Machine learning approach for studying the neural underpinnings of dyslexia on a phonological awareness task

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Abstract

Understanding the neural underpinnings of dyslexia is an open and fundamental question in developmental neuroscience. A widely agreed causal risk factor for dyslexia is phonological deficit (PD). However, the causal relationships between PD and dyslexia have been primarily investigated and theorized based on findings derived from behavioral measures. What is missing is evidence of the underlying neurophysiological origins of these relationships. The present study examined whether the performance on a phonological awareness task, namely *phoneme elision* (PE), differentiated children with dyslexia from their typically developing counterparts at a neural level. We proposed a novel machine-learning-based approach to extract neural activity from EEG to identify neural differences at the group level. Specifically, we formulated an optimization problem to first extract informative EEG components (termed phoneme-related neural-congruency components) by maximizing the congruency in neural activity among typically developing children during phoneme elision. Next, we utilized a machine-learning algorithm to optimally combine the resulting components to differentiate between children with dyslexia and controls. Results showed that the proposed phoneme-related neural-congruency components are predictive about the underlying neuronal differences amongst groups. These results provide empirical evidence towards the neural underpinnings of dyslexia and the potential neural origins of PD as a causal link to dyslexia. Notably, the proposed method could be used to study other behaviorally defined developmental disorders.

Introduction

Developmental dyslexia is defined as an unexpected disability to learning to read (Shaywitz & Shaywitz, 2020) and is considered the most common learning disability in children, with prevalence ranging from less than 5% to 20% (Wagner et al., 2020). Despite intensive research efforts in the field, there is still a substantial debate regarding the underlying causes of dyslexia (Parrila et al., 2020). Notably, there is a growing interest in studying the neural underpinnings of dyslexia. Core deficits in *phonological awareness* (PA) – which refers to one's ability to make judgments of and perform conscious manipulations on the sound structure of spoken words (Papadopoulos et al., 2009) - have been argued to be causally linked to dyslexia (Parrila & Protopapas, 2017). However, these causal relationships have been primarily investigated and theorized based on findings deriving from behavioral measures (O'Brien et al., 2012). Also, to date, most of the neural studies examining phonological deficit have focused mainly on group differences in speech perception as a precursor of PD (Papadopoulos et al., 2012). Therefore, there is an apparent need for studies focusing on extracting neural activity from EEG to identify neural differences at the group level on PA tasks.

The phoneme elision task is used as an experimental test to elicit and measure *phonological awareness at the phonemic sensitivity level* (Papadopoulos et al., 2012). Participants are asked to identify the word produced after eliminating a target word's initial, middle, or final sound during the PE task. Typically, *accuracy* (correct responses) or *response time* quantify performance. These measures are powerful concurrent and longitudinal predictors of children's reading ability (Papadopoulos et al., 2009) across languages (e.g., Caravolas et al., 2019). However, to our knowledge, only a few studies investigate the neural underpinnings of these effects in tasks such as *phoneme elision* (e.g., Kovelman et al., 2012). We argue that this lack of studies is due to methodological challenges in isolating informative neural components in PA tasks in general and in the *phoneme elision task* in particular.

In general, to study the neural underpinnings of reading disorders, neurophysiological responses are measured using electroencephalography (EEG) signals while participants engage in a reading-related task. Typical approaches involve designing an experiment that elicits time-locked event-related potentials (ERP) - short (up to 500ms) and measurable stereotypical neural-waveforms evoked in response to brief stimuli. ERP analysis is then used to differentiate neuronal

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responses among groups and conditions (Breznitz, 2005). In particular, ERP analysis involves averaging neural responses to estimate the event-related potential waveform in response to each event. Subsequently, the amplitude and latency measures of the ERP components (visually recognizable peaks or valleys in the ERP signal) are generated. Comparing differences in the amplitude/latency scores between groups or conditions provides insights into the neural underpinnings of cognitive processes. As such, traditional ERP analysis relies on the hypothesis that differences in neural responses appear in the peaks and valleys of the short (<500ms) ERP signal, ignoring neural activity in-between.

