Regularized Neural-Congruency on Spoonerism: Toward exploring the neural underpinnings of reading disorders on phonological processing.

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Abstract

Children's performance on the spoonerism task, a behavioral test that measures phonological processing skills, predicts reading abilities and related disorders. However, this relationship between phonological processing skills and dyslexia has been primarily examined based on behavioral responses to the spoonerism task. As a result, there is a growing interest in developmental neuroscience to explore the neural origins of this relationship and its relation to reading difficulties. Yet, traditional electroencephalography (EEG) analysis methods had little success identifying informative neural components that depict neural differences in children with reading disorders during spoonerism. The current study explores a novel computational approach to isolate informative neural signatures elicited during the spoonerism test. We apply our method to EEG data obtained from a group of children with dyslexia and controls during the execution of a spoonerism task. Our findings demonstrate that our method extracts components that characterize the neural origins of complex cognitive phonological processes, explains differences between children with dyslexia and controls, and generates novel insights into the neural underpinnings of dyslexia in children.

Introduction

Dyslexia is one of the most prevalent learning disabilities affecting between 5%-20% of children (Wagner et al., 2020), and its effects often persist thought out adulthood. Phonological processing deficits (PD), which refer to the difficulty in processing the sound structure of spoken words, are considered one of the most prominent factors of dyslexia (Ramus et al., 2003). The Phonological Deficit Hypothesis postulates that PD is causally linked to dyslexia (O'Brien et al., 2002). However, this relationship between PDs and dyslexia has been established primarily through behavioral performance on language measures designed to probe phonological processing mechanisms in the brain (e.g., Phone Elision or Spoonerism tasks). What is missing are evidence and insights into the underlying neurophysiological origins of these presumed associations as manifested in phonological processing tests. Hence there is a growing interest in developmental neuroscience of novel computational methods that can identify informative neural components in EEG signals that depict neural differences in children with dyslexia during complex phonological processing tests.

In this study, we focus on exploring the neural underpinnings of dyslexia during spoonerism, a behavioral test that measures phonological processing at the level of both phonological analysis and synthesis. Behavioral performance on the spoonerism task has been shown to differentiate between participants with dyslexia and controls in adults (Ramus et al., 2003) and children populations (Knoop-van Campen et al., 2018). Yet, traditional EEG analysis methods that explore Event-Related Potentials (ERP) had little success in identifying informative neural components elicited during spoonerism that explain the behavioral differences in children with dyslexia (Fella et al., 2022). Fella et al. (2022) attributed the lack of informative ERP components to the complexity of the spoonerism task. Their findings suggest that neural differences in spoonerism do not manifest during the stereotypical Event-related waveforms. Thus, the authors proposed the need for exploring adaptive computational methods that consider neural activations throughout the spatiotemporal EEG responses that span beyond the typical time window of ERPs.

Machine Learning (ML) approaches have also been used in analyzing EEG data to understand neurocognitive processes. These ML approaches typically seek to extract neural components by finding spatial projections (i.e., a weighted average across EEG sensors) of single-trial EEG epochs indicative of differences between conditions and groups. Single-trial Discriminant Analysis (Philiastides & Sajda, 2005), for example, was developed to define the neural correlates of perceptual decision-making using a moving-window classifier learned over the entire epoch's time course. Single-trial Correlation Analysis (Christoforou et al., 2014) was presented to investigate the neuro-

logical foundations of Stimulus Presentation Modality Effects in Traumatic-Brain-Injury therapy procedures by training a model that maximizes the correlation between local EEG components and behavioral responses. A Commons Spatial Pattern (CSP)-based single-trial analysis (Christoforou, Hatzipanayioti, and Avraamides, 2018) was introduced in the context of spatial cognition for the neural basis disambiguation of two spatial-cognitive processes, namely, Perspective Taking and Mental Rotation.

ML-based approaches extract more informative neural components than classic ERP analysis methods by improving the signal-to-noise ratio and optimizing the extraction process to focus on the most relevant brain sources relevant to the task. However, despite their success, most proposed ML-based analysis methods capture localized features time-locked on a trial's onset, confined within the ERP time window, and often constrained to within-participant analysis due to the high inter-subject variability in EEG signals (Christoforou, Haralick, et al., 2010). As a result, components identified using existing ML techniques are frequently localized at pre-defined timestamps within the ERP narrow time range and do not directly generalize across participants.

