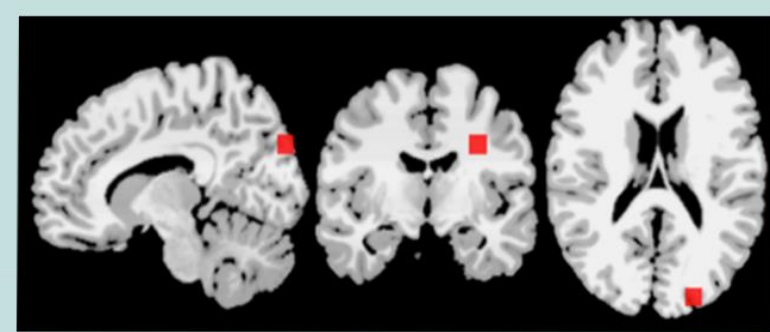
Maps were selected for further analysis.



Final Step – Validation Test: Compare the ERP activity of real and simulated sources.

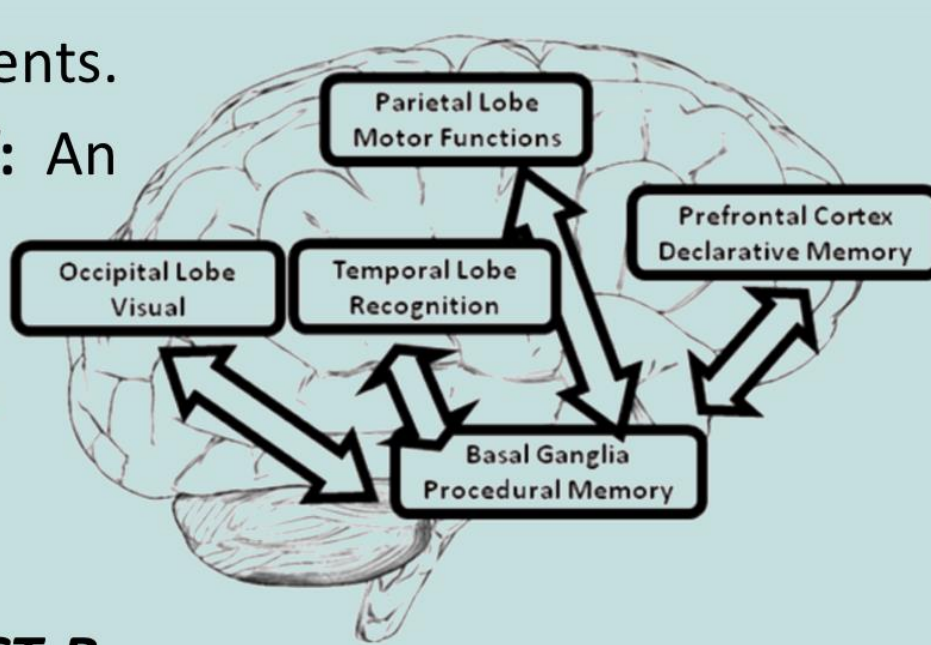
Step 6 – Dipole Analysis, Talairach Labelling:

The DIPFIT component of EEGLAB was used to estimate a set of dipoles in the averaged ERP data that would explain the independent components.



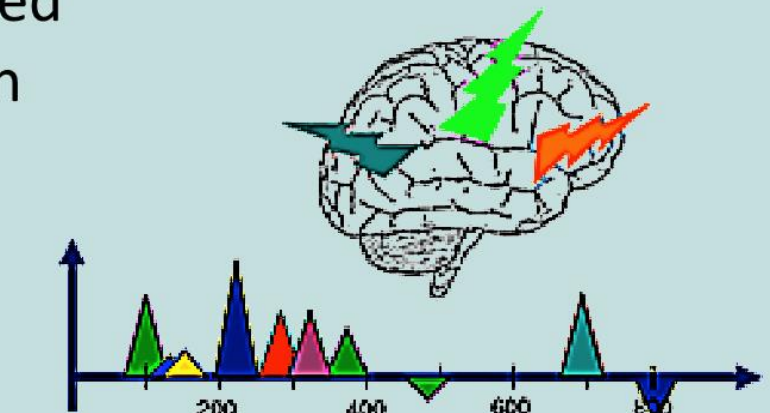
Step 7 – ACT-R Model:

An adapted version of Adaptive Control of Thought-Rational was used to model and simulate data.



