*Article*

# EEG Power Spectrum Correlates of Working Memory in Children with Learning Disorders

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**Abstract:** Learning disorders (LD) are diagnosed in children whose academic skills of reading, writing or mathematics are impaired and lagged according to their age, schooling and intelligence. Children with LD experience substantial working memory (WM) deficits, even more pronounced if more than one of the academic skills is affected. We compared the task-related EEG power spectral density of children with LD (n= 23), with a control group of children with good academic achievement (n= 22), during the performance of a WM task. sLoreta was used to estimate the current distribution at the sources, and 18 brain regions of interests (ROIs) were chosen with an extended version of the eigenvector centrality mapping technique. In this way, we lessen some drawbacks of the traditional EEG at the sensor space by an analysis at the brain sources level over data-driven selected ROIs. Results: The LD group showed fewer correct responses at the WM task, an overall slower EEG with more theta activity in all ROIs, less upper-alpha power at posterior areas, and less high-frequency beta activity in frontal areas. We explain these EEG patterns in LD children as indices of an inefficient neural resource management related with a delay in the neural development.

**Keywords:** learning disorders; working memory; school-age children; EEG power spectral density; source localization; sLORETA

## 1. Introduction

Learning disorders (LD) are a main neurodevelopmental impairment, with a prevalence of 5-15% in children between 5 to 16 years old [1–3]. A specific LD is diagnosed for persistent difficulties to learn academic skills such as reading, writing or mathematics. The LD diagnosis also requires the impaired academic skill to be significantly lagged for the age, schooling, and IQ of the child [2]. Moreover, an LD-child with a combined deficiency in two or three of these skills is a frequently found subtype of LD, formerly known as LD not otherwise specified [4], and this co-occurrence of academic impairments appear in between 30-70% of the LD cases in children [5].

Learning disorders usually include an heterogeneous frame of cognitive impairments [5]. A known source of this heterogeneity is a working memory (WM) deficit [6]. Working memory is the capacity to store and manipulate information for short periods of time [7]; and is the consistently most affected cognitive domain in LD children [8–10]. Indeed, WM performance not only distinguishes properly between LD and children with typical development [11]; it is also an adequate predictor of future academic difficulties [12], and is more severely affected in LD-children with more than one academic skill impaired (LD not otherwise specified) [5].

Neural correlates of LD have been identified with quantitative electroencephalogram (qEEG) analyses [13]. The qEEG of LD children show an abnormally slower resting-state activity compared to age-matched controls. This slower activity is akin to that of younger healthy subjects since it involves more theta activity in frontal regions and less alpha power in posterior (parietal and occipital) regions, similar to previous developmental stages of the healthy child. For this reason, LD are considered developmental disorders with a delay in their EEG maturation that impairs their ability to keep up with normal peers at school [14–16].

The neural correlates of cognitive performance, particularly WM, have been examined with main EEG techniques such as event-related potentials, power spectral density (PSD) analyses, and connectivity measures (*e.g., coherence*). In healthy adults, task-related PSD findings (while the individual performs a cognitive task) show an increased theta activity at frontal sites and a decreased global alpha power compared to a resting-state condition [17, 18], and the theta increase is even more pronounced for higher WM loads, with more items to memorize [19, 20]. The higher task-related theta power has been broadly regarded as an attentional control mechanism not specifically linked to WM, being increasingly affected according to the neural resources needed to properly perform the task [21–23]. Beta activity has also been found specifically in a verbal working memory task (compared to a visuospatial WM task), and this activity (of 14-28 Hz) has been involved with a role of subvocal rehearsal during the retention of items [24]. Also, in healthy adults, connectivity analyses (coherence) at WM tasks show a higher fronto-parietal gamma activity that has been proposed as an item-retention mechanism [25]. As for the role of alpha activity in memory, this frequency band has remained more equivocal, with its initial recognition as a mere idling state waiting to be suppressed during cognitive effort [26]; however, a greater alpha power mainly of the upper 10-12 Hz range in posterior regions has been implied with an inhibitory top-down control role to block the processing of irrelevant stimuli [27–29].

In the case of the task-related EEG research in children, a study with dyslexic children that responded to a phonological discrimination task [30] found the children with a higher frontal theta power over healthy controls; a finding explained as compensatory to an inefficient attentional control due to cortical immaturity. Likewise, Spironelli, Penolazzi, and Angrilliin [31] found a slower and greater theta activity peak in the right hemisphere of dyslexic children, coupled with an insufficient left hemisphere theta activity. As for children performing WM tasks, a study that compared the PSD of healthy children with adults [32] found the children with more theta and less alpha activity mainly at frontal sites, both occurrences also interpreted as compensatory mechanisms due to neural immaturity. Moreover, a work that compared poor readers *vs.* normal control children with an event-related potential analysis (ERP) in a Sternberg WM task [33], found the poor-readers with longer and larger P300 latencies at frontal sites [34]; this points to a greater effort required by the LD children, since the P300 relative amplitude is considered a marker of the amount of attentional resources given to a cognitive task [35].

The previous findings generally indicate a greater presence of EEG theta power (and a more salient P300 potential), in more difficult task conditions, and in less mature (or more unfit) populations with greater difficulties to perform cognitive tasks. This higher EEG power can be linked with the neural efficiency hypothesis, which states that a more efficient brain functioning involves less and more focused brain activation; given robust relationships between a higher IQ and an adequate task performance that involve less neural activity, including a lower hemodynamic response as measured with functional magnetic resonance imaging (fMRI) [36]. On the other hand, a lower IQ, the experience of learning a new task, and more difficult task conditions, involve a greater neural activation as an index of inefficient neural resource management [37, 38].