More recently, Christoforou and colleagues proposed a framework of ML-based methods that exploit neural congruency among groups of participants' neural responses to isolate relevant neural components that generalize across the entire group and capture differences beyond the ERP narrow range. The framework relies on the Neural-congruency hypothesis, which postulates that neural activity evoked during a cognitive task is more consistent (i.e., congruent) among participants who have mastered the task but less so otherwise (Christoforou and Theodorou, 2021). The framework has been applied in exploring the neural underpinnings of complex cognitive processes during reading tasks, including Rapid Automatized Naming (Christoforou, Theodorou, & Papadopoulos, 2021), Initial Phoneme Elision and Final Phoneme Elision (Christoforou, Theodorou, & Papadopoulos, 2022a, 2022b). However, Neural-congruency-based components have not been examined in the context of the spoonerism test.

We build on the neural-congruency hypothesis to identify neural components in the EEG signals informative of differences between children with dyslexia and controls. In particular, we formulate maximizing the neural congruency across participants as a constraint optimization problem, which allows us to introduce an additional regularization structure on the neural components based on the spatial proximity of EEG sensors. We identify a set of neural activations exhibiting maximal neural congruency across participants. We then train a classifier to identify those components that best capture differences between children with dyslexia and controls. We evaluate the utility of our approach on EEG data obtained from a group of children with dyslexia and a control group during the execution of the spoonerism test. We demonstrate that our method can generate novel insights into the neural underpinnings of reading disorders during complex reading tasks that eluded the traditional developmental neuroscience analysis method.

Materials and Methods

Experiment Design and EEG data collection

Spoonerism Experiment Adaptation

This study uses the Greek adaptation of the spoonerism test (Kendeou et al., 2015; Papadopoulos, Spanoudis, & Kendeou, 2009). This test comprises a set of 60 trials. On each trial, participants would first listen to a pair of words sequentially (i.e., target words) followed by a 2500ms pause. Participants had to think during this pause what words result after exchanging the initial phonemes/syllable of the two target words. As an example, when exchanging the initial phonemes to the target-word pair /μήλο/- /φίδι/ (pronounced as /mi/-/lo/ and /phi/- /di/; and translates to /apple/ and /snake/, respectively) results to the word pair /φύλο/- /μύδι/ (pronounced as /phi/-/lo/, /mi/-/di/; which translates to /leaf/ and / mussels/ respectively), which form actual words. After the pause, participants would listen to a second pair of words (i.e., the response words) and had to respond by selecting an appropriate key on the keyboard, whether the exchanged words are real words formed after swapping the initial phoneme of the target words. Half the trials had real words as exchanged-word pairs and half pseudowords. Participants had up to 2500ms to respond after listening to each exchange-word-pair. The trial order remained constant for all participants. The trial schematic is shown in Figure 1.

Participants and EEG Data Collection

EEG data were collected from 90 participants, ages 9 and 12, all native Greek speakers. Half the participants were children with dyslexia, and the other half were chronological age controls (CAC). Participants were fitted with a 64-channel EEG cap, and active electrodes were mounted according to the 10/20 layout. Electro gel was applied between each electrode and the scalp to keep DC offset below 20mV. After preparation, participants completed the spoonerism test. A Biosemi Active-two EEG amplifier (Biosemi, Amsterdam, Netherlands) recorded the EEG data at a sampling rate of 256 Hz. Onset and offset timestamps for each stimulus were recorded via a trigger channel. 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).

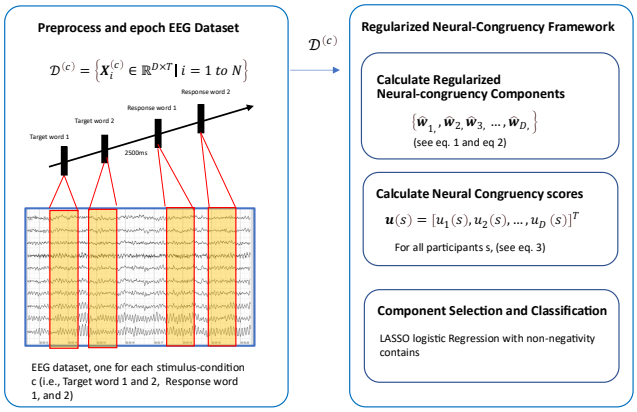

Figure 1:Schematic of the EEG pre-processing and the Regularized Neural-Congruency Framework.