ERPs have been successfully used to study several psychological processes, such as attention, memory and cognition, personality traits, perception, and intelligence. Pertinently to the study of dyslexia, ERP analysis has been used in conjunction with oddball experimental paradigms and the mismatch negativity component. The emphasis is placed mainly on the study of auditory speech-processing deficits and their relation to dyslexia (see Hämäläinen et al., 2018; Desroches et al., 2013; Schulte-Körne & Bruder, 2010; and references therein). However, we are not aware of any studies that directly explore how neural responses in a PA task, such as the *phoneme elision task*, relate to dyslexia.

Machine learning approaches have also been proposed in the study of neurocognitive processes. In this context, machine learning methods aim to isolate neural components within the EEG signals that are informative of differences between groups or conditions. For example, single-trial discriminant analysis has been proposed to identify neural components informative of the decision-making processes during perception categorization tasks (Philiastides & Sajda, 2005). Common Spatial Pattern (CSP)-based single-trial discriminant has also been proposed for the disambiguation spatial-cognition processes (Christoforou et al., 2018). Single-trial correlation analysis has been used for exploring the neural-underpinnings for the Stimulus Presentation Modality Effects in Traumatic-Brain-Injury treatment protocols (Christoforou et al., 2013). However, most of these methods rely on time-localized amplitude differences in the ERP signatures elicited by the experimental design or the discrepancies in the signal's average power over a time window (Christoforou et al., 2010). To the best of our knowledge, these features could not capture sufficient information as to the neural underpinnings of dyslexia in the *phoneme elision task*.

In this study, we propose a novel machine-learning-based approach to isolate differential neural activity in children with dyslexia in the *phoneme elision task*, overcoming much of the methodological constraints of existing methods. Our method first formulates an optimization problem to extract informative EEG components based on the "neural-congruency hypothesis", i.e., the premise that source neural activity elicited during a cognitive task is congruent among participants engaged in that task (Christoforou & Theodorou, 2021; Christoforou, Theodorou & Papadopoulos, 2021). Second, it uses a machine-learning algorithm to combine the resulting components to differentiate between children with dyslexia and controls. Finally, the ability of our approach to extract novel neuronal elements informative of the neural underpinnings of dyslexia in phonological awareness is demonstrated on a real EEG dataset involving children with dyslexia and controls in ages 9, and 12 (i.e. third and sixth grade).

Materials and Method

Experimental Paradigm and Data Collection

The data for this study were collected as part of a broader project aiming to study the neural underpinnings of dyslexia in children[1] (further exploited by Christoforou et al., 2021) and their relation to core cognitive deficits. This section introduces the design and data collection apparatus of the specific task this study focuses on, namely, *phoneme elision*.

Phoneme Elision Test

The *Phoneme Elision Test* measures phonological awareness at *the phonemic sensitivity level* in young children (Papadopoulos et al., 2012, 2009). In the present experiment, participants first listened to a target word, followed by a pause of 1500ms. Next, participants were instructed to think, during the pause, which word was formed after removing the first phoneme from the target word. Subsequently, the participants listened to a second word (i.e., the elision word). Finally, the participants had to respond (by pressing an appropriate key on the keyboard) whether the second word was formed by removing the first phoneme from the target word or not. Participants had up to 2500ms to respond. The task comprised 100 trials, half of which

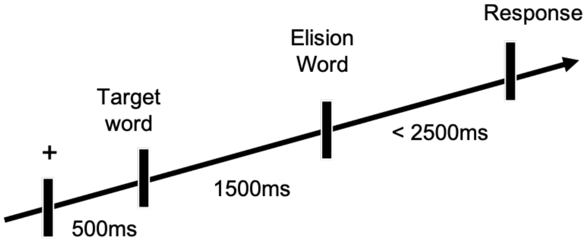

Fig. 1: Trial Schematic of the Phoneme Elision Task.

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[1] *Fella A. & Papadopoulos, T. C. (2017). Reading ability: Cognitive and neurophysiological performance indicators. Center for Applied Neuroscience, University of Cyprus.*

were trials with the second word being formed by removing the first phoneme of the target word and the other half with not. Before completing the trials, a training period of five trials demonstrated the task to the participants. The trial schematic for the task is shown in Fig. 1.