To our knowledge, the WM (task-related) EEG power spectrum has not been explored in children with LD. This is the main goal of the present work. Specifically, we aimed to compare the EEG PSD of children with LD, with a control group of children with good academic achievement during a Sternberg-type WM task.

The EEG analysis performed in most of the above-cited papers was done on the EEG voltage at the sensor space (over the scalp); a classic approach with two main drawbacks: the volume
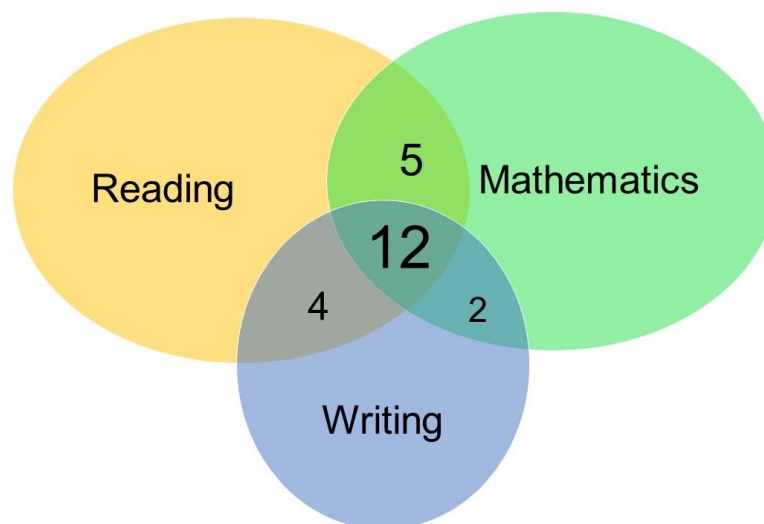
conduction effect, and the reference electrode effect, both of which induce a mixing of signals in the electrodes that distort the real neurophysiological events [39]. The volume conduction is a passive spread of electrical activity (non-dependent of post-synaptic potentials) through the brain tissue, cerebrospinal fluid, skull, and scalp. The reference electrode, on the other hand, affects differently according to its location, as a difference of electrical potential against the active electrodes of the scalp. Both shortcomings can be partially solved by spatial filtering measures (such as the surface Laplacian) and source localization methods. The latter methods require several assumptions about current source localization that are even more critical with fewer electrodes employed [40]. However, source localization techniques such as eLoreta and sLoreta have several advantages that remarkably diminish possible localization errors and overcome the sensor space limitations by analyzing the contribution of specific cortical brain areas [40, 41]. On this basis, using sLoreta we performed a power spectrum analysis of the estimated primary currents at the sources level (instead of the voltage signals at the sensors space).

## 2. Materials and Methods

The Ethics Committee of the Instituto de Neurobiología, Universidad Nacional Autónoma de México (UNAM), approved the experimental protocol, which followed the Ethical Principles for Medical Research Involving Human Subjects established by the Declaration of Helsinki [42]. Informed consent was signed by all the children and their parents.

### 2.1. Participants

Forty-five children from 8-11 years of age were selected (see the inclusion criteria below), from a larger sample of over 100 children referred by social workers from several elementary schools in Querétaro, México. The sample was divided into two groups: 22 control children with good academic achievement (Ctrl group) and 23 children diagnosed with LD involving problems in two or three academic domains (reading, writing, and mathematics). Figure 1 shows the frequency of academic impairments.



**Figure 1.** Venn diagram of the frequency of academic impairments found in our LD sample: 12 children were impaired in the three domains (reading, writing and mathematics); 5 children were impaired in reading and mathematics; 4 children were impaired in reading and writing; and 2 children were impaired in writing and mathematics.

All children fulfilled the following inclusion criteria: A normal neurological and psychiatric exam (except for the diagnostic requirements of the LD group), a low average or greater Intelligence Quotient (IQ) [43], a parent (mother) with at least a completed elementary school education, and a *per capita* income greater than 50 percent of the minimum wage.

The LD diagnosis was established based on the following three criteria: a) poor academic achievement reported by teachers and parents, b) percentiles at 16 or lower in the subscales of reading, writing and mathematics of the Infant Neuropsychological Scale for Children [44] and c) LD diagnosis by a psychologist according to the DSM-5 criteria [2]. Several of them presented problems in attentional processes, as it is common in this disorder [45, 46], however they did not meet the DSM-5 criteria of ADHD [2].

Children who belonged to the Ctrl group, in addition to good academic achievement, obtained percentiles of 26 or above in the reading, writing, and mathematical domains of the Neuropsychological Scale for Children [44]. Table 1 shows the characteristics of both groups.

**Table 1.** Sample composition.

|  | Ctrl group n= 22 | | LD group n= 23 | | Statistical differences between groups |
|---|---|---|---|---|---|
|  | mean | sd | mean | sd |  |
| Age | 9.5 | 0.9 | 9.4 | 1.10 | t = 0.31, (NS) |
| WISC test: | | | | | |
| Full Scale IQ | 109.3 | 16.4 | 88.5 | 7.9 | t = 5.46, p<0.001 |
| WM Index | 105.7 | 16.5 | 89 | 8.8 | t = 4.25, p<0.001 |
| Female/Male ratio | 14/8 | | 12/11 | | OR = 0.62; CI:(0.18, 2.05); (NS) |

### 2.2. Working memory task

The WM task used in this work was a modified version of the classical Sternberg WM task [33]. A verbal WM task was employed since LD children impaired in two or three academic skills show a more consistent deficit in the phonological loop subsystem of the Baddeley´s WM model [7, 47].

