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RESEARCH PAPER

Conflict-Related Brain Activity after Individualized Cognitive Training in Preschoolers from Poor Homes

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Abstract

Different interventions have shown effectiveness in modifying cognitive performance on cognitive control demanding tasks in children from poor homes. However, little is known about the influence of cognitive interventions on children's brain functioning and how individual variability modulates the impact of those interventions. In the present study, we examined the impact of two individualized cognitive training interventions on cognitive performance and neural activity in preschoolers from poor homes. Participants were classified based on their basal performance (i.e., high and low performers) in an inhibitory control task and then separated into intervention and control groups within each performance level. The control groups completed an intervention with three activities without cognitive control demands. The intervention groups performed three training activities with increased cognitive demands adjusted according to their cognitive baseline performance. Children were trained weekly for 12 weeks and tested before and after the intervention, at kindergarten, using EEG recordings during a Go/NoGo task performance. Results revealed significant training effects on midfrontal neural activity associated with conflict processing in both intervention groups. Low performers exhibited changes on preresponse conflict processing (i.e., N2). However, the high-performing group had larger training effects on both conflict-related activity (i.e., N2, ERN, and theta power) and fluid intelligence. These results suggest that the consideration of individual differences in the design of interventions could contribute to the adaptation of training demands and that the use of mobile EEG technology could be useful to assess eventual neural markers in more ecological contexts.

Keywords Training · Childhood poverty · Intervention · N2 · ERN · Theta · Go/NoGo

1 Introduction

Cognitive control (CC) constitutes a central mechanism of human cognition and plays an important role in learning and self-regulatory processes since early stages of development (Allan et al., 2014; Doebel, 2020; Garon et al., 2008; McClelland et al., 2015). It is a multidimensional construct that is expressed at different levels of organization (e.g., neural, cognitive, and behavioral) and has been associated with demands of control over behavior and thoughts to achieve particular goals.

A variety of tasks have been used to measure performance in CC tasks, which mainly consist of inducing conflict along information processing streams. A paradigm usually employed in this context is the Go/NoGo task, which induces conflict between responses by instructing participants to produce a speedy and accurate response to a frequently occurring stimulus ("Go"), but to inhibit their responses to a less frequently occurring stimulus ("NoGo"). Frequent Go trials cause a prepotent tendency to respond, and consequently, rare NoGo trials require using control to override the automatic response. Different event-related potentials (ERP) have been used as a measure for exploring the temporal dynamics of neural mechanisms involved during the performance of Go/NoGo tasks (Abdul Rahman et al., 2017; Bokura et al., 2001; Hoyniak, 2017, p. 201;

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Jonkman, 2006). This evidence suggests that the engagement of control, due to interference from conflicting information, modulates the amplitude of ERP components located at fronto-central midline electrodes (e.g., Fz and Cz). For instance, the N2 ERP component is a negative deflection that occurs approximately between 200 and 400 ms after the presentation of Go and NoGo stimuli in trials preceding a correct response (Cragg et al., 2009). The amplitude of the N2 is typically larger (more negative) to NoGo stimuli when compared to the Go stimuli; i.e., it is enhanced on trials involving greater conflict. Another ERP component generally analyzed in this task is the so-called error-related negativity (ERN) (Gehring et al., 2018). The ERN is a negative deflection that typically appears between 50 and 100 ms following an incorrect response.

Different theories have been aimed at identifying the precise nature of the ERN and N2. The N2 has been proposed to reflect the detection and attention allocation to relevant or novel stimuli, including conflict monitoring (i.e., detecting stimuli that require a change in response) and inhibitory control (Brooker et al., 2020; Folstein & Van Petten, 2007; Hoyniak, 2017; Lo, 2018). The ERN has been associated with error detection, reinforcement learning, and conflict monitoring (e.g., detecting inconsistencies between the required and the performed response) (Brooker et al., 2020; Lo, 2018). The source of activation of both components has been associated with the anterior cingulate cortex (ACC) (Debener, 2005; Jonkman et al., 2007; Lamm et al., 2006; Luu et al., 2003; Nieuwenhuis et al., 2003; van Veen et al., 2001; Veen & Carter, 2002). There is evidence suggesting that the ACC is involved in detecting information conflict and subsequently in the signalization of the need for increasing CC to minimize future conflicts (Botvinick et al., 2001, 2004; Shenhav et al., 2013). There is further evidence suggesting that midfrontal ERN and N2 components index the activity of brain networks supporting CC (Cavanagh & Frank, 2014; Iannaccone et al., 2015; Lo, 2018; Yeung & Cohen, 2006).

Recently, theta frequency oscillations recorded from frontal midline electrodes have been proposed as a mechanism by which neurons could calculate and communicate the need for increasing CC across distinct brain areas (Cavanagh & Frank, 2014; Cooper et al., 2019). In the case of the Go/NoGo task, the event-related theta activity and N2 and ERN components reflect a common neural response and are elicited by response conflict and motor commission errors. For instance, larger theta activity is observed following the presentation of NoGo stimuli when compared to Go stimuli (Brier et al., 2010; Harper et al., 2014; Nigbur et al., 2011; Van Noordt et al., 2016; Yamanaka & Yamamoto, 2010). Enhancements of theta activity are also observed following the commission of an error when compared to a correct response (Luu et al., 2003; Nigbur et al., 2011; Trujillo & Allen, 2007; Van Noordt et al., 2016; Wang et al., 2020).

An important source of variation in CC achievement is the individual developmental stage. Developmental literature indicates that between 4 and 13 years, children show important changes in the performance of conflict-induced tasks. In the Go/NoGo task, response execution becomes faster, whereas correct detection (e.g., Go accuracy) and response inhibition (e.g., NoGo accuracy and false alarms) increase with age (Grammer et al., 2014; Johnstone et al., 2005, 2007; Jonkman, 2006; Kim et al., 2007; Lamm et al., 2006; Torpey et al., 2012; Wiersema et al., 2007). This evidence is in line with data from studies using other conflict-inducing tasks, which indicate that childhood constitutes an important period for the development of CC (Abundis-Gutiérrez et al., 2014; Bedard et al., 2002; Checa et al., 2014; Davies et al., 2004; Jones et al., 2003). Changes in behavioral performance are accompanied by changes in brain activity, as suggested by the linear change in the amplitude of the N2 (i.e., on NoGo or high conflict trials) and the ERN from childhood to adolescence (Hoyniak, 2017; Lo, 2018). According to the conflict monitoring theory, these age-related changes could be related to changes in several control functions ascribed to ACC, such as conflict monitoring and specification of the optimal intensity of control resources that need to be allocated during the performance in the task (Shenhav et al., 2013).

CC efficiency can also be influenced by both the type of environmental experiences and the individual susceptibility of children to these. In particular, the perspective of the relational developmental systems (RDS) conceptualizes development as bidirectional and interdependent, in which there are associations between events at different levels of organization (i.e., genetic, epigenetic, cellular, neural, cognitive, behavioral, and contextual) (McClelland et al., 2015). Changes in the development of particular skills in using CC could depend on the degree to which individual characteristics of children align with the strengths and resources found in their context (Lerner, 2007). Thus, these changes could have different trajectories (e.g., increase or decrease in CC abilities) depending on the individual experiences of children in their context (McClelland et al., 2015).

There is growing empirical evidence from cognitive neuroscience investigating the relationship between brain function/structure and childhood poverty (Hackman et al., 2010; Jensen et al., 2017; Lipina & Posner, 2012; Ursache & Noble, 2016). Research in this area shows that early adverse experiences associated with poverty (e.g., language and cognitive stimulation at home, family stress, and malnutrition) are associated with changes in the development of different aspects of cognition at multiple levels of organization (Chan et al., 2018; Conejero & Rueda, 2018; Farah, 2017; Hackman et al., 2015; Ivanovic et al., 2019; Lawson et al., 2018; Lipina et al., 2013; Noble & Giebler, 2020; Noble et al., 2015). Studies that have implemented EEG methods to explore these associations have been centered on the study of socioeconomic (SES) and/or income disparities in brain activity related to the resting state or different cognitive tasks (Pietto et al., 2017). Most ERP studies have verified differences in the neural activity associated with CC-demanding tasks in children from different SES backgrounds. In particular, electrophysiological patterns of children from low-SES homes have been associated with reduced efficiency in abilities that require the engagement of CC to inhibit a response (Brooker, 2018; St. John et al., 2019), control information interference (D'Angiulli et al., 2008, 2012; Giuliano et al., 2018; Hampton Wray et al., 2017; Isbell et al., 2016; Stevens et al., 2009), and detect a perceptual conflict or novelty (Conejero et al., 2018; Kishiyama et al., 2009). In some cases, ERP evidence showed associations between low SES and neural processing even when behavioral differences in the same task did not emerge (D'Angiulli et al., 2008, 2012; Hampton Wray et al., 2017; Kishiyama et al., 2009; St. John et al., 2019; Stevens et al., 2009).

A central question is whether SES-related disparities can be modified by interventions and what levels of organization can support and guide these possible changes. The evidence from EEG studies in children from middle- and high-SES backgrounds indicates that task-related activity could be modified by individual interventions aimed at inducing changes in particular CC skills. Several works conducted in children of 4–6 years old have shown changes in neural activity associated with tasks that required using control to solve an information interference (Pozuelos et al., 2019; Rueda et al., 2005; Rosario Rueda et al., 2012), override a response (Liu et al., 2015), to shift the attention to a new aspect of the stimuli (Espinet et al., 2013), or to solve an arithmetic problem (Gouet et al., 2018), after a cognitive training intervention. In general, gains in neural activity were observed in relatively short times (~ 12 sessions) and through process-based training, which requires the systematic practice of specific processes through activities with demands for increasing difficulty. Although all studies show near-transfer effects on untrained but related tasks, some studies also show partial far-transfer effects (e.g., fluid intelligence, IQ, and control skills in regulating motivation and affect) (Pozuelos et al., 2019; Rosario Rueda et al., 2012).

Different interventions (e.g., activities into the academic curriculum, parenting interventions, process-based training, and multimodular interventions) have been associated with changes in cognitive performance on CC-demanding tasks in children from low-SES homes (Arán Filippetti & Richaud de Minzi, 2010; Brock & Kochanska, 2016; Campbell et al., 2001; Fisher et al., 2016; Goldin et al., 2014; Hermida et al., 2015; Korzeniowski et al., 2017; Segretin et al., 2014). However, intervention studies in this area usually have not explored the impact of training activities at the neural level. EEG methods can offer a more accessible and temporally accurate approach to reveal brain activity changes of the influences related to experiential factors, such as interventions. For instance, the study of Neville and colleagues (Neville et al., 2013) provides preliminary evidence supporting that brain activity that underlies CC processes in children from low-SES backgrounds can be modified through a two-generation intervention strategy (i.e., parental training plus individual attentional intervention for children). Children who participated in the parental plus individual intervention group had more gains in an ERP auditory selective attention paradigm.

Several intervention studies in children from middle and high SES have associated the baseline performance in CC-demanding tasks with the training effects. This evidence indicated that in some cases, children with lower baseline cognitive performance showed increased posttraining performances (Johann & Karbach, 2020; Karbach et al., 2017; Lövdén et al., 2012), whereas in other cases, children with higher baseline cognitive performance showed the same effects (Lövdén et al., 2012; Pozuelos et al., 2019). Specifically, individual differences in training effects were observed after applying both adaptive process-based and strategy training interventions (Johann & Karbach, 2020; Karbach et al., 2017; Lövdén et al., 2012; Pozuelos et al., 2019). However, interventions were not designed according to the initial performance level of each group. Nevertheless, the fact that some children show more effects than others could be associated with the correspondence (or lack of correspondence) between the specific paradigm used to train cognitive abilities (e.g., process-based training and metacognitive scaffolding) and the needs/resources of each performing group in the specific task.