EEG Preprocessing

The EEG data were first re-referenced to the average channel. Then, the continuous EEG signals were preprocessed by applying a high-pass filter at 0.5Hz to remove DC drifts, followed by 50Hz and 100 Hz notch filters to minimize power-line noise interference in the signals. After processing the continuous signals, EEG data were epoched. As this study focuses on exploring the neural activity following the onset of all four stimuli (i.e., two target words and two response words), we generated four epoch sets (one for each stimulus type). Each epoch spanned -200ms before the stimulus onset until the completion of the stimulus articulation. Next, baseline activity (-200ms to 0ms) was removed, and each epoch was normalized by dividing each channel by the standard deviation across time. All pre-processing and analysis were implemented using custom Python code.

EEG Dataset generation to analyze

EEG pre-processing resulted in four datasets of epoched EEG data, one for each stimulus type, as follows:

$$\mathcal{D}^{(c)} = \left\{ \boldsymbol{X}_i^{(c)} \in \mathbb{R}^{D\times T} | \, i = 1 \; to \; N \right\}$$

where c denotes the stimulus type of the dataset (i.e., first-target-word [c=1], second-target-word [c=2], first-response-word [c=3], and second-response-word [c=4]); $\boldsymbol{X_i}$ is the concatenation (along the time-dimension) of all EEG epoched trials of participant i and stimulus type c; D=64 denotes the number of EEG channels; T the number of time samples of all single-trial epochs; and N the number of participants.

Regularized Neural-Congruency Framework

The proposed Regularized Neural Congruency Framework (RNCF) formulates an optimization problem for extracting and selecting the most relevant EEG components that capture neural activity differential among children with dyslexia and controls. The subsections below introduce the framework, and Figure 1 shows a schematic of the overall approach.

Regularized Neural-Congruency Components

For the extraction of the Neural-congruency components, we consider a subset of participants $\mathcal{S} = \{s_1, s_2, .., s_S\}$ thatbelong to the CAC group, where $s_i \in \mathbb{Z}^+$denotes the index of the i-th participants in set $\mathcal{S}$ relative to the ordering of the dataset of EEG epochs $\mathcal{D}^{(c)}$. We define Neural-congruency components as the set of spatial projection vectors $\boldsymbol{w} \in \mathbb{R}^D$that maximizes the following expression:

$$\max \frac{1}{(S^2 - S)} \sum_{\substack{i=0, j=0 \\ i \neq j}}^{S} \boldsymbol{w}^T \boldsymbol{R}_{(s_i, s_j)} \boldsymbol{w} \quad (1)$$

$$such\ that$$

$$\frac{1}{S} \sum_{i=0}^{S} \boldsymbol{w}^T \left(\boldsymbol{R}_{(s_i, s_i)} + \sigma \boldsymbol{K} \right) \boldsymbol{w} = 1$$

where $\boldsymbol{R}_{ij} = \frac{1}{T} \boldsymbol{X}_i \boldsymbol{X}_j^T \in \mathbb{R}^{D\times D}$ is the cross-covariance matrix between epochs of i-th and j-th participant, and $\boldsymbol{K} \in \mathbb{R}^{D\times D}$ is a Matérn kernel function, defined as:

$$\boldsymbol{K}_{u,v} = \frac{1}{\Gamma(\mathrm{d}_{uv}) 2^{\nu-1}} \left(d_{uv} \frac{\sqrt{2\nu}}{l} \right)^{\nu} \mathrm{B} \left(d_{uv} \frac{\sqrt{2\nu}}{l} \right)$$

where $\Gamma(.)$ is the gamma function, $\mathrm{B}(.)$ is a modified Bessel function, l is the length-scale parameter of the kernel, ν is a scalar kernel parameter that controls the smoothness of the resulting function, and d_{uv} is proportional to the physical distance between sensor-u and sensor-v on the EEG cap montage. The Matérn kernel enforces a structure on the sensors' covariance matrix based on the physical proximity of the sensors and serves as a smoothness regularization on the parameter space.