The WM task (Figure 2) consisted in two conditions (low-load and high-load) presented in 180 trials, with 90 trials per condition appearing at random. At each trial, four digits appeared simultaneously on the screen. In the low load condition, all the digits were the same, in the high load condition the digits were different. The participants were instructed to memorize the numbers since after each trial a single digit appeared; they had to press one button (match response) if the digit was included in that trial and press another button if not (non-match response). Between the four digits (stimuli to remember) and the single digit (stimulus to respond), a segment of 800 ms was considered the main section of the retention phase of the task. In this segment, we performed the power spectrum analysis for the trials with correct responses. Stimuli were presented with the software MindTracer [48] and synchronized with the EEG data acquisition system.

**Figure 2.** Representation of a single trial (both conditions have been represented in the same Figure). In this case, the single digit ('stimulus to respond') was included previously in the 'stimuli to remember' from both conditions, and the subject had to press the button of the 'match response'. The segment in red corresponds to the retention phase, the section selected for the power spectrum analysis. The total trial duration is 4500 msec.

### 2.3. EEG recording and data analysis

Children were comfortably seated in a dim lit faradized and soundproofed room. The EEG was recorded during the task performance using a Medicid IV system (*Neuronic Mexicana*, *S.A.*; Mexico) and Track Walker TM v5.0 data system, from 19 leads of the 10–20 system (ElectroCap, International Inc.; Eaton, Ohio) referenced to the linked earlobes (A1–A2). The amplifier bandwidth was set between 0.1 and 50 Hz. The signal was amplified with a gain of 20,000 with electrode impedances at or below 5 kΩ. The EEG data was sampled every 5 ms and edited off-line with a sampling frequency of 200 Hz.

For each condition, at least 19 artifact-free segments of 800 ms of the retention phase (yielding 160 time-points per segment) from each trial with correct responses were used for the PSD analysis. There were up to 90 trials per condition, and this assured the minimal selection of 19 segments for the statistical requirement of at least as many segments as EEG leads, which guarantees that the cross-spectral matrix is positively defined, a requirement for the successive analyses [49].
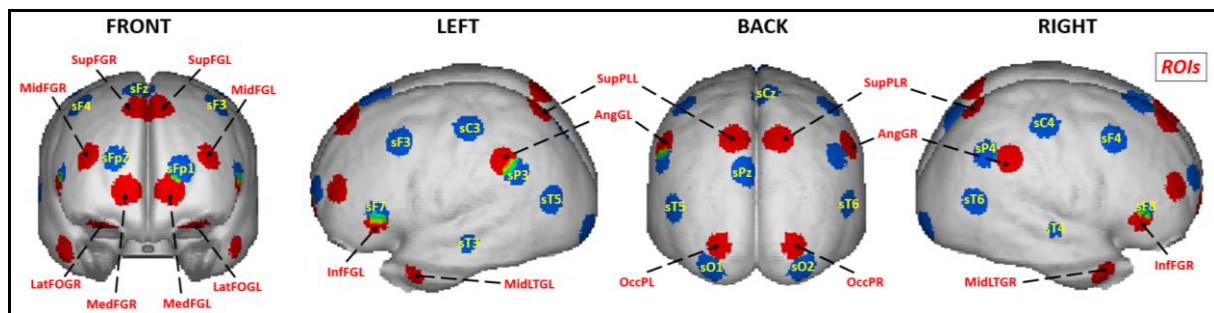
To attenuate the well-known problem of the mixing of the EEG signals at the scalp due to volume conduction [50], we performed our PSD analysis at the estimated primary current sources. For this, we first apply the *s-Loreta* technique [40], which transfers our data from 19 leads to a high resolution volumetric grid of 3244 sources. However, as stated in Biscay et al. [50], besides the difficulty of analyzing such high number of sources, there is the limitation that only a small number of sources can be independently estimated for a given number of EEG sensors; specifically, the maximum number of independent sources after solving the inverse problem by any linear method is the number of EEG sensors minus 1. In their paper, they also presented an algorithm which, under quite mild assumptions, can completely unmix the signals for that small number of sources when their domains are specified as corresponding to given regions of interest (ROIs) of said high resolution grid. In the present paper, we adhere to that methodology.

In the qEEG literature, in order to choose the specific sources (or ROIs) for the PSD analysis, it is frequent to use one of the following methods: 1) A selection based on prior alleged knowledge of brain functioning, such as working memory networks previously identified through neuroimaging [37]. 2) A selection of the sources closer to the 10-20 leads, which is not technically arbitrary since the source localization methods are usually more precise in the regions closer to the sensors; 3) a data-driven approach where the ROIs are selected based on the intrinsic variability of the data. The first two methods are not optimal since they ignore the data itself and do not provide the real brain areas involved in a specific experimental task. In this work, we used a data-driven approach based on the eigenvector centrality mapping technique (ECM) [51] adapted to the present work by the authors.