The inclusion of neural recordings in experimental designs often imposes limitations for the use of the technology outside the laboratory, because of the added burden of noise and logistic implementation. Laboratory settings are controlled scenarios, ideal for the implementation of EEG techniques, which are sensitive to background noise generated by sounds, frequency radio waves, and/or electric current. Unfortunately, these benefits are also accompanied by certain disadvantages, as they are not fully applicable to nonlaboratory settings such as homes, schools, or other contexts of the daily life of children. Therefore, any effort to transfer laboratory methodologies to different everyday contexts creates the possibility for their inclusion in studies with greater ecological value (Aspinall et al., 2015; Kuziek et al., 2017; Mavros et al., 2016; Toppi et al., 2016).

The experiment that we report here is part of a research project carried out in an educational setting. It was aimed at evaluating the impacts of an intervention designed to enhance cognitive self-regulatory processes in a sample of preschoolers from poor homes, focused on their CC baseline performance. Part of the effects on a battery of cognitive tasks tapping inhibitory control, cognitive flexibility, working memory, and planning such tasks was recently published (Giovannetti et al., 2020). The first aim of this experiment was to evaluate near-transfer effects of the same intervention to an untrained but CC-related task, considering aspects of neural activity and individual differences to complement previous findings (Pietto et al., 2018a, b). To this purpose, the brain activity associated with CC was recorded using a mobile EEG device during the performance of a Go/NoGo task before and after the intervention, to explore changes in the amplitudes of the N2 and ERN components and associated theta power. Based on their performance on an inhibitory control task (i.e., Stroop-like task) at the pre-intervention stage, children were classified into two groups (high and low performers) and then assigned to intervention and control groups within each performance level. The aim of this classification is based on evidence suggesting that cognitive control baseline performance may be associated with different effects after a cognitive intervention (Benson et al., 2013; Jaeggi et al., 2014; Könen & Karbach, 2015; Segretin et al., 2014). Each intervention group completed a set of activities during the intervention stage with different difficulty levels based on their baseline performance. Based on results from previous intervention studies (Goldin et al., 2014; Neville et al., 2013), we expected to observe training-induced changes at the cognitive and neural levels. We also expected to observe comparable intervention effects in both performance groups, given that training menus implemented for each group were designed to meet the needs of children in CC. Thus, the proposed hypotheses are the following: (1) both training menus will produce changes, which will be related to a better efficiency in CC (i.e., RT, accuracy, and conflict-related electrophysiological indices), and (2) both performance intervention groups will show comparable intervention effects, even though it is possible to find impact modulations depending on the processes and levels of analysis. The second aim was to evaluate far-transfer effects on an untrained task tapping fluid processes. Through demanding the use of CC-related processing (i.e., inhibitory control, working memory, flexibility, and planning), we expected to find an increase in fluid intelligence performance.

2 Materials and Methods

2.1 Participants

One hundred and twenty children (56 girls) from a public kindergarten were authorized to participate in the study. Among them, 84 (40 girls) of 5.3 (SD = 0.33) years old were analyzed in the present study. All procedures included in the study followed national and international recommended research with children proceedings and norms and were reviewed and approved by the Institutional Review Board (CEMIC, Protocols No. 682, 961). See Appendix 1 for more details.

2.2 Study Design and General Description of Procedures

The study design was quasi-experimental, longitudinal, controlled, and randomized, with intervention and control groups and measures assessed in the pre- and post-intervention stages to the same children (see Fig. 1a). Each child was assessed or assisted by a research assistant who was unaware of the design and hypotheses of the study and was previously trained for task implementations.

The initial assessment (pre-intervention) included a Go/NoGo EEG task (see Fig. 1b), the matrix subscale of Kaufman Brief Intelligence Test (K-BIT; (Kaufman, 1990)), and a Stroop-like cognitive task. The last one was used to establish the baseline performance groups of children in the inhibitory control domain. Children were assigned to high- or low-performance groups based on their performance on the Stroop task (see details in Appendix 1). Then, they were randomly assigned to the experimental condition (cognitive training) or control (games without specific cognitive demands). Thus, four groups were generated: control low and high performers and intervention low and high performers (CTL-LP, CTL-HP, INT-LP, and INT-HP, respectively; Fig. 1a). A total of 21 children (7 girls, mean age = 5.29, SD = 0.33) were included in the CTL-LP group, 20 children (6 girls, mean age = 5.36, SD = 0.28) in the CTL-HP group, 19 children (11 girls, mean age = 5.18, SD = 0.32) in the INT-LP group, and 24 children (16 girls, mean age = 5.38, SD = 0.35) in the INT-HP group. The control groups completed three games without specific cognitive control demands (i.e., bubble shooter, painting, and dots) (see details in Appendix 1), while the intervention group performed three activities with increased cognitive demands for inhibitory control, working memory, and planning (Giovannetti et al., 2020; Pietto et al., 2018a, b). Broadly, the two training menus were differentiated by the initial difficulty level and the difficulty slope of each activity. The LP group started from lower levels and had more gradual progress than the HP group. The post-intervention assessment stage consisted of reassessing all children with the same cognitive tasks (i.e., GoNoGo, K-BIT, and Stroop). In addition, during the school year, caregivers were administered questionnaires to collect information on children's health and family social and economic conditions (see more details in Appendix 1).

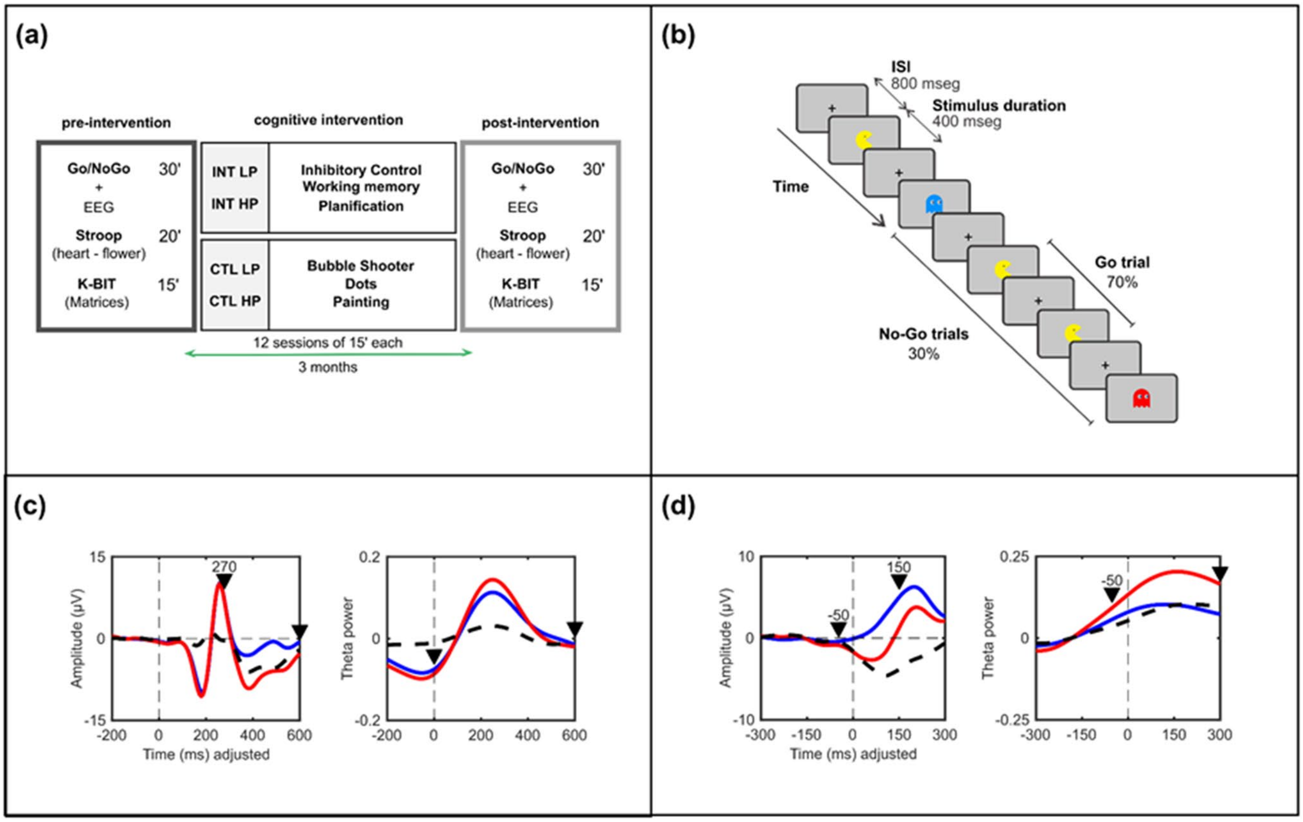

Fig. 1 **a** Study design. **b** Schematic representation of the Go/NoGo task. **c** Stimulus-locked activity (blue = Go trials, red = NoGo trials, dotted line = NoGo–Go trials). **d** Response-locked activity (blue = correct trials, red = error trials, dotted line = error–correct trials) in the ERP and ERSP (theta frequency band) domains located on frontal electrodes (average of the F3 and F4 channels). In **c** and **d**, time windows for significance analysis (i.e., nonparametric permutation *t*-tests) are depicted

2.3 Go/NoGo Task and EEG Recording

Neural activity was recorded using the EMOTIV EPOC + system (www.emotiv.com) while participants performed a child version of the Go/NoGo task. Each trial began with the presentation of a stimulus (Go or NoGo) that remained visible for 400 ms. It was immediately replaced by a black cross (visual angle: 2 degrees) for 800 ms. The Go condition was presented in 70% of the trials. The children were instructed to respond as quickly as possible (press the "space" key) every time they saw the Go stimuli and not to respond when the NoGo stimuli appeared. Each participant completed a minimum of three blocks and a maximum of eight blocks of 90 trials (720 trials in total), which were distributed in two sections of four blocks (1—Pacman; 2—Angry Birds). The information was collected after exposing children to no less than 20 trials of practice. Go/NoGo stimulus presentation and recording were carried out on the same computer. Recordings were synchronized with the stimuli and retrieved from the same python program using our own functions (Pietto et al., 2018a, b) (see details in Appendix 1).

2.4 EEG Data Preprocessing

2.4.1 Event-Related Potentials

The data of each participant were filtered with a FIR (finite impulse response) bandpass filter with a high cutoff frequency of 30 Hz and a low cutoff frequency of 0.5 Hz. Then, stimulus-locked data were segmented into epochs of 200 ms before to 800 ms after target onset (in trials associated with correct responses); response-locked data were segmented into epochs of 400 ms before to 600 ms after the press of the button (in trials associated with correct and error responses). Baseline activity was subtracted from each epoch using the average activity in the intervals [−200, 0] ms and [−400, -50] ms for stimulus-locked and response-locked waveforms, respectively. Independent component analysis (ICA) was used to remove artifacts related to eye movements, blinks, and signal noise. The remaining artifacts were rejected automatically from epochs that contained voltage fluctuations exceeding ± 110 µV. Stimulus-locked waveforms were rereferenced offline to the algebraic average of P7/P8 channels (the closest electrodes to the right/left mastoids), and response-locked signals were rereferenced to a pseudo-average reference including channels O1, O2, T7, T8, AF3, and AF4. Finally, the average activity was calculated over a frontal ROI (F3/F4 electrodes).

A denoising algorithm was used to obtain clean single-trial ERP (Pietto et al., 2018a, b). As shown previously (Ahmadi & Quian Quiroga, 2013; Navajas et al., 2013; Quian Quiroga, 2000), this method improves the estimation of the single-trial ERP significantly when compared with the nondenoised, single-trial waveforms. The ERP was reconstructed by averaging clean trials for each participant and condition. Signal latency was corrected to the peak of the P2 component of stimulus-locked ERP. After shifting the waveform, the baseline activity was resubtracted from each segment. The minimum number of clean trials per participant used in the analyses was 15 for response-locked ERP and 32 for stimulus-locked ERP.

2.4.2 Event-Related Spectral Perturbation

The EEG data preprocessing pipeline for oscillatory analyses was similar to the one used for event-related potentials. Additionally, after ICA, EEG data of each participant were bandpass-filtered using an FIR filter of size 1 Hz over the frequency range 1–30 Hz. The Hilbert transform (hilbert.m) was applied to extract the instantaneous power values over each signal. For theta band analysis, power data were calculated for frequency range 4–7 Hz.