Rewriting the optimization in equation (1) in terms of its Lagrangian, taking its derivative for vector $\boldsymbol{w}$ and setting it to zero, we arrive at the following solutions:

$$\left(\boldsymbol{R}^{(w)} + \boldsymbol{K} \right)^{-1} \boldsymbol{R}^{(b)} \boldsymbol{w_k} = \lambda_k \, \boldsymbol{w_k} \quad (2)$$

$$\boldsymbol{R}^{(b)} = \frac{1}{(S^2 - S)} \sum_{\substack{i=0, j=0 \\ i \neq j}}^{S} \boldsymbol{R}_{(s_i, s_j)} \quad , \quad \boldsymbol{R}^{(w)} = \frac{1}{S} \sum_{i=0}^{S} \boldsymbol{R}_{(s_i, s_i)}$$

Therefore, the optimal solutions of equation (1) are the eigenvectors of the generalized eigenvalue problem of equation (2), where $\boldsymbol{w_k}$ is the k-th eigenvector of the ma-

trix $\left(\boldsymbol{R}^{(w)} + \boldsymbol{K}\right)^{-1} \boldsymbol{R}^{(b)}$ and defines the neural components that exhibit the k-th strongest correlation in neural activity among participants in the $\mathcal{S}$ group, its corresponding eigenvalue λ_k quantifies the strength of that component's correlation. We note that equation (2) has D solutions $\{\widehat{\boldsymbol{w}}_{1,}, \widehat{\boldsymbol{w}}_{2,} \dots, \widehat{\boldsymbol{w}}_{D,}\}$ corresponding to the D eigenvectors of the matrix, and those solutions are ordered from highest to lowest correlation strong according to their eigenvalues. We refer to these D vector solutions as the *Regularized Neural-congruency* components.

Neural-congruency Scores

Given the set of optimal neural-congruency components $\{\widehat{\boldsymbol{w}}_{1,}, \widehat{\boldsymbol{w}}_{2,} \dots, \widehat{\boldsymbol{w}}_{D,}\}$, we calculate a feature vector $\boldsymbol{u}(s) \in \mathbb{R}^D$ of neural congruency scores for each new participant $s \notin \mathcal{S}$ (i.e., not in the original set of participants used to calculate the neural-congruency components) as follows:

$$\boldsymbol{u}(s) = [u_1(s), u_2(s), \dots, u_D(s)]^T \quad (3)$$

$$u_k(s) = \frac{\widehat{\boldsymbol{w}}_k^T \boldsymbol{R}(s)^{(b)} \widehat{\boldsymbol{w}}_k}{\widehat{\boldsymbol{w}}_k^T \boldsymbol{R}(s)^{(w)} \widehat{\boldsymbol{w}}_k},$$

$$\boldsymbol{R}(s)^{(b)} = \frac{1}{S} \sum_{i \in \mathcal{S}} \boldsymbol{R}_{si} + \boldsymbol{R}_{is}, \boldsymbol{R}(s)^{w} = \frac{1}{S} \sum_{i \in \mathcal{S}} \boldsymbol{R}_{ss} + \boldsymbol{R}_{ii}$$

The kth neural congruency score $u_k(s)$ measures the average correlation strength between the neural activity originating from the source associated with the kth neural congruency component of participants s to the same source of all participants in the set $\mathcal{S}$. Intuitively, the more similar the neural activity of participant s is to that of the group of participants $\mathcal{S}$ is, the higher the neural congruency score associated with that neural-congruency component.

Component Selection and Classification.

We aim to evaluate the degree to which the extracted neural congruency components and their corresponding neural-congruency scores capture differential neural activity among children with dyslexia to control (i.e., DYS vs. CAC) and further identify those components most informative of the differences. For that, we formulate a classification problem with neural-congruency scores of each participant as features and the group's assignment (i.e., DYS vs. CAC) as the dependent variable. We use a LASSO Logistic Regression with non-negativity constraints on the parameters as a classifier. This classier model results in a sparse set of non-zero weights. The generalization performance of the classifier indicates the degree to which neural-congruency components capture neural activity that characterizes the behavior differences between DYS and CAC; further, the sparseness of the weights allows us to identify which neural-congruency components carry the most information.