Participants and EEG Data collection

Two groups of 30 children were formed; one group comprised children with dyslexia (DYS), and the other was a chronological-age control (CAC) group. Participants were recruited from Grades 3 (age 9) and 6 (age 12) from inner-city public elementary schools in Cyprus, all native Greek-speakers. Participants were instructed to complete the *phoneme elision task* while collecting their EEG signals. A Biosemi Active-two system (BioSemi, Amsterdam, Netherlands) was used to collect the EEG data. Participants were fitted a standard 64-channel EEG cap, and electrodes were placed following the 10/20 layout. DC offsets of all sensors were kept below 20mV using electro-gel. EEG signals were recorded at a sampling rate of 256Hz. In addition, a trigger channel was used to record time markers indicating the beginning and end of each trial according to the trial schematic of Fig. 1. The study was carried out per the Cyprus National Bioethics Committee recommendations and received approval from the Ministry of Education and Culture, Cyprus (#7.15.01.27/17).

EEG Pre-processing

In this study, we aimed to identify differential neural activity relating to the ability of participants to perform *phoneme elision*. As such, we focused on the neural activity following the listening of the second word (i.e., elision word, see schematic in Fig. 1). Therefore, we pre-processed the continuous EEG data and extracted epochs time-locked at the onset of the second word pronunciation. All channels were first re-referenced to the average channel as part of the EEG pre-processing. Subsequently, a high-pass filter at 0.5Hz was used to remove DC drifts, followed by a 50Hz notch filter to minimize the power-line noise interference. The continuous EEG was then epoched starting -200ms before the second word's onset until the second word's articulation. Each epoch was then normalized by dividing each channel by the standard deviation across time.

Thus, for each participant i, the EEG observations comprised a set of trials $\{X_i^1, X_i^2, \dots, X_i^N\}$, where each $X_i^k \in \mathbb{R}^{D\times T_k}$ corresponds to the neural activity following the onset of the elision word of the k-th trial; T_k is the trial duration; $D = 64$ denotes the number of channels, and $N = 100$ the number of trials.

Phoneme-related Neural-congruency Components

Our objective was to isolate neural components in EEG elicited during *phoneme elision* and are informative of differences between the DYS and CAC groups. We hypothesized that participants who have intact phonological awareness skills (i.e., CAC) and thus can more efficiently recognize *phoneme elision* would exhibit neural activation patterns congruent within the group. On the contrary, participants with phonological deficits (i.e., DYS) would have neural responses that deviate from such a stereotypical pattern. Towards this, we formulated an optimization procedure to isolate neural components congruent among participants in the CAC group and explore those components as potential differentiating metrics between CAC and DYS. This section provides details of our approach to isolate such phoneme-related neural-congruency components. The following section discusses how we employ machine learning on those components to differentiate between DYS and CAC groups.

Consider the group of participants in the CAC group, as $\mathcal{S} = \{s_1, s_2, .., s_S\}$ where $s_i \in \mathbb{Z}^+$denotes the participants' index. We define the *between-subject* $\boldsymbol{R}_b \in \mathbb{R}^{D\times D}$ and *within-subject* $\boldsymbol{R}_w \in \mathbb{R}^{D\times D}$ cross-covariance matrix as follows:

$$\boldsymbol{R}_b = \frac{1}{S(S-1)} \sum_{i\in\mathcal{S}} \sum_{j\in\mathcal{S}} (1 - \dot{\delta}_{ij}) \boldsymbol{R}_{ij}$$

$$\boldsymbol{R}_w = \frac{1}{S} \sum_{i\in\mathcal{S}} R_{ii}$$

where

$$\boldsymbol{R}_{ij} = \frac{1}{K} \boldsymbol{X}_i \boldsymbol{X}_j^T$$

K is a normalizing constant, $\dot{\delta}_{ij}$ is the kroneker delta and $X_i \in \mathbb{R}^{D\times T}$ is the matrix comprised of all single-trial EEG of participant i, concatenated across columns, defined as:

$$\boldsymbol{X}_i = [X_i^1, X_i^2, \dots X_i^N]$$

For a given projection vector $\boldsymbol{w} \in \mathbb{R}^D$, the average Pearson Product Moment Correlation Coefficient between the concatenated single-trial responses, projected onto vector $\boldsymbol{w}$, across every pair of participants in group $\mathcal{S}$ is defined as:

$$\rho = \frac{\boldsymbol{w}^T \boldsymbol{R}_b \, \boldsymbol{w}}{(\boldsymbol{w}^T \boldsymbol{R}_w \, \boldsymbol{w})}$$