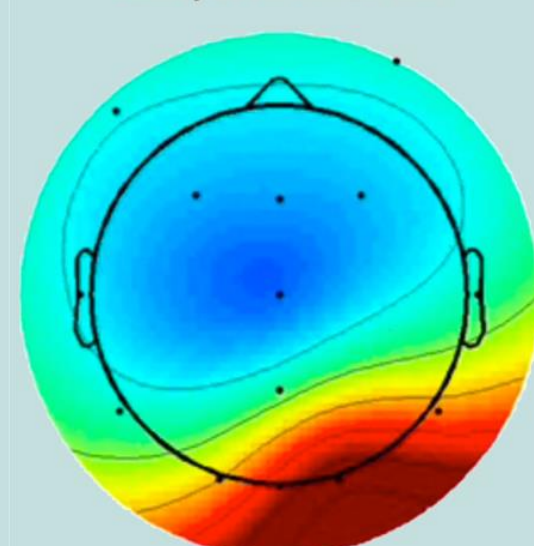
Step 8 – Simulated ACT-R-based Spike-series:

Simulated electrical activity in the brain using the neurocognitive model. Calculated the resulting electric field at the surface of the head for each electrode.



Step 9 – Simulation of ERP Topographical Maps, Standstills:

Simulated electrical activity in the brain using the neurocognitive model and calculated the resulting voltage at each electrode. Simulated maps were created by converting the ACT-R spike-series into a relative voltage scale (with range from blue/black, -6µV, to red/orange, 6µV).



RESULTS

- Regression analysis between the actual child data (Fig.A) and the dynamically-guided DSLA simulation data (Fig.B) showed high fit, $R^2 > 0.97$ ($p < 0.005$), with the exception of the data at 695ms ($R^2 = 0.40$; $p = 0.47$).
- Comparison with the "static" DSLA simulated adult data (Fig.C) revealed that dynamically-guided DSLA modelling and simulation produced a higher fit with the actual child data. This comparison shows large differences in the timing attributed by ACT-R to the same sources under the two DSLA approaches, indicating important deviation from homology in the putative sequence of neural processes.