Spatial Profile of Neural-congruency Components

Given the set of extracted Neural-congruency components (i.e., $\{\widehat{\boldsymbol{w}}_{1,}, \widehat{\boldsymbol{w}}_{2,} \dots, \widehat{\boldsymbol{w}}_{D,}\}$), their topographical profile can be calculated as the forward model.

$$\boldsymbol{a}_k = \frac{\boldsymbol{R}_w \widehat{\boldsymbol{w}}_k}{\widehat{\boldsymbol{w}}_k^{\mathrm{T}} \boldsymbol{R}_w \widehat{\boldsymbol{w}}_k}$$

These are known as the forward model that captures the covariance in each sensor of the cortical source activity encoded by each extracted neural-congruency component and typically visualized as scalp maps.

Model learning, Generalization and Statistical Analysis

The model parameters- i.e., the extracted neural-congruency components and the classifier weights- are trained using a leave-one-participant-out cross-validation procedure to avoid training bias. The generalization performance of the classifier is calculated as the area under the Receivers Operator Characteristic curve (AUC) on the

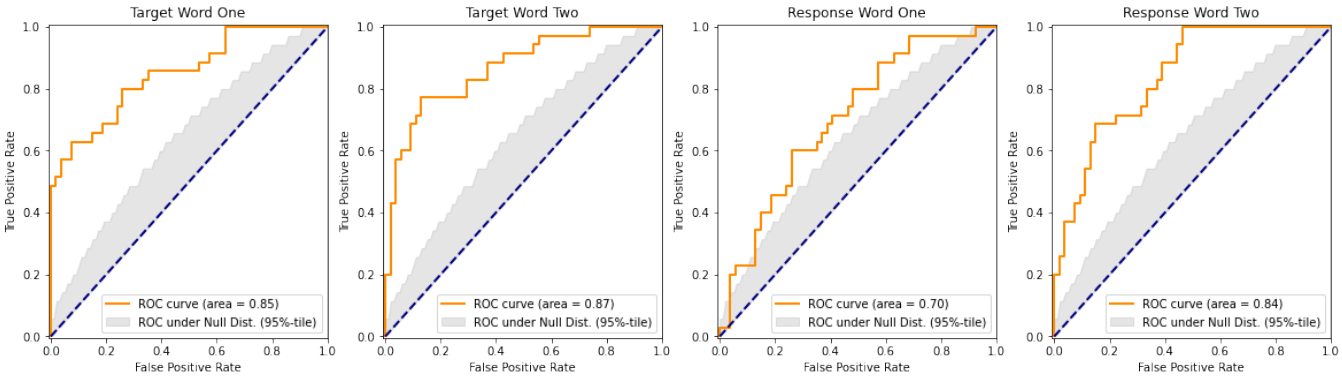

Figure 2: Shows the ROC curves and AUC scores based on the selected LASSO-weighted Neural-congruency components for all four conditions. The gray area denotes the ROC curve under the null hypothesis (i.e., neural-congruency scores between DYS and CAC)

cross-validated scores. The statistical significance levels over AUC scores are 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.

Neural-Congruency Component on Spoonerism

For our analysis of the spoonerism EEG data, we employ the Regularized Neural-Congruency Framework separately on each of the four stimuli (i.e., First Target word, Second Target word, First Response word, and Second Response word). The spoonerism test requires participants to activate a complex set of cognitive processes that differ among the processing of the four stimulus types. For example, processing the target words elicits phonological analysis processes (i.e., phonological recording and segmentation) that reflect the participant's ability to remember the word heard and break it into its constituent phonemes. In contrast, the processing of the response words engages phonological synthesis processes that reflect the ability of participants to blend isolated phonemes to form whole words. Therefore, in our analysis of the spoonerism EEG data, we first aim to determine whether (a) the extracted neural-congruency components capture neural activations relevant to phonological processes that differentiate children with dyslexia and controls and (b) explore whether phonological synthesis or phonological analysis processes better explain these differences.