2.5 Sociodemographic Information

A socioeconomic scale (*Encuesta de nivel económico y social*—NES) was administered to one parent of each child in a school room to obtain information on unsatisfied basic need (UBN) indicators related to socioeconomic and family living conditions (Giovannetti et al., 2020; Pietto et al., 2018a, b). A total SES score was determined using the level of parental education and occupation and the dwelling characteristics and overcrowding. See more details in Appendix 1.

2.6 Training

Based on the performance groups generated after the pre-intervention stage, different and specific training menus for inhibitory control, working memory, and planning were designed for each group, which differed in difficulty and complexity (see details in Appendix 1). Activities comprised 12 sessions (4 sessions for each activity) of 15 min each, administered on a weekly basis, with an average time between sessions of 7.61 days (SD = 0.99). All activities were performed on a Samsung Galaxy Tab E tablet with a 9.6″ screen at a distance of about 30 cm away from the child.

The inhibitory control activity consisted of a Stroop-like task. Stimuli were displayed one at a time on one side of the tablet screen, pointing to the right or to the left within different congruence conditions. In the congruent condition, the child was instructed to press the button in accordance with the direction in which the stimulus was pointing at. In the incongruent condition, the child was instructed to press the opposite button to which the stimulus was pointing at. Finally, in the mixed condition, both congruent and incongruent trials appeared randomly, and the child was instructed to respond according to the previous rules. In advanced levels, some distractors appeared. The advanced criteria differed between performance groups. In the first place, congruent and incongruent conditions for the LP group included a larger number of trials compared to the HP group. Further, in the congruent condition, the stimulus appeared more frequently on the opposite side of the button the participant had to press. This was done in order to extend the time to which the LP group was exposed to inhibitory control trials before facing the mixed condition, giving a smoother difficulty slope for the LP group than for the HP group. Finally, the LP group disposed of longer response times than the HP group (e.g., while the former had 9000 ms available to respond in the first level, the latter had only 4000 ms).

The working memory activity (Goldin et al., 2014) was designed to measure working memory for visual patterns and was based on the self-ordered pointing task (SOPT) (Luciana & Nelson, 1998; Petrides & Milner, 1982). Various stimuli (i.e., cards with different pictures and colors) were displayed on the screen and reappeared in a different order when the participant touched one of them. The child was invited to touch all the stimuli one at a time without repeating the preceding ones. The trial ended when all cards were selected or when the child selected a stimulus that had already been selected. The number and difficulty of the cards increased as the children won more trials. The LP group was exposed to simpler items comprising two features, whereas the HP group was exposed to items with three features. On the other hand, both groups were taught to use a mnemonic strategy in the largest levels. However, the intervention menu for the LP group was designed to give children more opportunities to practice that strategy than the HP menu.

The planning activity was an adaptation of the dog–cat–mouse task (Klahr, 1985). A square was displayed with a diagonal and three "houses" distributed in the four corners. Three characters were placed in one house each in different corners, and the aim was to guide them to their houses in a determined number of moves. Children were given three rules: (1) the characters could be moved one at a time and could only be moved to an empty corner, (2) they could only be moved through the "paths" (sides and diagonal), and (3) characters could not share a house. As the activity progressed, the number of movements required to reach the objective increased, thereby increasing the path length. For the HP group, difficulty levels included only the number of movements required. For the LP group, difficulty parameters included the following: path length, use of the diagonal (which would make the work easier), the number of possible paths, the number of possible moves in the first movement (the probability of making a bad choice decreases with two possible moves compared to three), and the search depth (the number of necessary moves to guide the first character to its house).

2.7 Data Analysis

2.7.1 Selected Variables

Data analysis included variables from the NES and the assessment tasks (i.e., Go/NoGo, Stroop, and K-BIT).

NES variables. Indicators corresponding to the UBN measure of chronic and structural poverty were extracted from caregivers' interviews and transformed into dichotomous variables. In addition, the SES score and the variables that compose it were computed (i.e., education, occupation, housing, and overcrowding).

Stroop. The dependent variable for this task included the proportion of correct trials (correct/total trials).

K-BIT. The dependent variables for this task included the raw score (last number question answered – number of incorrect answers), errors (number of incorrect answers), and proportion of correct responses (number of correct answers divided by the last number question answered).

Go/NoGo cognitive performance variables. (1) Proportion of false alarms: number of error responses/number of total trials; (2) efficiency: proportion of correct responses – false alarms; (3) reaction times Go (RT Go): average of response times in Go trials; and (4) relative reaction time after an error (relative RT after error): average of response times in Go trials after having made an error/RT Go.

Go/NoGo neural activity variables. (1) Stimulus-locked waveforms: ERP and ERSP related to Go and NoGo trials; (2) Δstimulus-locked waveforms: difference of amplitude or power between Go and NoGo conditions, calculated by subtracting the Go condition from the NoGo condition; (3) response-locked waveforms: ERP and ERSP related to correct and error responses; (4) Δresponse-locked waveforms: difference of amplitude or power between error and correct responses, calculated by subtracting the correct response from the error response; (5) ΔN2 component: the area of Δstimulus-locked waveforms, calculated within the time window 300–600 ms for ERP and 100–400 ms for ERSP; and (6) ΔERN: the area of Δresponse-locked waveforms, calculated within the time windows -50–150 ms and -50–300 ms for ERP and ERSP, respectively (see Fig. 1c,d). For training-related changes in neural activity, the ΔN2 and ΔERN time windows were defined based on the bootstrapping procedure. Following the topography of the effects reported in previous studies (Abdul Rahman et al., 2017; Brooker et al., 2020; Cragg et al., 2009; Hoyniak, 2017; Johnstone et al., 2007; Jonkman, 2006; Kim et al., 2007; Lamm et al., 2006; Lo, 2018; Torpey et al., 2012; Trujillo & Allen, 2007; Wiersema et al., 2007), all variables were estimated on a frontal ROI (F3/F4). See more details in Appendix 1.

2.7.2 Preliminary Analysis

Normality of dependent variables was conducted via the Kolmogorov–Smirnov test. In addition, the homogeneity of variances between study groups for each dependent variable was tested using Levene's test. Considering the presence of variables that did not meet the normality and/or homoscedasticity assumptions, it was decided to proceed with nonparametric methods for the contrast analyses. See Appendix 1 for more details.

Descriptive analysis of sociodemographic characteristics. In order to characterize the population of children who participated in the project, univariate analyses of the NES variables corresponding to the UBN and SES indicators were carried out. For this purpose, sample sizes, medians, and minimum and maximum values of the selected variables were determined based on the total sample.

Conflict-related activity in the Go/NoGo task. Contrast analyses were conducted on EEG data of the Go/NoGo task to test for significant differences between task conditions for the entire sample and for each study group in both intervention stages. Based on previous studies using Go/NoGo tasks (Abdul Rahman et al., 2017; Brier et al., 2010; Hoyniak, 2017; Johnstone et al., 2005; Lamm et al., 2006; Nigbur et al., 2011; Trujillo & Allen, 2007; Wang et al., 2020), it was expected to find a modulation of neural activity at frontal channels: in particular, (1) a larger amplitude in the negativity of N2 and ERN components and (2) a greater power in theta band, following NoGo stimuli compared to Go stimuli and following error responses compared to the waveform following correct responses, respectively. In this sense, differences among conditions were assessed for significance via Monte Carlo permutation tests (2000 permutations), combined with bootstrapping at frontal ROI (F3/F4). These contrasts were conducted for each sample along typically defined time windows; stimulus-locked ERP and ERSP were [270, 600] ms and [0, 600] ms, whereas response-locked ERP and ERSP were [-50, 150] ms and [-50, 300] ms.

High- and low-performing group classification. The experimental data obtained from the child Stroop task were collected to classify children into two groups, i.e., high-performing (HP) and low-performing (LP) groups according to their baseline performances in the task. This classification was aimed at identifying task performance profiles in order to apply different intervention schemes based on the complexity of the task and the activities that each group was required to solve. Children performing below the median of correct trials were assigned to the LP group, while children above the median were assigned to the HP group.

Baseline homogeneity analysis. It was performed to test for similarity between study groups in the performance of the Go/NoGo task and the sociodemographic characteristics before the start of the intervention. See more details in Appendix 1.

2.7.3 Training Impact

To test the effect of intervention on neural activity, nonparametric permutation *t*-tests for each sample along the same time windows used for the conflict-related activity analysis were conducted. These were performed on Δstimulus-locked (i.e., difference of amplitude or power between Go and NoGo conditions, calculated by subtracting the Go condition from the NoGo condition) and Δresponse-locked (i.e., difference of amplitude or power between error and correct responses, calculated by subtracting the correct response from the error response) activity at the frontal ROI between intervention stages within each study group. Additionally, within-group contrast analyses were performed between intervention stages in order to examine the impact of the intervention on cognitive performance and to further characterize training-related changes in neural activity. To this end, the Wilcoxon signed-rank test was used for comparing the medians (i.e., cognitive performance: Stroop task—proportion of correct trials; K-BIT—raw score, errors, and proportion of correct responses; Go/NoGo task—RT Go, RT after error, false alarms, and efficiency, and neural activity: ΔN2 and ΔERN for ERP and ERSP) of two related samples (pre- vs. post-intervention), for each study group (i.e., CTL-LP, CTL-HP, INT-LP, and INT-HP). Contrast analyses within each cognitive variable were corrected for multiple comparisons using the Bonferroni approach (Bonferroni, 1936). For neural activity, Wilcoxon signed-rank tests were performed to assess significance in the regions of interest determined by the nonparametric permutations analysis. For all measures, effect sizes were calculated using *r* values (Tomczak & Tomczak, 2014).

3 Results

Descriptive statistics for the variables of all the tasks used in the current study (i.e., Go/NoGo, Stroop, and K-BIT) and for pre- and post-intervention stages are listed in Table 7 in Appendix 6.

3.1 Descriptive Analysis of Sociodemographic Characteristics

This analysis showed that 95.5% of children came from families with UBN. In particular, sociodemographic characteristics of the families comprised 93.8% living in disadvantaged neighborhoods, 29.5% absence of a waste discharge system in household, 26.8% inappropriate dwelling, 15.2% overcrowding, 13.4% presence of school-aged children not attending any educational system, and 9.8% head of household with incomplete secondary schooling with more than four dependents. Regarding the number of UBN indicators, 49.1% of homes showed the presence of one indicator, 24.1% 2 indicators, 15.2% 3 indicators, 4.5% 4 indicators, 0.9% 5 indicators, and 1.8% 6 indicators (see Table 5 in Appendix 2 and Table 6 in Appendix 3 for sociodemographic characteristics of participants and study groups).

3.2 Conflict-Related Activity in Go/NoGo Task

On average, children completed 616 (SD = 141) trials in the pre-intervention stage and 676 (SD = 107) trials in the post-intervention stage. The number of trials completed by each study group did not differ in both the pre- (Kruskal–Wallis test: $X^2 = 3.64$, $p = 0.304$, df = 3) and post-intervention stage (Kruskal–Wallis test: $X^2 = 1.32$, $p = 0.724$, df = 3).

To test differences in N2 and ERN amplitudes and theta power between task conditions, nonparametric bootstrap permutation *t*-tests were conducted for each sample along typically defined time windows (i.e., stimulus-locked ERP [270, 600] ms, stimulus-locked ERSP [0, 600] ms, response-locked ERP [-50, 150] ms, and response-locked ERSP [-50, 300] ms), for the frontal ROI at each session. Permutation analysis revealed differences in amplitude and power between stimulus-locked ERP conditions for both intervention stages (bootstrapping: $p < 0.05$ light gray; $p < 0.01$; Fig. 8 in Appendix 4). In particular, NoGo trials elicited a larger N2 amplitude and a larger theta power compared to Go trials. Similarly to the stimulus-locked results, nonparametric bootstrap permutation *t*-tests indicated significant differences between response-locked ERP (see Fig. 9) conditions, for both intervention stages (bootstrapping: $p < 0.05$ light gray; $p < 0.01$; Fig. 9 in Appendix 5). In particular, the ERN showed to be significantly more negative in amplitude and to have larger theta power than the waveform following correct responses.