The correlation coefficient ρ can be considered as a measure of the degree of congruency in neural activity of the component $\boldsymbol{w}$, among participants with intact phonological awareness. Therefore, we aim to identify those components $\boldsymbol{w}$ that maximize ρ. That is

$$\widehat{\boldsymbol{w}} = \arg_w \max \frac{\boldsymbol{w}^T \boldsymbol{R}_b\, \boldsymbol{w}}{(\boldsymbol{w}^T \boldsymbol{R}_w\, \boldsymbol{w})} \qquad (1)$$

The solution of the optimization problem in equation (1) are the eigenvectors of the generalized eigenvalue problem $(R_w^{-1}R_b)\boldsymbol{w}_k = \lambda_k \boldsymbol{w}_k$, where $\boldsymbol{w}_{\boldsymbol{k}}$ is the k-th eigenvector of the matrix $(R_w^{-1}R_b)$ and corresponds to the components that capture the k-th largest correlation in neural activity, while λ_k is the corresponding eigenvalue that captures the strength of the correlation. We note that equation (1) has D solutions (i.e., $\{\widehat{\boldsymbol{w}}_{1,}, \widehat{\boldsymbol{w}}_{2,} \dots, \widehat{\boldsymbol{w}}_{D,}\}$) corresponding to the D eigenvectors of the matrix $(R_w^{-1}R_b)$, and the solutions are ordered from the highest to the lowest eigenvalue.

Given the set of solution vectors $\{\widehat{\boldsymbol{w}}_{1,}, \widehat{\boldsymbol{w}}_{2,} \dots, \widehat{\boldsymbol{w}}_{D,}\}$, we define the *phoneme-related neural-congruency* (PRNC) of an individual $s \notin \mathcal{S}$ with respect to the k-th component $\widehat{\boldsymbol{w}}_{k,}$ as:

$$PRNC_{s,k} = \frac{\widehat{\boldsymbol{w}}_k^T \boldsymbol{R}_s^b \widehat{\boldsymbol{w}}_k}{\widehat{\boldsymbol{w}}_k^T \boldsymbol{R}_s^b \widehat{\boldsymbol{w}}_k}$$

where

$$\boldsymbol{R}_s^b = \frac{1}{S} \sum_{i \in \mathcal{S}} R_{si} + R_{is}\,, \quad \boldsymbol{R}_s^w = \frac{1}{S} \sum_{i \in \mathcal{S}} R_{ss} + R_{ii}$$

We calculated the *phoneme-related neural-congruency* scores (i.e. PRNC) for each participant separately. Participants' data for which the PRNC score was calculated was excluded from the component extraction step to avoid training bias during the optimal component extraction. The PRNC measures the strength of the congruency of the neural activity between a given individual and the CAC group for each component. Therefore, the congruent activity of each participant for the first $\dot{D} = 10$ components (i.e., those with the highest eigenvalues) is captured by a vector $\boldsymbol{u}(s)$ defined as:

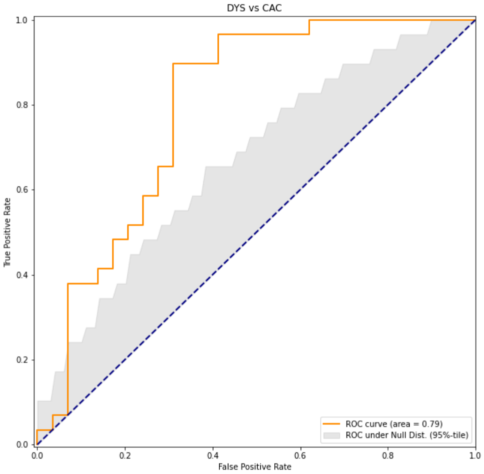

Fig. 2: Receiver Operating Characteristic (ROC) curve showing the cross-validation classification performance. Light-gray indicates the expected performance under the null-hypothesis.