Results

In our analysis, we first explored the predictive capacity of Neural-congruency components extracted from neural activity elicited in response to the articulation of the two target words in the spoonerism experiment. All neural-congruency Components and their corresponding neural congruency scores were calculated separately for each of the two words. A separate classifier was also trained on each of the two word-condition. Parameter estimation was performed using a leave-one-participant-out to avoid training bias. The cross-validation accuracy of the model trained on the first target word was AUC= 0.85 ($p < .001$), while the model trained on the second target word was AUC= 0.87 ($p < .001$); both were statistically significant. Classifier weights identified a subject of components with non-zero weights.

Similarly, we explored the predictive capacity of the Neural-congruency components extracted from neural activity elicited in response to the articulation of the two response words in the spoonerism experiment. Same as in the case of the target-word condition, the model was applied to each word stimulus separately. The cross-validation accuracy of the model trained on the first response word was AUC= 0.70 ($p < .001$), while the model trained on the second response word was AUC= 0.84 ($p < .001$).

Discussion

Despite the well-known association of the spoonerism test to phonological processing deficits and its use as a screening tool for dyslexia, little is known about the neurophysiological origins of the cognitive mechanisms engaged during the actual spoonerism test that explain this link. We set out to investigate the neurophysiological underpinnings of the relationship between phonological impairments and dyslexia, as those arise in the spoonerism test. We proposed the regularized neural-congruency analysis framework to identify EEG components that capture neural activity during spoonerism differentially among children with dyslexia and controls. We demonstrated the predictive capacity of the extracted components on EEG data we collected while a group of children (half with dyslexia) performed the spoonerism test. Our findings generate novel insights into the neural underpinnings of spoonerism's relation to dyslexia that eluted the traditional analysis method of developmental neuroscience. We highlight some of the key findings below.

A central finding of this study is evidence suggesting that the proposed neural-congruency components extracted by our method on EEG data during spoonerism performance capture cortical neural activations associated with phonological processes and characterize dyslexia. Furthermore, the classification model operating on the resulting neural congruency scores achieves high accuracy in differentiating between DYS and CAC while processing either of the four stimuli conditions. Even more, these findings are observed when traditional analysis methods exploring ERP components fail to identify neural differences between similar groups (Fella et al., 2022). Therefore, our results indicate that the neural-congruency components extracted by our method carry information about the differential neural activity among the two groups and have added value to the search for neurophysiological group differences that are meaningful. Moreover, these resulting components are novel and capture neural activations that have eluted the current analysis methods employed in developmental neuroscience on spoonerism.

Further, the neural components extracted by our proposed method generate novel insights into the neural underpinnings of phonological processes and dyslexia. Neural components extracted on the first and second response-word conditions differentiate between the two groups with accuracy AUC=0.70 ($p < .001$) and AUC=0.85 ($p < .001$). The processing of the response words in spoonerism is associated with cognitive processes of phonological synthesis (the ability to blend isolated phonemes to form

whole words) (Papadopoulos et al., 2012). This fact suggests that the informative neural-congruency components that capture cognitive differences are associated with phonological synthesis processes. Moreover, the difference in classification accuracy between the two-word stimuli signifies that phonological synthesis processes are more actively engaged during the articulation of the second response word (i.e. when participants have all the information needed to evaluate the phoneme reversal result). Neural components extracted on the first and second target-word condition differentiate between the two groups with accuracy AUC= 0.85 and AUC=0.87, both statistically significant ($p < .001$). The pronunciation of the target words in spoonerism engages phonological analysis processes (i.e., the ability to break whole words into their constituent phonemes). This fact suggests that the neural-congruency components, extracted during the target-word pronunciation, capture differential cognitive processes associated with phonological recording and segmentation processes. Together, these results indicate that differences between DYS and CAC appear in both phonological synthesis and phonological analysis processes at the neural level.

In summary, we proposed a new approach for extracting informative neural-congruency components from EEG signals that enforce a regularization structure on the parameters based on the spatial proximity of EEG sensors. We apply our method to EEG data of children with dyslexia and controls obtained during the spoonerism test. We demonstrated that our approach identifies novel neural components during spoonerism that current developmental neuroscience studies fail to detect. These components capture cortical neural activations associated with both phonological analysis and phonological synthesis processes and characterize neural differences in children with dyslexia and generate novel insights into the neural underpinnings of dyslexia. Notably, our approach could be applied to study the neural underpinnings of a broader class of developmental disorders (Papadopoulos, 2023) previously overlooked by developmental neuroscience research.

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