3.3 Baseline Homogeneity Analysis

The results of baseline homogeneity indicated that the differences between study groups were not significant for the variables of neural activity, cognitive performance, and sociodemographic context (see Table 6). However, the analysis of baseline homogeneity between performance groups suggested that HP and LP groups were different in their control capabilities at the pre-intervention stage (see more details in Appendix 1).

3.4 Training Impact

3.4.1 Cognitive Performance

Stroop task. Contrast analyses revealed a significant increase in the proportion of correct trials in the post-intervention phase for both LP groups (Wilcoxon s-r test; CTL-LP: Z=-2.84; p=0.005; r=-0.71; CTL-HP: Z=-0.81; p=0.420; r=-0.19; INT-LP: Z=-3.17; p=0.002; r=-0.82; INT-HP: Z=0.09; p=0.926; r=0.02; Bonferroni corrected α=0.0125).

K-BIT. Except for the CTL-HP group, the remaining groups showed significant higher raw scores in the post-intervention stage (Wilcoxon s-r test; CTL-LP: Z=-3.30; p<0.001; r=-0.74; CTL-HP: Z=-2.25; p=0.025; r=-0.60; INT-LP: Z=-2.67; p=0.008; r=-0.63; INT-HP: Z=-2.63; p=0.009; r=-0.60; Bonferroni corrected α=0.0125). Post-intervention errors were not significantly different than pre-intervention errors for all groups (Wilcoxon s-r test; CTL-LP: Z=-0.30; p=0.765; r=-0.07; CTL-HP: Z=0.28; p=0.779; r=0.08; INT-LP: Z=-1.50; p=0.132; r=-0.35; INT-HP: Z=2.14; p=0.033; r=0.49; Bonferroni corrected α=0.0125). Finally, contrast analyses revealed a significant increase in the proportion of correct responses in the post-intervention stage only for the INT-HP group (Wilcoxon s-r test; CTL-LP: Z=-2.45; p=0.014; r=-0.55; CTL-HP: Z=-1.57; p=0.115; r=-0.42; INT-LP: Z=-1.16; p=0.247; r=-0.27; INT-HP: Z=-2.85; p=0.004; r=-0.65; Bonferroni corrected α=0.0125).

Go/NoGo task. Contrast analyses of accuracy data indicated no significant differences between intervention stages for efficiency (Wilcoxon s-r test; CTL-LP: Z=0.78; p=0.434; r=0.17; CTL-HP: Z=0.45; p=0.654; r=0.10; INT-LP: Z=0.40; p=0.687; r=0.09; INT-HP: Z=0.26; p=0.797; r=0.05) and false alarm scores across all groups (Wilcoxon s-r test; CTL-LP: Z=0.16; p=0.876; r=0.03; CTL-HP: Z=-0.78; p=0.433; r=-0.18; INT-LP: Z=-0.16; p=0.872; r=-0.04; INT-HP: Z=1.03; p=0.304; r=0.21) (Fig. 2a). The pattern was different for RT, where contrast analysis indicated that post-intervention RT for Go trials were significantly lower than pre-intervention RT for Go trials for all groups (Wilcoxon s-r test; CTL-LP: Z=2.83; p=0.005; r=0.62; CTL-HP: Z=3.70; p=0.0002; r=0.83; INT-LP: Z=3.14; p=0.002; r=0.72; INT-HP: Z=3.23; p=0.001; r=0.66; Bonferroni corrected α=0.0125) (Fig. 2b). Finally, post-intervention relative RT after error did not show changes between intervention stages (Fig. 2c; Wilcoxon s-r test; CTL-LP: Z=1.61; p=0.108; r=0.35; CTL-HP: Z=1.08; p=0.279; r=0.24; INT-LP: Z=-2.29; p=0.022; r=-0.53; INT-HP: Z=-1.60; p=0.110; r=-0.33; Bonferroni corrected α=0.0125).

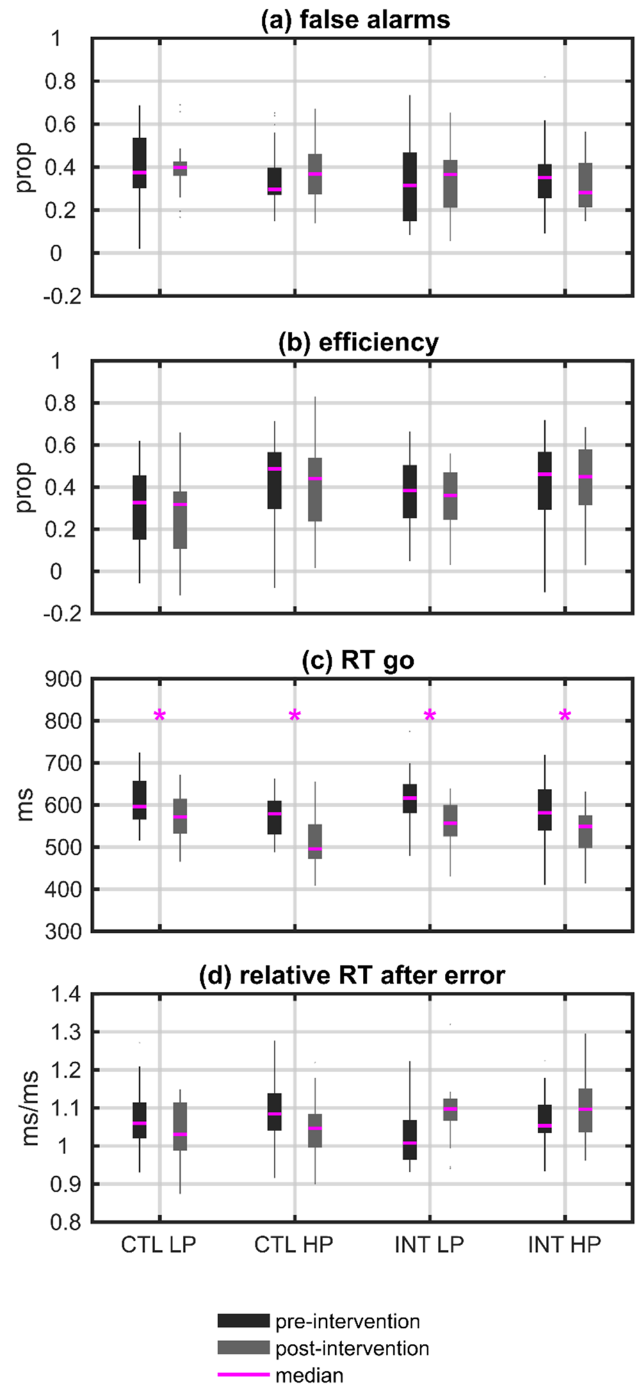

Fig. 2 Boxplots of behavioral data in the Go/NoGo task averaged by study groups (i.e., low-performing (LP) and high-performing (HP) groups, intervention (INT) and control (CTL) groups) and stage (i.e., pre- and post-intervention). The asterisk denotes significant differences (p<0.05) between intervention stages

3.4.2 Electrophysiological Data

N2 and ERN ERP Components To test differences in N2 amplitude from the stimulus-locked ERP between task conditions (Fig. 3), nonparametric bootstrap permutation *t*-tests were conducted for each sample along the ERP time window from 270 to 600 ms for the frontal ROI at each session and for each study group. Permutation analysis revealed differences in amplitude between Go and NoGo conditions for all groups and intervention stages (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 3). In particular, NoGo trials elicited a larger N2 amplitude compared to Go trials. In addition, permutation results showed significantly larger differences in amplitude between task conditions in the post-intervention session when compared with the pre-intervention session, for children in the INT-HP and INT-LP groups (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 3).

To further characterize training-related changes on ERP, the area of the ΔN2 was calculated. The time window of the area was determined from the results obtained from permutation analysis (i.e., [300, 550] ms). Results revealed significant differences in the area of ΔN2 between intervention stages for INT-HP (Wilcoxon s-r test; $Z=2.69$; $p=0.007$; $r=0.59$) and INT-LP (Wilcoxon s-r test; $Z=2.20$; $p=0.031$; $r=0.51$) groups, indicating a larger area in the post-intervention session compared to the pre-intervention session.

For response-locked ERP, nonparametric bootstrap permutation *t*-tests (tested in the time window ranging from [-50, 150] ms) indicated the difference between correct and error response waveforms to be significant for all groups and intervention stages (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 4). In particular, the amplitude was more negative after errors than following correct responses, which is the typical ERN effect. The permutation analysis to test training-related permutation showed significantly larger differences in amplitude between responses in the post-intervention session when compared with the pre-intervention session, for children in the INT-HP group. Subsequent ΔERN comparisons (time window: [-50, 150] ms) revealed a significant difference in area

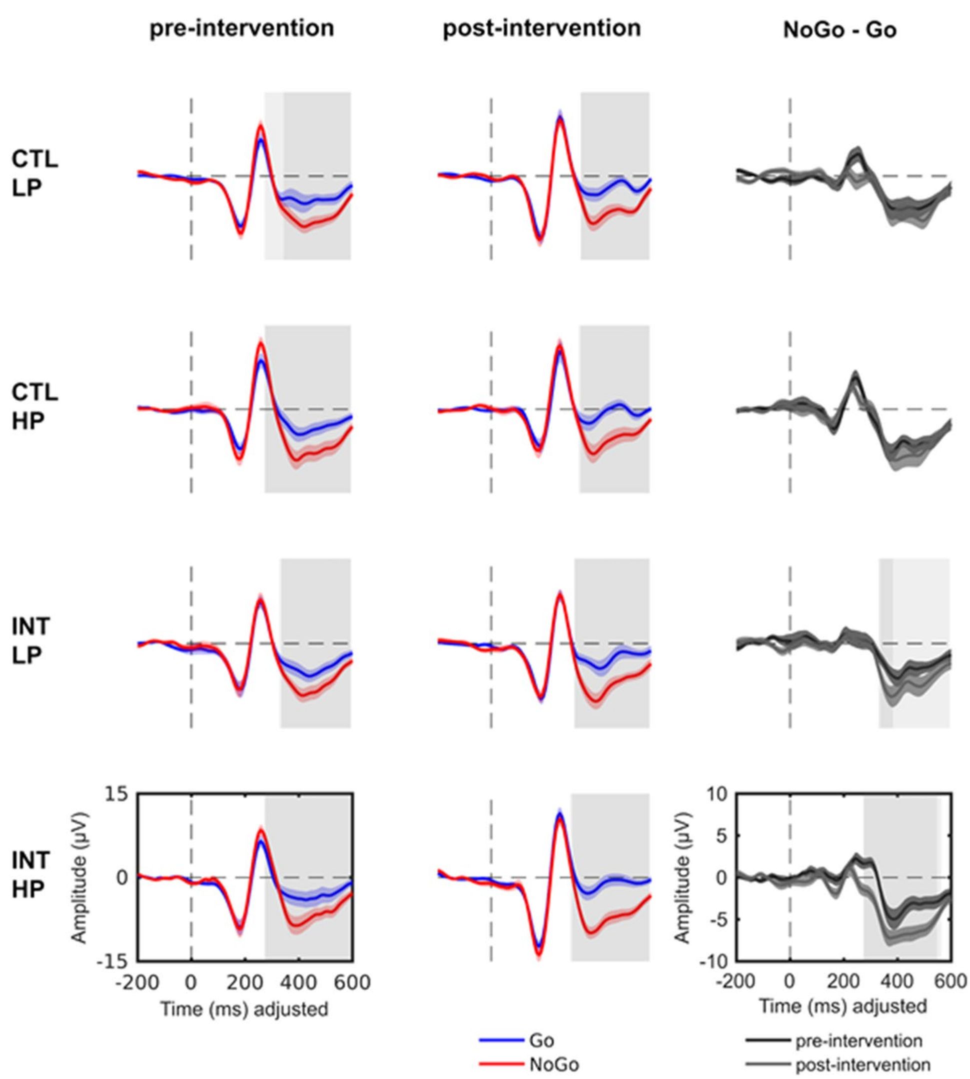

Fig. 3 Stimulus-locked ERP in the Go/NoGo task from frontal electrodes (F3/F4) and averaged by study groups (i.e., low-performing (LP) and high-performing (HP) groups, intervention (INT) and control (CTL) groups) and stage (i.e., pre- and post-intervention). Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p<0.05$ light gray; $p<0.01$ dark gray)