The ECM is a technique based on the calculation of the principal components decomposition of a similarity matrix, usually based on the signal in the time domain over all the voxels. It computes its first principal component and interprets each entry of this vector as an index of global connectivity for the corresponding brain voxel. The voxels with the higher connectivity indexes are considered the most connected voxels in the brain. In general, the ECM method is calculated for each subject separately, and for group analysis, a statistical test is performed among the subjects to select those voxels with a high connectivity index in most subjects. In our case, we constructed the similarity matrix as the one formed by the absolute values of the correlations between the sources of all voxels. We developed an optimized version of the power method algorithm in terms of memory usage and CPU intensity, which can obtain the first principal component for all the subjects at the same time. In this way it is not required to perform a statistical analysis to select the most connected voxels, since the global connectivity index that comes out from our approach is a group index of connectivity; and

the voxels with a high global connectivity index will be common for most of the subjects. With this index of global connectivity obtained by the above-described procedure, 18 ROIs (the number of scalp sensors minus 1) were selected. More specifically, not only the sources identified by this index were obtained, but we also included the equivalent sources in the contralateral hemisphere in the cases when they were not selected according to their values of the connectivity index. The reason for this addition was to be able to compare how the homologous sources in both hemispheres participated in the task. Figure 3 shows in red the 18 selected ROIs by the data-driven approach. For a better insight of its configuration, the cortex regions nearest to the positions of the sensors at the scalp are also illustrated in blue. Note that many of the relevant areas detected by our algorithm are far from the sources immediately below the scalp sensors. The source signals at the 18 ROIs were processed by the unmixing algorithm elaborated by Biscay et al. [50]. Then, the segments of unmixed signals of such 18 sources (with 160 time points each) in each condition of all subjects were transformed to the frequency domain with the Fast Fourier Transform. This procedure yielded a source spectrum of 24 frequencies, from 1.25 to 30 *Hz* (frequency bins every 1.25 *Hz*) for every ROI for each subject under each task condition and group. Finally, for the main group and task condition comparisons, we performed an ANOVA of two factors (Group and Task Condition, with two levels per factor). To safeguard the statistical significance of our results given the high number of comparisons, the alpha level was corrected using the permutations technique [52].
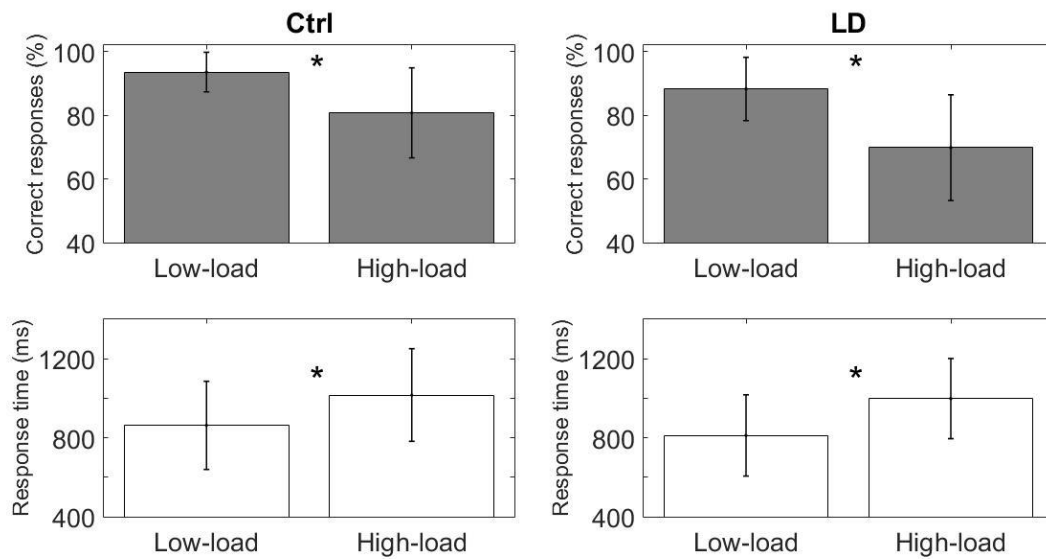


**Figure 3.** ROIs selected by the populational ECM. The sources closer to the 19 leads are in blue, and the 18 ROIs are in red: LatFOGL, Left lateral orbitofrontal gyrus; LatFOGR, Right lateral orbitofrontal gyrus; MedFGL, Left medial frontal area; MedFGR, Right medial frontal area; InfFGL,Left inferior frontal gyrus; InfFGR, Right inferior frontal gyrus; MidFGL, Left medium frontal gyrus; MidFGR, Right medium frontal gyrus; SupFGL, Left superior frontal gyrus; SupFGR, Right superior frontal gyrus; MidLTGL, Left medial temporal gyrus; MidLTGR, Right medial temporal gyrus; SupPLL, Left superior parietal area; SupPLR, Right superior parietal area; AngGL, Left angular gyrus; AngGR, Right angular gyrus; OccPL, Left occipital pole; OccPR, Right occipital pole.