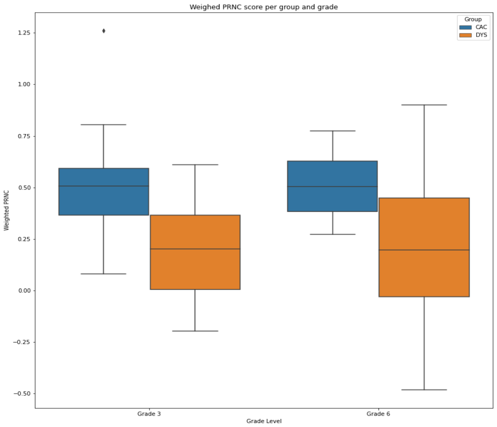

Fig. 3: Box-plot of the average neural-congruency scores for each group.

$$\boldsymbol{u}(s) = \left[PRNC_{s,1}, PRNC_{s,2}, \dots PRNC_{s,\dot{D}},\right]^T$$

The vector $\boldsymbol{u}(s)$ is a feature vector that captures the strength of congruency in neural activity of participant s to the CAC group for the first $\dot{D}$ components.

Classification of Phoneme-related Neural-congruency Components

Our goal was to explore the use of the feature vector of neural-congruency components $\boldsymbol{u}(s)$ as a predictor of a participant's group assignment (i.e., DYS or CAC). Moreover, we aimed to investigate which neural-congruency components carry predictive information. Towards this goal, we formulated a classification model. Specifically, we considered the dataset

$$\left\{\boldsymbol{u}(s) \in \mathbb{R}^{\dot{D}}, y_s \in \{DYS, CAC\}\right\}_{\forall s \in \mathcal{S}}$$

and employed a sparse logistic regression classifier using the vector $\boldsymbol{u}(s)$ as independent variables, and an individual's group y_s as the dependent variable. The classifier was trained using a leave-one-participant-out cross-validation procedure to avoid training bias. The generalization performance of the classifier was calculated as the area under the Receivers Operator Characteristic curve (AUC). The statistical significance levels over AUC scores were established using a permutation test (10,000 repetitions). Finally, the coefficients of the lasso classifier were inspected to identify components that likely carry predictive information between the groups.

Spatiotemporal profiles of Phoneme-related Neural-congruency components.

Given the solutions to the generalized eigenvalue problem, the temporal profile of each component was calculated as the product of each component $\boldsymbol{\hat{w}_k}$, with each of the single-trial responses, and then taking the grand-average response of the projected components. Moreover, the topographical profile (i.e. the forward model) of each component was calculated as:

$$\boldsymbol{a_k} = \frac{\boldsymbol{R_w}\,\boldsymbol{\hat{w}_k}}{\boldsymbol{\hat{w}_k^{\mathrm{T}}}\boldsymbol{R_w}\boldsymbol{\hat{w}_k}}$$

The forward model captures the covariance between each component's activity as measured by each electrode.

Results

The purpose of the study was to explore whether neural activity captured by the proposed phoneme-related neural-congruency components was informative of differences between children with dyslexia (DYS) and without (i.e., CAC); therefore, investigating whether these components could provide evidence of the neural underpinnings of dyslexia in a PA task such as *phoneme elision*. We trained the sparse lasso classifier using the phoneme-related neural-congruency components as a feature vector. We also assessed the ability of the classifier to differentiate between the two groups. A leave-one-participant-out cross-validation evaluation showed that the classifiers achieved an AUC score of 0.78. A permutation test indicated the classifier performance is statistically significantly better than random performance with $p < .001$, suggesting that neural activity of the phoneme-related neural-congruency components carry differential information about the neural underpinnings. The Receiver Operating Characteristic (ROC) curve that illustrates the classifier's performance is shown in Fig. 2. The dotted diagonal line shows the random performance, while the gray shaded area indicates the 95th percentile envelope of the ROC curve under the null distribution, estimated using the permutation test.