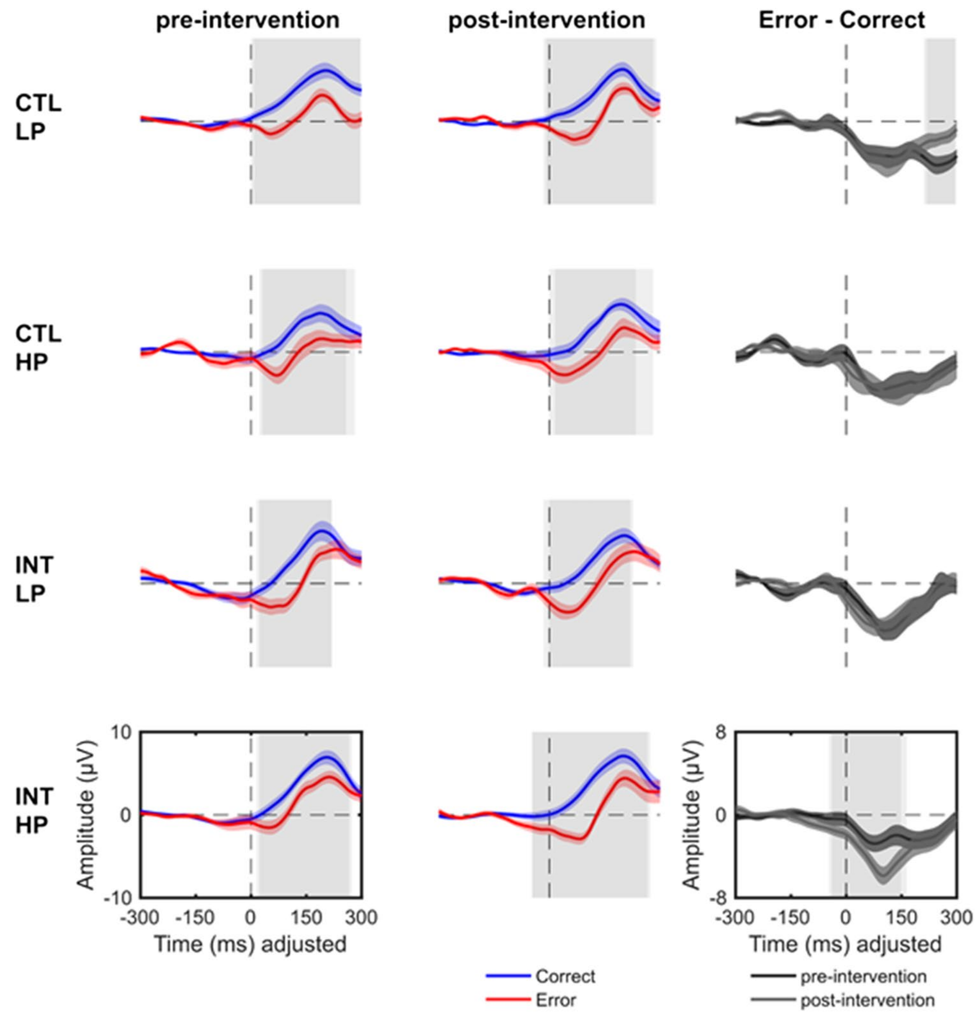

Fig. 4 Response-locked ERP in the Go/NoGo task from frontal electrodes (F3/F4) and averaged by study groups (i.e., low-performing (LP) and high-performing (HP) groups, intervention (INT) and control (CTL) groups) and stage (i.e., pre- and post-intervention). Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p<0.05$ light gray; $p<0.01$ dark gray)

between intervention sessions for the INT-HP group (Wilcoxon s-r test; $Z=2.65$; $p=0.008$; $r=0.55$), indicating a larger area in the post-intervention stage.

3.4.3 Time–Frequency

For stimulus-locked ERSP in the theta band (i.e., 4–7 Hz), nonparametric bootstrap permutation *t*-tests (tested in the time window ranging from [0, 600] ms) indicated differences in power between Go and NoGo trials. This was true for all groups and intervention stages (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 5). Specifically, the result showed that theta power was significantly larger for NoGo than for Go trials. However, training-related permutations on NoGo-Go ERSP yielded no significant disparities in the power difference between task conditions in the post-intervention, for all groups.

Regarding response-locked ERSP, nonparametric bootstrap permutation *t*-tests (tested in the time window ranging from [-50, 300] ms) indicated differences in power between correct and error responses. This was true for all groups and intervention stages (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 6), except for the children in the INT-LP group in the pre-intervention stage. Significant comparisons showed larger theta power in the error responses. Subsequent training-related permutations revealed significantly larger differences in power between responses in the post-intervention session, for the INT-HP group (bootstrapping: $p<0.05$ light gray; $p<0.01$; Fig. 6). However, further characterization analysis (time window: [-40, 140] ms) did not confirm differences in the theta effect between intervention stages for the INT-HP group (Wilcoxon s-r test; $Z=1.64$; $p=0.101$; $r=-0.34$).

3.4.4 Relationship Between K-BIT and Go/NoGo Effects of Intervention

To examine the association of training-related changes in the Go/NoGo task to changes in intelligence, a training gain

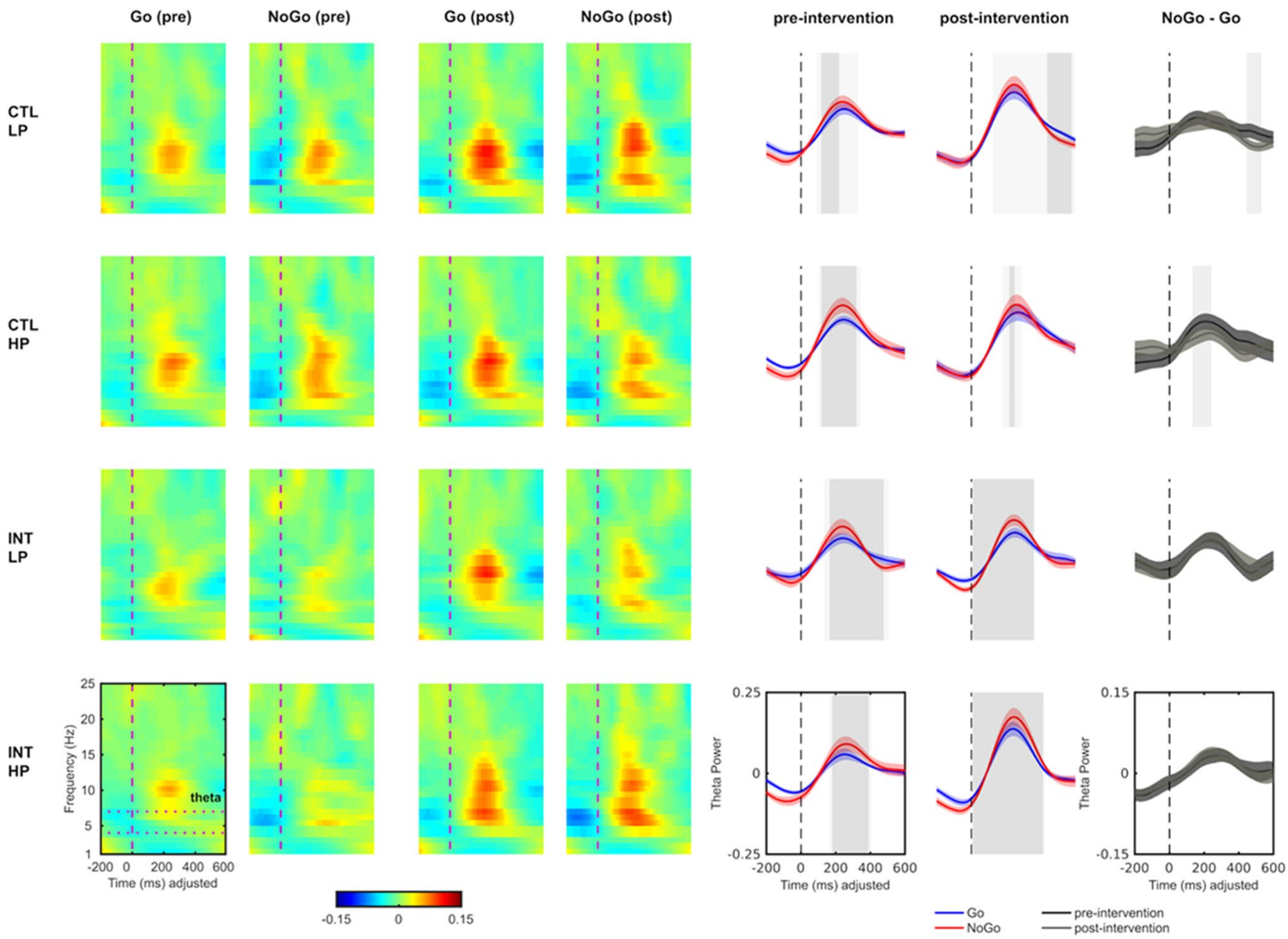

Fig. 5 Stimulus-locked ERSP in the Go/NoGo task from frontal electrodes (F3/F4) and averaged by study groups (i.e., low-performing (LP) and high-performing (HP) groups, intervention (INT) and control (CTL) groups) and stage (i.e., pre- and post-intervention). The first four columns represent spectrograms at all frequencies from 1 to 25 Hz. The last three columns represent theta band power (4–7 Hz) for Go and NoGo trials and theta power difference between these conditions in the pre- and post-intervention stages. Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p < 0.05$ light gray; $p < 0.01$ dark gray)

index ((post – pre)/sd pre) was computed and a Spearman correlation analysis was conducted between gains. The gain index was calculated using the area of the ΔERP for the Go/NoGo task and the raw score and proportion of correct responses for K-BIT. Results revealed a significant gain correlation between Go/NoGo and K-BIT only for the INT-HP group. Specifically, an increase in posttraining gains in ΔN2 (i.e., larger negativity area) was significantly related to a decrease in gains in the raw score (rho = 0.50, $p = 0.048$) and marginally related to a decrease in gains in the proportion of correct responses (rho = 0.48, $p = 0.061$). Further analyses were conducted to explore potential associations between pre-intervention fluid intelligence performance and training-related gains in ΔN2. Results indicated a significant correlation between the raw score in K-BIT at the pre-intervention stage and gains in ΔN2 (rho = -0.54, $p = 0.032$) and a marginal correlation between the proportion of correct responses at the pre-intervention stage and gains in ΔN2 (rho = -0.44, $p = 0.085$).