## 3. Results

According to the comparison of the main characteristics of both groups (see Table 1), the Ctrl and LD groups did not differ in age or gender. For the intelligence measurement (with the WISC test), the Ctrl children showed a higher full-scale IQ (t= 5.46, p<0.001), and a higher WM index (t= 4.25, p<0.001), compared to the children with LD.
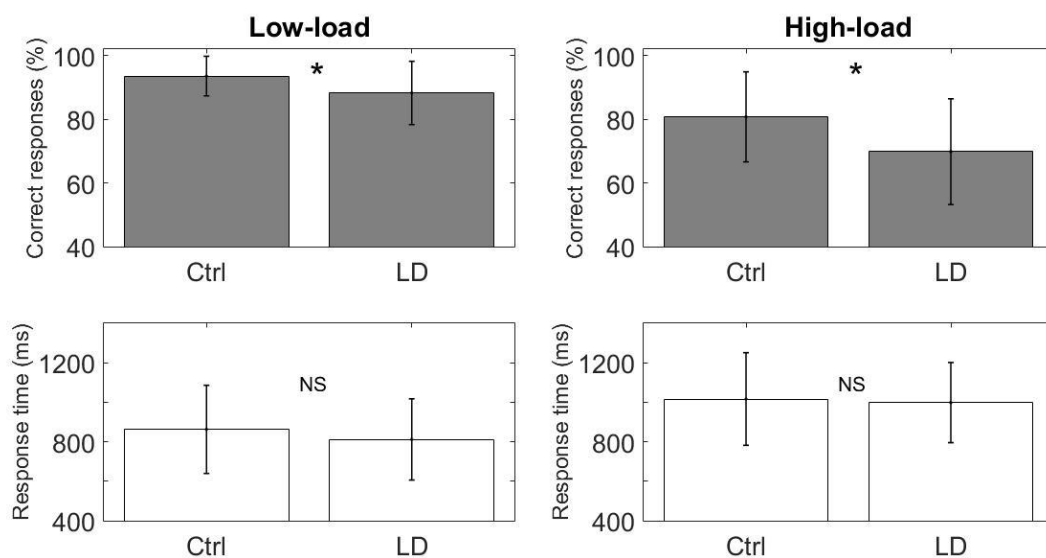
### 3.1. Behavioral Results

Both groups showed performance differences between the WM task conditions (low-load vs. high-load), with a lower percentage of correct responses (Ctrl: low-load=93.5±6.2, high-load=80.7±14.1,t=-5.49, p<0.001; LD: low-load=88.2±9.9, high-load=69.8±16.6, t=-6.45, p<0.001) and longer response times (Ctrl: low-load=862.6±223.4, high-load=1016.3±234.6, t=3.14, p<0.01; LD: low-load=811.7±205.8, high-load=998±203, t=4.37, p<0.01) to the high-load condition. These results show that the high-load condition was indeed more difficult for both groups (see Figure 4).
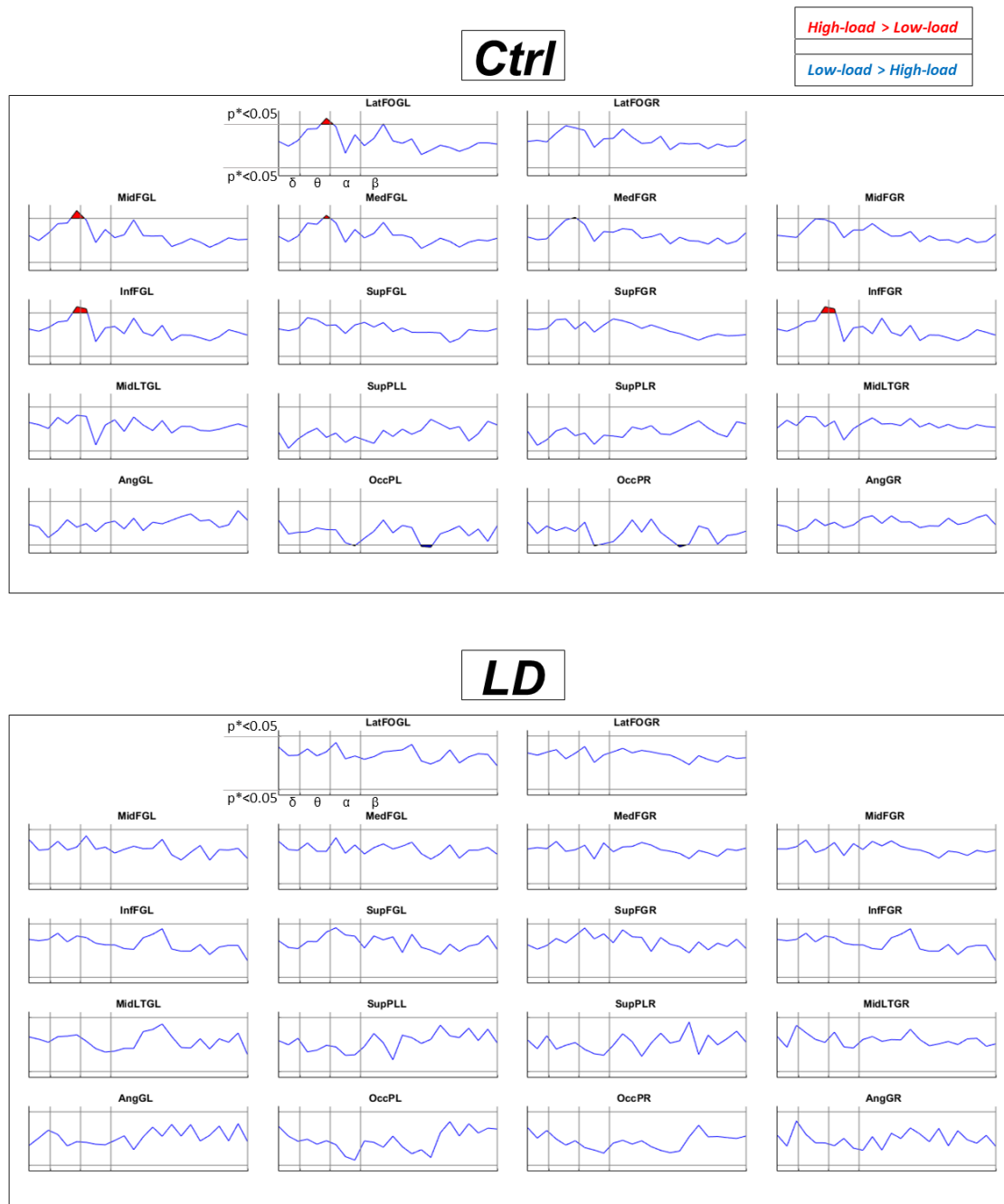
**Figure 4.** Within-groups behavioral results for the WM task (percentage of correct responses above in grey, response time below in white). The Ctrl group appears in the left, the LD group in the right. The asterisk indicates statistical differences.