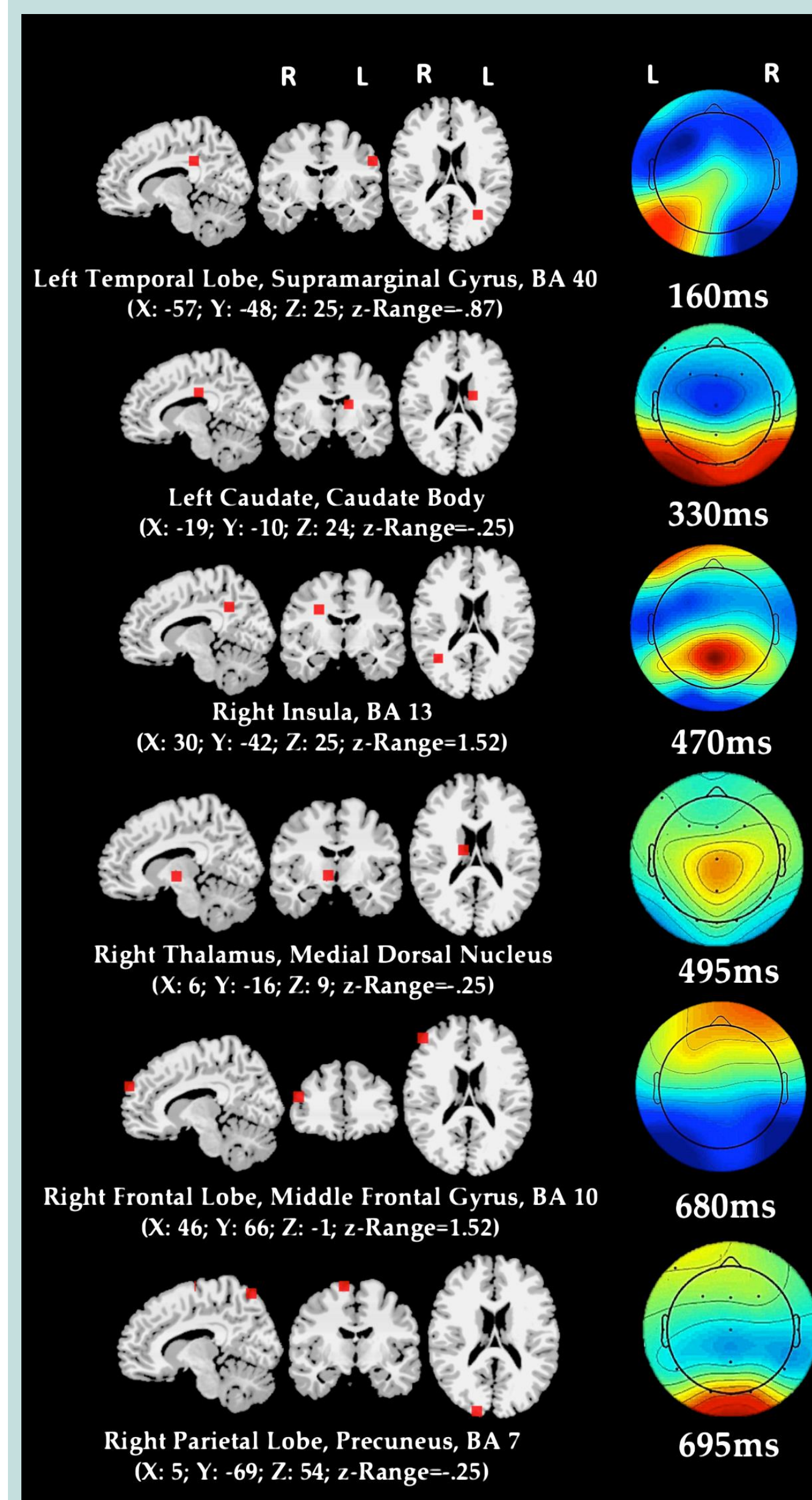


Fig.A: Actual child data

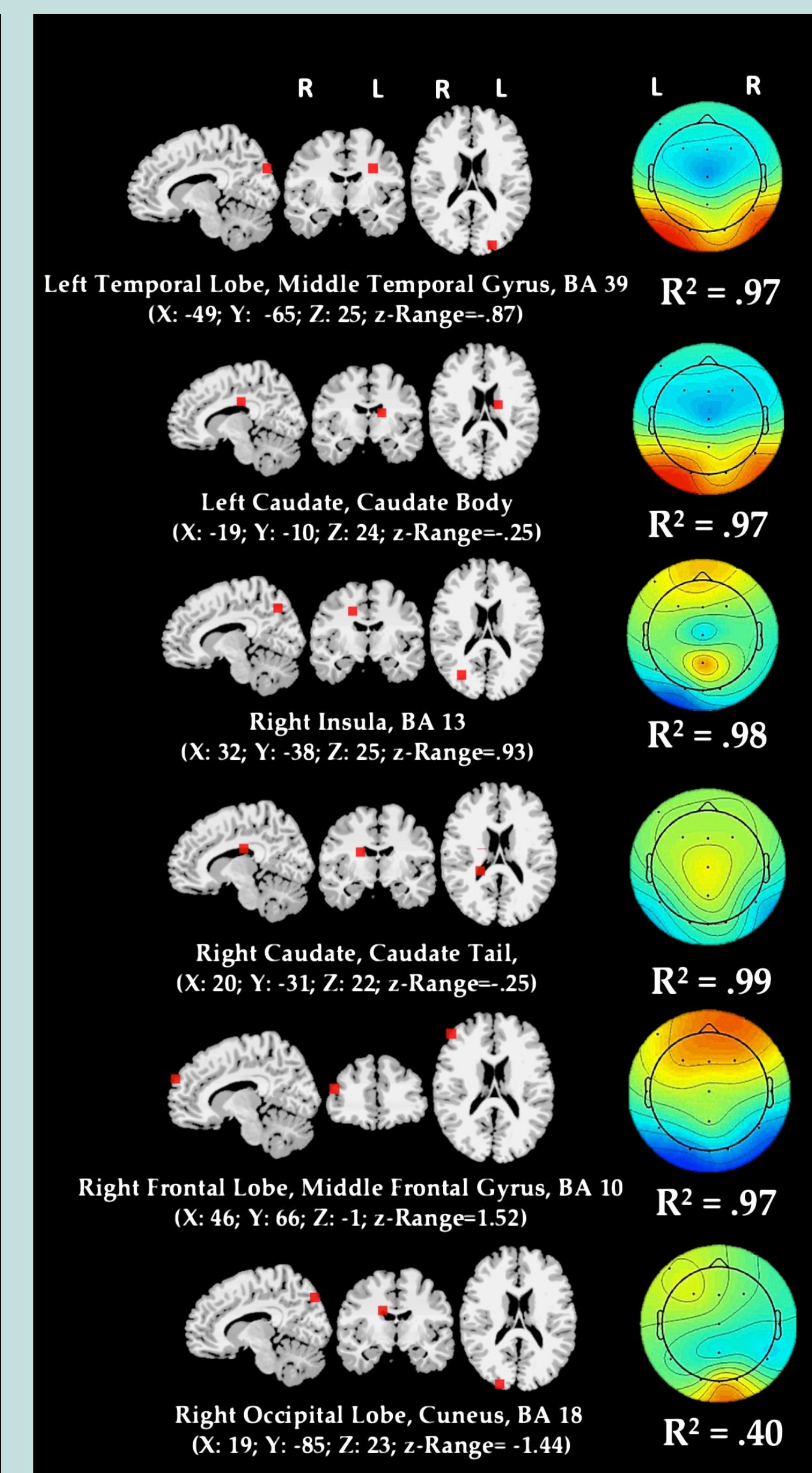


Fig.B: Dynamically-guided DSLA simulation data

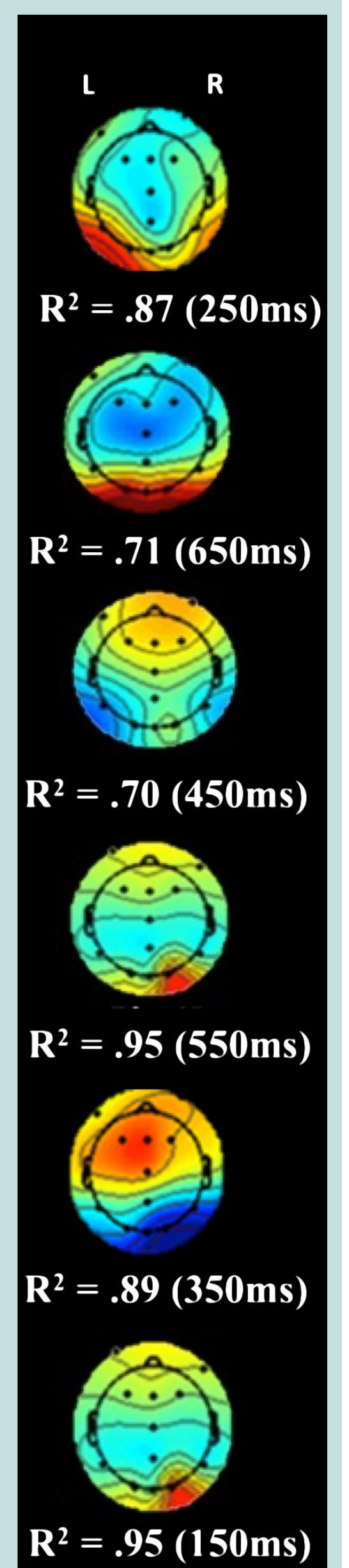


Fig.C: "Static" DSLA adult simulation data

CONCLUSIONS

- These findings demonstrate that readily available modeling and simulation tools can be appropriated to reliably fit the neural responses and corresponding behaviours of an understudied demographic sample.
- It may be possible to employ dynamically-guided DSLA as a method to identify structural and functional similarities within and between populations, this could have a variety of applications across multiple disciplines, which include: examining specific characteristic biomarkers of neurodevelopmental disorders, informing and evaluating the effectiveness of specific interventions, investigating the efficacy of educational strategies, and more.
- The specific components employed by this iteration of dynamically-guided DSLA can be replaced by more powerful and accurate techniques as they become available, while the analytical framework and objective of producing comparable visualizations of neural activity in a studied demographic and a simulation model remain unchanged.
- The modular nature of dynamically-guided DSLA is what makes it a particularly suitable technique in a field of study where rapid technological progress is the expected norm, and it affords many opportunities for future research and development into its application as a valuable process of examining neurofunction.

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