4 Discussion

The aim of the present study was to evaluate the impact of a cognitive training intervention on CC abilities of preschoolers from poor homes from both neural and cognitive perspectives. Different intervention menus were administered to children according to their initial performance in an inhibitory control task. Four groups were formed according to performance, i.e., high and low performers for intervention and control conditions. Before and after the intervention, the neural activity of children performing a Go/NoGo task was recorded. Results revealed training effects on brain activity associated with the Go/NoGo task. In particular,

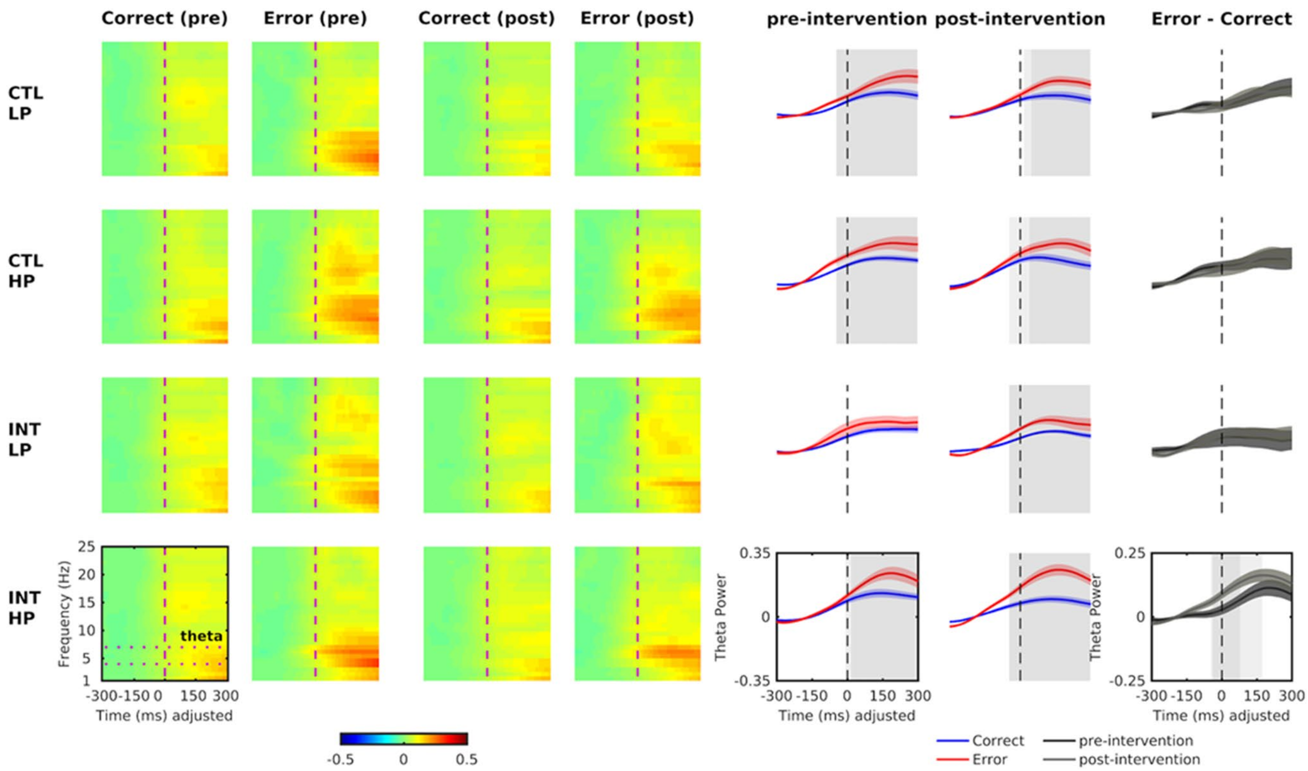

Fig. 6 Response-locked ERSP in the Go/NoGo task from frontal electrodes (F3/F4) and averaged by study groups (i.e., low-performing (LP) and high-performing (HP) groups, intervention (INT) and control (CTL) groups) and stage (i.e., pre- and post-intervention). The first four columns represent spectrograms at all frequencies from 1 to 25 Hz. The last three columns represent theta band power (4–7 Hz) for correct and error responses and theta power difference between these conditions in the pre- and post-intervention stages. Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p<0.05$ light gray; $p<0.01$ dark gray)

brain activity findings revealed significant changes in conflict-related activity at frontal scalp electrodes in both INT groups. Also, children from the INT-HP group showed changes in matrices performance of K-BIT test, indicating transfer effects of training to fluid intelligence. This pattern of results could not be associated with differences between children on task-related variables in the pre-intervention stage nor the sociodemographic characteristics, since the study groups showed homogeneity in both aspects. Thus, the verified changes in cognitive performance and neural activity might be associated with the intervention. In line with other intervention studies conducted with children between 2–6 years of age (Espinet et al., 2013; Gouet et al., 2018; Liu et al., 2015; Pozuelos et al., 2019; Rueda et al., 2005, 2012), the results of this study suggest (1) that neural activity underlying CC-demanding task can be modified through the implementation of cognitive training aimed at optimizing CC control skills, and (2) that effects in CC-related neural activity are observed after a relatively short intervention (e.g., 10–12 sessions over a period of two to three months).

The results of this study provide evidence regarding differences in the impact of training in distinct levels of analysis in a low-SES background sample. There are no studies, except for Neville et al. (Neville et al., 2013) and Romeo et al. (Romeo et al., 2018), that include different levels of organization in the impact analysis of training activities in poor contexts. Our findings are particularly important given the documented CC disparities among children from low-SES backgrounds when considering different levels of analysis (D'Angiulli et al., 2008, 2012; Hampton Wray et al., 2017; Kishiyama et al., 2009; St. John et al., 2019; Stevens et al., 2009) and their contributing role to learning and memory abilities (Allan et al., 2014; Garon et al., 2008; Luciana & Nelson, 1998).

The results of this study address two complementary aspects. The first one is the importance of considering the neural level in the analysis of cognitive interventions, given that training-related effects were found only at such a level. In this sense, techniques with high temporal resolution such as EEG may reveal subtle differences in neural mechanisms at each stage of information processing that otherwise could not be captured at the behavioral level. In addition, the neural evidence in the study of childhood poverty could eventually contribute to the comprehension of the mechanisms underlying plasticity and the identification of adequate intervention activities and sufficiently sensitive transfer tasks to promote cognitive development in children from low-SES homes. Second, in the present study, different performance profiles were generated, and an individualized and adaptive cognitive training intervention was implemented for each group. Results revealed that training-related effects were not equal for all performance groups. This finding suggests the importance of supporting efforts in the design of intervention to explore how individual characteristics influence mechanisms of plasticity in children from low-SES homes.

The first hypothesis that we proposed was that training menus will produce changes associated with a better efficiency in CC. Despite the fact that effects were verified only at the neural level, results provided evidence in favor of this hypothesis since intervention effects were associated with increased conflict-related activity at frontal scalp electrodes. The second hypothesis was that both intervention performance groups will show comparable post-intervention effects. The hypothesis was sustained since changes were observed for children who participated in both intervention activities, although with differences according to the variable considered (i.e., children from both INT groups exhibited changes in stimulus-locked activity, whereas only the INT-HP group showed changes in response-locked activity). Particularly, increased midfrontal ΔN2 was observed in the INT-LP and -HP groups following training. Additionally, it was observed an increased midfrontal ΔERN in the INT-HP group, which was accompanied by an effect in the power of the theta band (i.e., larger differentiation in power between correct and incorrect trials following training). The training effects observed on the ΔN2 are similar to some reported intervention studies aimed at optimizing inhibitory control skills in preschool children, which found larger amplitude in midfrontal ΔN2 following training, in tasks that required using control to solve an information interference (Flanker task: Pozuelos et al., 2019; Rueda et al., 2005, 2012)), or to override a response (Go/NoGo task: (Liu et al., 2015)). Likewise, other studies with children, adults, and older adults, have previously shown changes in conflict-related electrophysiological indices following cognitive interventions aimed at improving CC abilities related to resisting interference from distracting information (Millner et al., 2012; Stevens et al., 2008), or attentional shifting (Espinet et al., 2013; Olfers & Band, 2018), and following an intervention on multiple cognitive domains (Gajewski & Falkenstein, 2012). The effect of training on brain activity was similar to the changes observed in more developed samples as was reported in other studies. The pattern of brain activation observed in ΔERN resembles a more adult-like activation. However, changes in ΔN2 following training might be a bit more difficult to interpret. Developmental studies examining conflict-related ERP trajectories indicate that the amplitudes of the N2 (e.g., NoGo) and the ERN change linearly from childhood to adolescence (review studies: Hoyniak, 2017; Lo, 2018)). Mostly, it is observed that the ERN and ΔERN increase their amplitudes (e.g., Davies et al., 2004; Kim et al., 2007; Torpey et al., 2012; Wiersema et al., 2007)), whereas the high conflict N2 (e.g., NoGo) becomes less negative (e.g., Johnstone et al., 2005; Jonkman, 2006; Lamm et al., 2006)). Nonetheless, studies that analyze ΔN2 trajectories in conflict-inducing tasks have shown contrasting evidence, reporting more negative (Abundis-Gutiérrez et al., 2014; Checa et al., 2014; Cragg et al., 2009), less negative (Johnstone et al., 2005; Jonkman, 2006), or stable (Johnstone et al., 2007) amplitudes with age.

It is plausible that the nature of training impact may reflect changes on mechanisms engaged in processing conflict in the different trial types (i.e., Go and NoGo trials, correct and error responses). As expected, the occurrence of conflict in the task modulated the effect of both stimulus-locked and response-locked activity in all groups and stages. The N2, ERN, and event-related theta oscillations showed larger amplitudes in trials involving conflict (i.e., with NoGo stimuli and error response). These findings are consistent with prior studies using conflict-inducing tasks, which had reported that preschool children show modulation of mid-frontal negativity and theta power in the stimulus-locked and response-locked activity as a function of the occurrence of conflict (Abdul Rahman et al., 2017; Abundis-Gutiérrez et al., 2014; Canen & Brooker, 2017; Checa et al., 2014; Grammer et al., 2014; Lahat, 2010; Torpey et al., 2012). Source localization evidence and neuroimaging studies have suggested that midfrontal effects observed on the N2, ERN, and theta power during conflict-inducing tasks are likely generated by the activation of ACC (Debener, 2005; Jonkman et al., 2007; Lamm et al., 2006; Luu et al., 2003; Nieuwenhuis et al., 2003; van Veen et al., 2001; Veen & Carter, 2002). There is evidence indicating that the ACC is involved in detecting the occurrence of conflict, evaluating current demands for control, and deciding how to allocate control (Botvinick et al., 2001; Shenhav et al., 2013). Specifically, the activity of ACC has been associated with afferent and efferent information, which would be used to monitor conflict information (integration and evaluation processes), and to the specification of the optimal intensity of control resources that need to be allocated during the performance in the task (Shenhav et al., 2013). Given that the difference score of neural activity (i.e., ΔN2, ΔERN, and event-related theta effect) might reflect processing unique to high conflict, training effects on brain function could be linked to a better efficiency of mechanisms involved to distinguish between low and high conflict trial types. More specifically, larger amplitude after training in these components could be indicative of an incremented need for either the detection (monitoring processes) of and/or signaling (specification processes) for increased CC in high conflict trials compared to low conflict trials.

The impact of intervention on different electrophysiological indices could reflect specific changes on the engagement of CC during conflict processing. In this sense, there is evidence suggesting that midfrontal N2, ERN, and concomitant theta oscillations seem to index a common and dissociable functioning in both the activity within CC-related brain networks (e.g., Cavanagh & Frank, 2014; Downes et al., 2017; Iannaccone et al., 2015; Luu et al., 2004; Nigbur et al., 2011; Trujillo & Allen, 2007)) and the responsibilities in supporting CC (e.g., Garavan, 2002; Harper et al., 2014; Lo, 2018; Van Noordt et al., 2016; Wang et al., 2020; Yamanaka & Yamamoto, 2010; Yeung & Cohen, 2006)). There is evidence indicating that the amplitude of the ERN and N2 is sensitive to different aspects of the task. For example, it has been observed that the difficulty of the task modulates the amplitude of the N2 through the manipulation of trial-type probability (Bruin, 2002; Donkers & van Boxtel, 2004; Nieuwenhuis et al., 2003; Yamanaka & Yamamoto, 2010), or reaction time deadline (Benikos et al., 2013; Wessel, 2018), suggesting a need for increased CC (i.e., larger N2) when the response conflict or inhibitory needs are augmented. Contrarily, the amplitude of the ERN seems to be modulated when task instructions emphasize accuracy over speed (Gehring et al., 2018) or add a value/significance to errors (Simons, 2010), indicating a need for increased CC (i.e., larger ERN) when the level of performance is relevant to task goals. Conflict-monitoring theory posits that the N2 and ERN are elicited when there are several possible response choices that compete for control over the executed action, but these components would be exclusively sensitive to preresponse or postresponse conflict processing (Lo, 2018). In the context of the Go/NoGo task, preresponse conflict occurs when competing response tendencies are simultaneously activated (i.e., withholding and producing a response), which signal an increased CC need for controlling dominant response in favor of selecting the less dominant one, whereas postresponse conflict is determined by the detection of a mismatch between the represented correct response and the one made, which signals an increased need for CC for correcting the error in later performance. Thus, training-related effects in N2 and ERN components could reflect changes on conflict monitoring and/or control signal specification processes, at preresponse and postresponse stages, respectively.