The figure 5 shows the between-group comparisons (Ctrl *vs.* LD); the LD group displayed a significantly lower percentage of correct responses both for the high-load condition (t= 3.35, p<0.01) and the low-load condition (t= 3.01, p< 0.01); however, a greater difference was found for the high-load condition, which reflects major difficulties for LD children to simultaneously retain more items compared to the low-load condition (Figure 6). No significant response time differences were found between the groups.



**Figure 5.** Between-groups behavioral results at the WM task (percentage of correct responses above in grey, response time below in white). The asterisk indicates statistical differences.

*3.2. Power spectral density results*

The power spectrum comparison between the conditions (low-load *vs.* high-load) for each separate group (Figure 6, top panel), showed differences only for the Ctrl group. Children with good academic achievement had greater theta power in the high-load condition (compared to the low-load condition) mainly at the left frontal regions (left orbitofrontal gyrus, left medial frontal

gyrus, left medium frontal gyrus, and bilateral inferior frontal gyri); and lower beta power in the high-load condition at the occipital poles. The LD group did not show statistical differences in the comparison between the conditions (Figure 6, bottom panel).
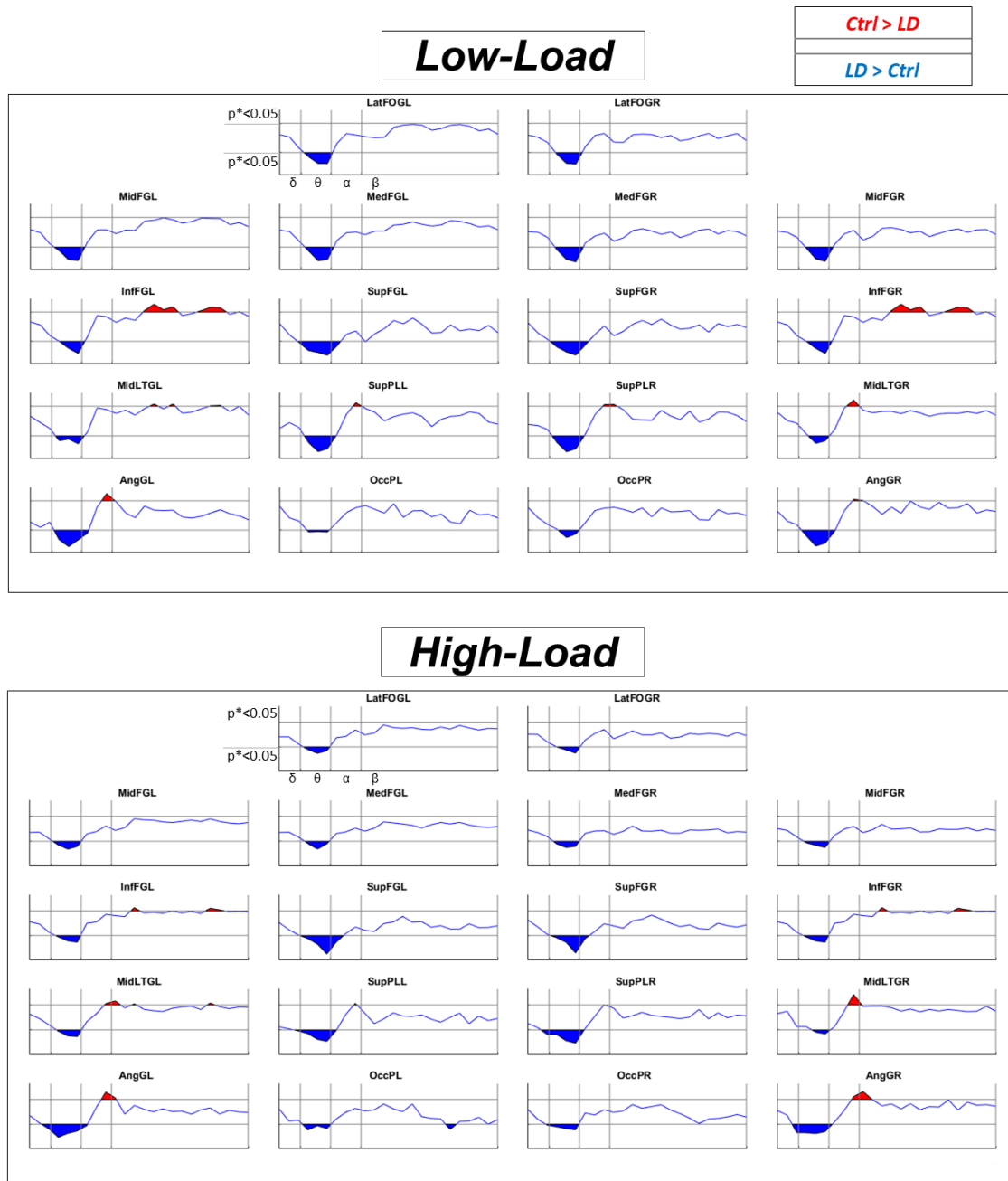