Moreover, a two-way ANOVA was performed to compare the effect of participants' age (i.e., Grade 3 vs Grade 6) and Group (DYS vs CAC). The analysis showed a significant main effect ($F(2,58) = 9.18$, $p < .001$). Also, significant group differences ($T(2,58) = 4.28$, $p < .001$), and intercept ($T(2,58) = 2.85$, $p < .01$) were revealed. The ANOVA model did not yield significant age group differences ($T(2,58) = 0.28$, *ns*). Fig. 3 shows the box plots for the two-way ANOVA.

The forward models of the ten components and their associated eigenvalues are shown in Fig. 4. The topography of each forward model informs of the approximate location of the underlying neuronal activity eliciting the components. At the same time, the associated eigenvalue shows the degree to which this neural activity is "synchronously" observed across participants.

Discussion and Conclusions

This study proposed and validated a new computational approach to uncover the underlying neurophysiological differences between children with dyslexia and typically developing children in a phonological awareness task, *phoneme elision*. In particular, we formulated an optimization problem to identify a set of phoneme-related neural-congruency components. We used a machine-learning algorithm to assess whether these components carry predictive information about the participants' condition (i.e. DYS or CAC). Our approach overcame methodological constraints of existing EEG analysis methods and allowed us to discover more informative components in EEG. The utility of our method is demonstrated on a real-life EEG dataset.

A key finding of this study is that the proposed phoneme-related neural-congruency components extracted indeed capture information about the underlying neural activity that differentiates children with dyslexia and controls. Specifically, the classifier, using the phoneme-related neural-

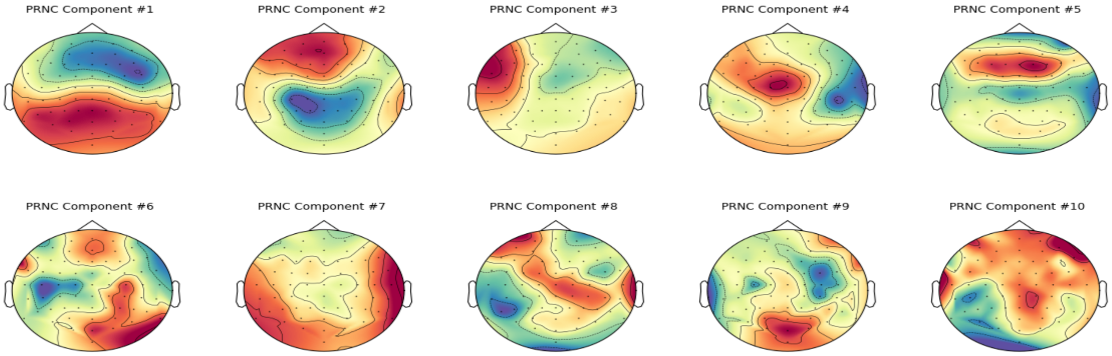

Fig. 4: Forward model of the 10 PRNC components, ordered by their corresponding eigenvalue.

congruency components, can distinguish DYS and CAC with an AUC performance of 0.78 (*p* < .001), which is significantly higher than the performance under the null distribution (i.e., the two groups are indistinguishable from each other). In addition, the forward models of several phoneme-related neural-congruency components (see Fig. 4) exhibit topographies consistent with those of a single-source dipole model. This finding suggests that each neural-congruence component captures neural activity from different underlying sources in the brain. Furthermore, since the differences captured by the classifier are a weighted aggregate of each of those sources, we can argue that neural differences in *phoneme elision* occur by contributions from multiple brain regions involved in the neural pathway of *phoneme elision* detection.

Furthermore, the two-way ANOVA comparison of the weighted phoneme-related neural-congruency scores showed a main effect on the condition but no effect on the participants' age. This finding suggests that the neural-congruency components capture the neural activity of phonological awareness as a core deficit independent of age or education. Finally, an inspection of Fig. 3 shows that weighted phoneme-related neural-congruency scores exhibit significantly higher values in CAC than DYS, providing empirical evidence towards the support of the neural-congruency hypothesis.

Taken together, our findings demonstrate that our approach does generate novel insights towards the neural underpinnings of dyslexia during the execution of a phonological task, *phoneme elision*. Moreover, they also decipher the potential neural origins of phonological deficits as a causal risk factor for dyslexia. Notably, as a novel approach, the proposed method could be used to study other behaviorally defined developmental disorders.

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