In this study, training-related ΔERN effects were accompanied by changes in response-locked theta power. However, the nature of changes in the event-related theta could be partially differentiated from changes in the ERP component. Midfrontal theta activity has been linked to several ERP (e.g., ERN and N2) that are elicited by tasks that require the engagement of CC in the service of different goals (Cavanagh & Frank, 2014; Nigbur et al., 2011; Van Noordt et al., 2016). Although these ERP components have been related to CC, they represent a small portion of the dynamic and multidimensional space of neural activity recorded by EEG technique (Cohen, 2014). A large portion of this space can be captured through time–frequency analysis. In particular, the ERP captures only time-locked activity and phase-locked activity, whereas the time–frequency power measures time-locked activity regardless of whether it is phase-locked or non-phase-locked. There is evidence that the ERN emerges from phase locking of theta band EEG activity, but, following errors, the increase in non-phase-locked theta power is larger and longer-lasting than phase-locked theta power (Luu et al., 2004; Trujillo & Allen, 2007). In addition, previous evidence indicates that theta power is larger following conscious errors, while the amplitude of the ERN does not seem to show this modulation, possibly due to other frequency bands being involved in affecting their amplitude (Navarro-Cebrian et al., 2013; Wang et al., 2020). Thus, training effects on midfrontal theta power might reflect specific changes of the CC-related brain activity, other than those captured by changes on the ERP. Based on this evidence, it could be argued that children in the INT-HP group were the ones who had larger training-induced effects at the neural level because they showed changes on several brain activity markers related to different CC processing.

At the cognitive level, all groups showed significant changes in the Go RT variable, which decreased in the post-intervention stage. Changes in RT were verified within a range of median values consistent with those observed in the literature for the Go/NoGo task in preschool children (Abdul Rahman et al., 2017; St. John et al., 2019). A decrease in RT could be related both to an effect of practice (Benikos et al., 2013) and to individual changes in development. The latter is consistent with some evidence suggesting that during development children would significantly improve speed to resolve conflicts in inhibitory control tasks (e.g., Go/NoGo and Flanker) (Bedard et al., 2002; Grammer et al., 2014; Johnstone et al., 2007; Kim et al., 2007; Lamm et al., 2006; Rueda et al., 2004). In the Stroop task, both LP groups (i.e., CTL-LP and INT-LP) showed an increase in the proportion of correct trials in the post-intervention stage. The effect size was large in both groups, but it was more pronounced in the INT-LP group. It should be noted that the dependent variable used for Stroop task was a composite of the general performance in the task, involving blocks with congruent, incongruent and mixed trials. Hence, this result may be associated with changes in inhibitory control and/or cognitive flexibility processes.

Based on the available evidence it was expected to find transfer of training to fluid intelligence. Both trained (i.e., INT-LP, INT-HP) and untrained (i.e., CTL-LP) children showed an increase in raw score of matrices subscale, however, children in the INT-HP group also showed an increase in the proportion of correct responses. The proportion of correct responses involved both raw score and errors, indicating that children in the INT-HP group not only achieved a greater number of correct trials but also committed fewer errors in the post-intervention stage. This result replicates previous evidence indicating that fluid reasoning abilities may be improved with training in basic (e.g., inhibitory control, and working memory) and more complex cognitive skills (i.e., planning and problem-solving), which are intended as significant contributors to fluid intelligence (Jaeggi et al., 2011; Neville et al., 2013; Pozuelos et al., 2019; Rueda et al., 2005). Further examination revealed that performance in the pre-intervention stage and improvements in the post-intervention stage in fluid intelligence were associated with conflict-related activity gains for children in the INT-HP group. Specifically, larger gains in ΔN2 were associated with both lower increment in fluid intelligence performance in the post intervention stage, and higher performance in fluid intelligence in the pre-intervention stage. In other words, children with worse performances in fluid intelligence in the pre-intervention stage were the ones who showed a larger increase in fluid intelligence and lower gains in ΔN2. In contrast, those with better performances in fluid intelligence in the pre-intervention stage, showed lower increments in fluid intelligence but higher gains in ΔN2. Thus, children who had better performances in both inhibitory control and fluid intelligence in the pre-intervention stage were the ones who showed larger gains in preresponse conflict-related activity. This would suggest that the amount of influence of training on preresponse conflict-related activity may have been related to the performance in both inhibitory control and fluid intelligence in the pre-intervention stage—something that future studies must confirm. In sum, these results could be consistent with the notion that more complex processes such as fluid reasoning involved more basic processes related to CC (Demetriou et al., 2008; Garon et al., 2008). In line with this interpretation, there is evidence indicating associations between intelligence performance and efficiency in CC processing at multiple levels of analysis (Hilger et al., 2017a; Rueda, 2018; Unsworth et al., 2014). Most notably, EEG (Langer et al., 2012) and fMRI (Hilger et al., 2017b) data indicated that the centrality degree and the nodal efficiency of regions within brain networks supporting CC (e.g., the dorsal ACC) are positively associated with intelligence performance.

Intervention effects were not equal for all children. Training-induced neural changes were verified in both performing groups (i.e., INT-LP and INT-HP). Such effects were found to be greater in the group of children who had higher performance in the inhibitory control task (i.e., Stroop) at the pre-intervention stage (i.e., INT-HP). Further, children in the INT-HP group showed transfer effects of training at the cognitive level in an untrained task (i.e., K-BIT). One possible interpretation of this pattern of results could be that the children with better initial performance in the inhibitory control task were more able and efficient to apply resources and processes suited to the training task, and thus demonstrate changes at both neural (i.e., conflict-related activity) and cognitive (i.e., reasoning abilities) levels. The fact that inhibitory control changes were verified only at the neural level could be due to that children's functioning was already high, making it difficult to reach higher performance levels (Karbach et al., 2017). Another possibility would be to relate the differential pattern of results with the specific training menus designed for the inhibitory control activity of each group. In this sense, children with worse performance in inhibitory control may need more practice at easier levels of the inhibitory control activity. Despite the complexity of training activity designed for the low-performing group was lower than that designed for the high-performing group, perhaps it was not easily enough to promote performance flexibility, and consequently may enable eventual greater training effects. It is also plausible that greater neural effects in the group of children with better baseline performance in the inhibitory control task could be partly explained by the fact that the INT-HP group contained twice more girls than boys. In fact, cognitive gender differences have been reported in multiple cognitive tasks, levels of analysis and ages (Guillem & Mograss, 2005; Lynn & Irwing, 2004; Miller & Halpern, 2014). Further, there is data in preschool children, suggesting that girls overperform boys in tasks that required inhibition of a motor response (e.g., Go/NoGo task) (Wiebe et al., 2012) and that they may improve their conflict-related neural activity with training easier (Liu et al., 2015). Nevertheless, there is evidence indicating that family, culture and SES influence gender differences, changing or reversing cognitive disparities. Therefore, it is necessary to continue examining it in future designs, also including nonbinary measurements of gender identity that account for the full range of gender experiences (Rubin et al., 2020). Furthermore, it is also possible to consider that the activities proposed in the intervention were not efficient enough to induce changes according to the different performance possibilities of the intervention groups. In addition, the characteristics of the assessment task (i.e., Go/NoGo) could have influenced the findings (Benikos et al., 2013; Simpson & Riggs, 2006). Specifically, it contained many repetitive trials and was lengthy, which could have differently affected motivation and sustained attention during performance in both intervention groups (i.e., INT-LP and INT-HP).

The present study was carried out in an educational setting. The advantages of this sort of approach have been indicated in previous studies (Hermida et al., 2015; Segretin et al., 2014). Nonetheless, the analysis of training-related impact from different levels of organization (e.g., neural and cognitive) is not usually applied outside laboratory settings, because of the added burden of noise and logistics. In this study, a mobile EEG technology and method were added to the impact evaluation of a cognitive intervention as a neural activity measure. Although previous intervention studies have included EEG measures (Espinet et al., 2013; Gouet et al., 2018; Neville et al., 2013; Pozuelos et al., 2019; Rueda et al., 2005, 2012), to our knowledge, this is the first study to assess the training-related neural impact of preschool children from poor homes outside a laboratory setting.

This study has some limitations that are necessary to consider for future research. The intervention design did not allow elucidating the degree to which training-induced impacts could be attributed to individual characteristics or the training menus implemented given that each performance group received only their corresponding menus. Thus, the potential underlying mechanisms of effects need to be further investigated. It is possible that the low to moderate explanatory power of the intervention can be related at least partially, to the sample size. In addition, because of the gender disbalances in the groups of our study, it is also necessary to advance in the exploration of potential gender effects, since recent findings showed a post-intervention effect on the N2 component only in girls (Liu et al., 2015). Furthermore, the performance groups were formed based on a different cognitive task (i.e., Stroop) than the one employed for training impact evaluation (i.e., Go/NoGo). The results could have shown other profiles if the groups' classification and training had been implemented according to the performance in the Go/NoGo task. This consideration is based on the fact that cognitive-related paradigms (e.g., Flanker versus Go/NoGo) can generate different patterns of neural activity and performance efficiency (Hoyniak, 2017). The results at the cognitive level seem not to show a clear benefit of the training compared to the control condition. Such an aspect could be related to the training activities proposed to the intervention groups, which consisted in three different tasks, with two not tapping CC specifically, and characterizing the majority of the training sessions. Future experiments should consider the inclusion of more specific and intense CC activities (Shawn Green et al., 2019), as well as a finer groups classification including the performance on multiple CC-demanding tasks. The analysis of training-related impact involved two EEG sessions (i.e., pre- and post-intervention). Although short-term effects can be evaluated through this design, future studies would benefit from including the possibility to analyze long-term effects. Also, to verify whether changes at the level of neural activity would be associated with subsequent behavioral changes (Benasich et al., 2008; Brito et al., 2016, p. 201) information about the same and other aspects related to cognitive development (e.g., academic performance) through the school records should be included in such longitudinal designs.

The findings of this work contribute to speaking about the importance of applying methods of neural assessment in contexts outside laboratory settings and studying the impact of cognitive interventions on preschool children living in poor contexts. Specifically, results of this study suggest that (1) it is possible to transfer electroencephalographic evaluation methodologies in contexts other than the laboratory, trough mobile EEG technology, and (2) the neural activity related to CC of preschool children with no history of developmental disorders can be modified through cognitive training activities adjusted to individual differences in baseline performance. Finally, the findings presented here suggest that training interventions based on cognitive characteristics of children (i.e., baseline performance) and the impact evaluation of training activities at multiple levels of analysis (i.e., neural and cognitive) could lead (1) to a better characterization and identification of individual resources and needs, adequately considering the diversity of cognitive development trajectories and (2) to appropriately identifying what levels of analysis (e.g., neural, cognitive, and behavioral) can support and guide possible training-induced changes of children living in poor contexts.

Appendix 1: Supplementary Information of "Conflict-Related Brain Activity after Individualized Cognitive Training in Preschoolers from Poor Homes"

Materials and Methods

Participants

Participants attended a public kindergarten in Buenos Aires City. The school schedule was full-time, including naptime and three meals (breakfast, lunch, and an afternoon snack). Informed consent was obtained from parents or legal caregivers. The sample size was reduced due to the following causes: (a) data loss due to that not all children participated in the intervention phase ($n=7$), (b) data loss due to not completing both evaluation phases ($n=13$), and (c) data loss due to the presence of excessive artifacts in the EEG signal ($n=16$).

Study Design and General Description of Procedures

All activities were implemented in a table of 1.30×0.5 m, in a kindergarten room. In both the evaluation and intervention sessions, a maximum of three children was seated at the table. A separator was used to visually isolate the evaluation space in order to reduce eventual interferences and distractions during the performance of tasks and activities.