**Figure 6.** Power differences between the conditions for each group. The *X-axis* represents the frequencies (1.25-30 *Hz*), separated by vertical lines to the classic frequency bands: delta (δ)= 1-3 *Hz*, theta (θ)= 4-7 *Hz*, alpha ($\alpha$)= 8-12 *Hz*, and beta (β)= 13-30 *Hz*. The *Y-axis* represents the F-values. The red patches (above the horizontal lines) indicate a higher power for the high-load condition than for the low-load condition (p*<0.05, randomization-corrected). The blue patches (below the horizontal lines) indicate a higher power for the low-load condition (p*<0.05, randomization-corrected). *LatFOGL/LatFOGR:* Left/Right lateral orbitofrontal gyrus; *MedFGL/MedFGR:* Left/Right medial frontal area; *InfFGL/InfFGR:* Left/Right inferior frontal gyrus; *MidFGL/MidFGR:* Left/Right medium frontal gyrus; *SupFGL/SupFGR:* Left/Right superior frontal gyrus; *MidLTGL/MidLTGR:* Left/Right medial temporal gyrus; *SupPLL/SupPLR:* Left/Right superior parietal area; *AngGL/AngGR:* Left angular gyrus; *OccPL/OccPR:* Left/Right occipital pole.

In the comparison between the groups (Ctrl vs. LD) for each separate WM load condition, differences were found for the two conditions. At the low-load condition (Figure 7, top panel), the Ctrl group showed less theta power in all ROIs (frontal, temporal, parietal and occipital), a greater upper-alpha power at bilateral parietal areas (angular gyri and superior parietal areas) and the right medial temporal gyrus; and a greater beta power in bilateral inferior frontal gyri and the left medial temporal gyrus.

In the high-load condition (Figure 7, bottom panel), the findings showed a similar tendency to the low-load condition, with less overall theta activity for the Ctrl group; but with higher upper-alpha power for the bilateral angular gyri and medial temporal gyri, and with a less pronounced higher beta power at the inferior frontal gyri (compared to the low-load condition).



**Figure 7.** Power differences between the groups for each condition. The *X-axis* represents the frequencies (1.25-30 *Hz*), separated by vertical lines to the classic frequency bands: delta ($\delta$)= 1-3 *Hz*, theta ($\theta$)= 4-7 *Hz*, alpha ($\alpha$)= 8-12 *Hz*, and beta ($\beta$)= 13-30 *Hz*. The *Y-axis* represents the F-values. The red highlighted areas (above the horizontal lines) indicate a superior power for the Ctrl group in comparison with the *LD* group ($p^* < 0.05$, randomization-corrected). The blue values (below the

horizontal lines) indicate a superior power for the *LD* group (p*<0.05, randomization-corrected). *LatFOGL/LatFOGR:* Left/Right lateral orbitofrontal gyrus; *MedFGL/MedFGR:* Left/Right medial frontal area; *InfFGL/InfFGR:* Left/Right inferior frontal gyrus; *MidFGL/MidFGR:* Left/Right medium frontal gyrus; *SupFGL/SupFGR:* Left/Right superior frontal gyrus; *MidLTGL/MidLTGR:* Left/Right medial temporal gyrus; *SupPLL/SupPLR:* Left/Right superior parietal area; *AngGL/AngGR:* Left angular gyrus; *OccPL/OccPR:* Left/Right occipital pole.

## 4. Discussion

We aimed to examine the EEG power spectrum density of children with LD (compared to children with good academic achievement) during the performance of a WM task. The ENI test was employed as the main criterion to assign the subjects into either group (LD subjects obtained percentile scores at 16 or fewer); therefore, the groups differed in the scores of two or three academic domains among reading, writing and mathematics. No statistical differences were found between the groups in age or gender, but they differed significantly in both the full-scale IQ and the WM index of the WISC test. This lower IQ and WM index (compared to Ctrl children) was an expected finding in our children with LD [5]; and according to our inclusion criteria, we did make sure that our children had at least a low average IQ with no intellectual disabilities [2].

Regarding the behavioral results of the task, the main difference observed between the groups was the fewer percentage of correct responses for the LD group. This suggests that the task is capable of distinguishing between LD and children with typical development by revealing an expected WM deficit in children with LD, who showed a greater difficulty to memorize digits than their peers with good academic achievement.

The PSD analysis was performed not in the sensor space but at 18 source regions. An adaptation of the eigenvector centrality mapping (ECM) was used as a data-driven procedure for the selection of ROIs. It allowed to estimate a populational global index of connectivity for each voxel, thus providing a more robust algorithm for the ROIs selection. We consider this data-driven procedure a worthy approach of ROIs selection since it does not assume arbitrary, uninformed criteria such as a selection of the sources closer to the electrodes, or a putative prior knowledge of brain structure-function, like a pre-specified WM network that could not apply to LD children with insufficiently mapped task-related neural correlates, or with a possibly different strategy to solve the task. Instead, our ROIs broadly explained the sample variance as active regions present in all subjects during the WM performance. An advantage of this approach was that many ROIs were arranged at prefrontal areas, with no ROIs selected in the central cortex, i.e., near the placement of the electrodes Cz, C3 and C4 (see Figure 3). This finding coincides with other task-related EEG works that do not recognize central areas, while mainly frontal regions have indeed been involved in WM performance [20, 25].

Regarding the PSD between-conditions comparison (low-load vs. high-load) for each separate group, only the Ctrl children showed a higher left frontal theta power for the high-load condition (compared to the low-load condition). In young adults it has been reported that in greater WM loads they show more theta power [19, 20]. Since frontal regions are engaged in the maintenance and recovery of WM representations [53]; following Jensen and Tesche [20], this increase in theta with memory load could be due to a sustained neuronal activity to actively maintain the memory representations. Moreover, these authors have shown that the theta activity is sustained during the retention period of the task, the actual segment that we took as our analysis. However, our LD group did not show between-condition statistical differences, which suggests that the LD children require a greater overall recruitment of neural resources to properly respond even to the easy condition of the task. Thus, they are prone to overly recruit a poorly selective EEG theta power irrespective of the demands, which could suggest a less specialized WM neural activity due to their neurodevelopmental lag [15, 54].

The between-group analysis (Ctrl vs LD) for the low-load condition revealed that the children with LD (compared to control children) had more theta power in all the regions, less upper-alpha power at the bilateral parietal regions and the right temporal region; and less beta activity at the

inferior frontal gyri. For the high-load condition, the LD group also showed the greater theta power in all regions; but with less upper-alpha power for both the angular gyri of the parietal cortex and the medial temporal gyri, and a less pronounced beta power difference at the inferior frontal gyri (compared to the low-load condition). As mentioned before, a greater theta power is implied in attentional control and it appears stronger with higher memory loads [19, 20]. And a greater upper alpha (10-12 Hz) power regulates a top-down inhibition of irrelevant-stimuli processing, with a role in WM such as the active blocking of items from previous trials [28]. We presume that our Ctrl children showed the appropriate high theta power only for the high-load condition, such that for the low-load condition, a less effortful state of attention is required to solve the task. As for the higher theta power in all the sources of the children with LD, at first sight it could be interpreted in relation to the maturational lag as a greater resting-state theta activity in LD children [16]; since the low-load condition was an easy task that required to remember one item, with responses close to a 100% accuracy for both groups, and thus similar to a resting-state condition. Yet this explanation is unsuitable, since the resting-state is a fairly different condition from even an easy task [17], and we must take into account the role of a higher theta power involved in attentional control. Given that the task lasted 14 minutes and the trials of both conditions appeared at random, this required a constant vigilance and was harder for the LD group which had to maintain a higher state of focused attention to solve the task, thus resulting in a greater theta power throughout the task. Thus, we explain the larger theta activity in LD children (compared to Ctrl children) as an index of a greater and effortful attentional control required to properly remember the items required by the task. In relation to this, another work also reported a higher theta power in dyslexic children that performed a phonological discrimination task [30], a finding also understood as an inefficient usage of the attentional control.

As for the group differences in upper-alpha, with Ctrl children showing a higher upper-alpha power than LD children in the parietal regions and medial temporal gyri, mostly for the high load condition; we explain this by stating that, although a decrease in lower-alpha power is expected during cognitive tasks [17, 18], an upper alpha power increase in Sternberg WM tasks is actually expected mostly at posterior sites for healthy adults [27, 28]. Thus, we explain this higher upper-alpha in Ctrl children (compared to LD children) as an adequate functioning of a top-down inhibition of irrelevant processes, possibly to overcome the interference induced by the previous items of the WM task [28]; and given that this upper-alpha difference between the groups was increased for the high-load condition, the LD children could have failed to properly engage this process of inhibition required for the increased demands. About the between-groups power differences found in the beta frequency, a higher activity at frontal sites has been previously explained as a correlate of a subvocal rehearsal of items [24]. Our control group did show a greater beta power at the inferior frontal gyri compared to the LD children, mostly for the low-load condition. These frontal differences would be expected mainly for the high load comparison. However, our finding could be understood in the sense that, to achieve the demands of WM rehearsal, the control group showed a greater high frequency beta activity overall during the 14 minutes of the task to perform both conditions, while the LD group failed to significantly increase this activity; and they partially achieved this increase in the high-load condition to attend the demands of the task, thereby diminishing the beta differences between the groups in this condition.

We wrap up our main findings as follows: The LD children showed an under-recruitment of the prefrontal resources involved in the generation of upper-alpha and beta power, which are healthy neurophysiological correlates of WM, involved in a top-down inhibitory control and an a subvocal rehearsal of items, respectively. They also showed a greater overall theta activity in both conditions, which has been associated to a compensatory mechanism that implies a greater effort of attentional control as an attempt to overcome the demands of cognitive performance. Thus, our findings point to a picture of child with LD who is not able to recruit neural processes at the adequate high frequencies for the proper functioning of the WM system; hence requiring the recruitment of greater neural resources at low theta frequencies as an attempt to overcome their neurodevelopmental lag. This finding is consistent with the neural efficiency hypothesis [37] that links an efficient brain

functioning with less and more focused brain activation. Lastly, our work overcomes some relevant problems of the EEG literature by selecting ROIs at the brain sources with a data-driven ECM technique in accordance with their implication in the WM task, an approach that offers advantages above the traditional EEG analysis at the sensors space.

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