Go/NoGo Task

The Go/NoGo involves the recruitment of inhibitory control processes that include the ability to suppress dominant or automatic responses (Hoyniak, 2017; Johnstone et al., 2005). This task comprises two types of stimuli that occur one at a time: one is called Go, associated with the activation of behavioral response, and another is called NoGo, associated with the inhibition of such response. Participants must give a behavioral response each time the Go stimulus appears and must not respond when the NoGo stimulus appears. Go stimuli are presented more frequently than NoGo to make the Go response dominant and increase the difficulty of the task.

In the version used for this study, stimuli were presented on a laptop monitor (15.6″) at a screen resolution of 1366 × 768 pixels with a refresh rate of 60 Hz, and responses were collected with a standard keyboard. All stimuli were generated using PsychoPy toolbox (v3.0) (Peirce, 2007) for Python programming language (v2.7, Python Software Foundation, www.python.org). The computer was placed at a distance of about 40 cm away from the child. The stimuli were images of characters from the Pacman and Angry Birds games. Four NoGo-type stimuli and one Go-type stimulus were employed. The Go stimulus was the Pacman/bird character and the NoGo stimuli were the ghosts/pigs. Five colors were used for the bodies of the images (RGB values; Pacman/bird: yellow = 253, 217, 47; ghost/pig: Blue = 47, 140, 253; green = 48, 253, 72; orange = 253, 135, 48; and magenta = 250, 47, 253). All stimuli were presented in the center of the screen and occupied a visual angle of 8.84 in the vertical and horizontal plane on a gray background (RGB values, grey = 150, 150, 150).

EEG Recording

Neural activity was recorded using the EMOTIV EPOC + system (www.emotiv.com). The EEG signal was digitized at 128 Hz and 0.16–43 Hz band pass-filtered during the recording. Impedances were measured prior to recording and kept according to EPOC calibration at the threshold between *yellow* and *green*. Go/NoGo stimuli presentation and recording were carried out on the same computer. Recordings were retrieved from the same python program using our own functions (Pietto et al., 2018a, b).

EEG Data Processing

EEG data was processed on EEGLAB (version 13.5.4b) MATLAB (version R2016a) toolbox.

Event-Related Spectral Perturbation

For oscillatory analyses, EEG data of each participant were bandpass-filtered using an FIR filter of size 1 Hz over the frequency range 1–30 Hz. As a result, for each record, 30 different signals were generated, each of which was filtered at 1 Hz size. Hilbert transform (hilbert.m) was applied to extract the instantaneous power values. For spectrograms, power data were calculated separately for each 1 Hz band. For theta band analysis, power data were calculated for frequency range 4–7 Hz. The EEG data preprocessing was the same as used for event-related potentials, and it was completed in the following order: (1) 0.1–30-Hz band-pass filtering, (2) ICA component removal, (3) 1-Hz band filtering, (4) signal rereferencing, (5) envelope calculation from the Hilbert transform, (6) signal segmentation into epochs, (7) epoch rejections, and (8) frontal ROI calculation.

Child Stroop Task

The Stroop-like task for children (Davidson et al., 2006) involves inhibitory control and cognitive flexibility processes. The task was performed on a tablet Samsung Galaxy Tab E with a 9.6″ screen at a distance of about 30 cm away from the child. In the version used for this study (Goldin et al., 2014), responses were collected through buttons located on the sides of the screen. The task comprised three conditions organized in different blocks. In the congruent block, a strawberry would appear to the left or right side and the child was instructed to press the button located on the same side of the stimulus. In the incongruent block, a slice of watermelon would appear on the left or right side and the child was instructed to press the button located on the opposite side of the stimulus. In the mixed block, both stimuli (strawberry and watermelon) would appear randomly on both sides and the child had to respond according to the previous rules. Each trial began with the presentation of the target that remained visible for 1500 ms. During that interval, the child could press the corresponding button on one side of the tablet. The intertrial interval was 1500 ms. A fixation cross was displayed on the center of the screen for the entire trial duration. The first and second blocks comprised 12 trials plus 6 trials each, while the third block included 24 trials with no practice trials. The dependent variable for this task included the proportion of correct trials (correct vs. total trials).

The experimental data were collected to classify children into two groups, i.e., high-performing (HP) group and low-performing (LP) group according to their baseline performances in the task. This classification was aimed at identifying task performance profiles in order to apply different intervention schemes based on the complexity of the task and the activities each group was required to solve.

Children performing below the median of the correct trials were assigned to the LP group, while children above the median were assigned to the HP group.

Kaufman Brief Intelligence Test

Children completed the Matrices Subscale of the Kaufman Brief Intelligence (K-BIT; (Kaufman, 1990)) to assess the far-transfer effect of the intervention to nonverbal abilities.

Sociodemographic Information

A total socioeconomic score (SES score) was determined, based on the following criteria: (1) higher parental educational level (values between 0 and 12: no education = 0, incomplete primary school = 1, primary school degree = 3, incomplete high school = 6, high school degree = 9, incomplete technical studies = 9, complete technical degree = 10, incomplete college studies = 10, college degree or higher = 12), (2) higher parental occupation level (values between 0 and 12: unoccupied = 0, unstable worker = 1, unskilled laborer = 2, skilled laborer = 4, small autonomous producer = 6, administrative employee = 7, technical professional = 8, small business owner = 10, professional = 11, company manager = 12), (3) dwelling characteristics (values between 3 and 12 based on type of house, floor, ceiling, and external wall materials, access to drinking water, bathroom with sanitation system, and home property), and (4) overcrowding (values between 0 and 9 based on the amount of people and rooms: 1 to 2 people per room = 9, 2.01 to 4 people per room = 6, 4.01 to 6 people per room = 3, and more than 6.01 per room = 0). A home was considered to have UBN if at least one of the following indicators was identified: (1) inappropriate dwelling (housing), (2) absence of a waste discharge system in the household, (3) absence of water supply pipes inside the house or land, (4) overcrowding (more than 3 people per room), (5) living unfavored neighborhoods, (6) presence of school-aged children not attending any educational system, and (7) head of household with incomplete secondary schooling with more than four dependents.

Additionally, the questionnaire included items to describe children's general health condition and history of developmental disorders, and they were used as the study's exclusion criterion. The information collected was referred to the pre-, peri-, and postnatal health of the child, such as medical care and iron nutrition during pregnancy, prematurity, weight, size and cephalic perimeter at birth, loss of consciousness due to head injury, surgery operations, and prolonged hospitalizations.

Intervention Program

Training Group Activities A research assistant ensured the children's engagement with the task and assisted them when difficulty was experienced. For example, if children showed difficulty accomplishing the task, they were encouraged to continue practicing, when the task was misunderstood, trainers repeated the instructions as many times as necessary, and when an impulsivity-related error was detected, children were taught to wait and to think carefully before acting. Finally, activities followed two main principles, i.e., the inclusion of new challenges with increasing difficulty and repeated practice (Diamond, 2012). Participants in the training group were given three activities designed for cognitive training. Each training activity was given for two consecutive sessions in the order of inhibitory control activity, working memory activity, and planning activity.

The *inhibitory control activity* consisted of Stroop-like task, where children had to press a button (right or left) when a specific stimulus was given. Stimuli were displayed one at a time (a plane or a rocket of different colors) on one side of the tablet screen, pointing to the right or to the left. The child was required to recognize the direction of the stimulus and give a response depending on different task conditions. In the congruent condition, a yellow plane or rocket appeared and the child was instructed to press the button in accordance with the direction in which the plane was pointing. In the incongruent condition, a red plane or rocket appeared and the child was instructed to press the opposite button to which the stimulus was pointing at. Finally, in the mixed condition, both yellow and red stimuli appeared randomly, and the child was instructed to respond according to previous rules. In advanced levels, some distractors appeared (other flying objects, such as paper planes, balloons, or paper planes of other colors). Before congruent and incongruent conditions, the rules were explained with a short video. Task difficulty was manipulated by the time available to pressing the corresponding button and the presence of distractors.

The *working memory activity* (Lopez-Rosenfeld et al., 2013) was designed to measure working memory for visual patterns and was based on the self-ordered pointing task (SOPT) (Luciana & Nelson, 1998; Petrides & Milner, 1982). Various stimuli (i.e., cards with different pictures and colors) were displayed within a 4×3 rectangular grid, and children had to choose one of them. After this, the stimuli disappeared and reappeared in a different order. The child was invited to choose a different card than the one selected in the preceding intra-trial decisions. The trial ended when all cards had been selected or when the child selected an incorrect card (one that had previously been selected). In each trial, an equal number of stimuli appeared. The number and difficulty of the cards increased as the children won more trials. The activity began with children having to remember a low number of cards (three). If the child answered correctly three consecutive times, the number of items was increased to four. If they answered wrong in four consecutive trials, the level decreased by one.

According to Cragg and Nation study (Cragg & Nation, 2007), adults and children committed more errors in the SOPT task when it contained abstract items than when the objects carried meaning. In the version used for this study, the activity began with simple images (e.g., plain color background and a cartoon character) and a low number of stimuli to recall and advanced to more complex and numerous items (e.g., items with images containing a plain color background and a cartoon character in an abstract shape). Finally, this activity allowed the use of mnemonic rules or strategies to remember all stimuli, which was usually performed by the subjects sorting the list of objects into categories (e.g., if there were two items with a red background and another two with a blue background, one could first select the two blue items and then two the red ones). Children were encouraged to use this strategy when they started to experience difficulties.

The *planning activity* was an adaptation of the Dog–Cat–Mouse task (Klahr, 1985). A square was displayed with a diagonal and three "houses" distributed in the four corners. Three characters were placed in one house each in different corners and the aim was to guide them to their houses in a determined number of moves. Children were given three rules: (1) the characters could be moved one at a time and could only be moved to an empty corner, (2) they could only be moved through the "paths" (sides and diagonal), and (3) characters could not share house. As the activity progressed, the number of movements required to reach the objective increased, thereby increasing the path length. In addition to the path length, other difficulty parameters were controlled, including the use of the diagonal (which would make the work easier), the number of possible paths, the number of possible moves in the first movement (the probability of making a bad choice decreases with two possible moves compared to three), and the search depth (the number of necessary moves to guide the first character to its house). The activity consisted of two phases. A free exploration phase, in which trials were considered correct if the child guided all characters to their respective houses with an unlimited number of moves, and a restricted movement phase, in which the child was given a number of movements in which the trial had to be solved. After three consecutive errors, the activity stopped and started again from where the session had started.

Control Group Activities The control group (CTL) completed three games downloadable for free from Google Play Store. The Bubble Shooter required the child to eliminate a bunch of bubbles placed at the top of the screen, directing and shooting a bubble of the same color from the bottom. In the Painting activity, the child was invited to paint a wide variety of animals, cars, and objects with the fingers. Finally, the dots activity consisted of a series of colored circles that disappeared when the child connected adjacent circuits with a similar color. These activities were not expected to generate training effects in participants due to the fact that they were not created for cognitive training purposes and no evidence suggests that they involve or train the cognitive processes that were proposed for the intervention group.

Intervention Activities for Performance Groups Based on the performance groups created after the pre-intervention session, different and specific training menus were designed for each group, which differed in difficulty. Such differences are described below for each activity.

For the inhibitory control activity, two training menus were designed with four levels each. Each level was started again from the beginning when eight consecutive errors were committed. The level advance criteria differed between groups. In order to advance to level 2, the LP group had to complete the congruent and incongruent conditions (60 trials each); whereas the HP group had to perform both conditions (40 trials each) and 20 mixed trials. To reach the following levels, the LP group had to complete the congruent and incongruent conditions, and perform 40 mixed trials (120 trials in total); and the HP group had to accomplish both conditions and 50 mixed trials (130 trials in total). In addition, the number of trials per condition, trial times, and position orientation and the number of distractors were taken into account, for the design of activity menus. In the LP group, congruent and incongruent conditions included a larger number of trials compared to the HP group. Further, in the congruent condition, the stimulus (i.e., plane or rocket), 80% of the time, appeared on the opposite side to which it was pointing at, whereas in the incongruent condition, the stimulus appeared 80% of the time on the same side to which it was pointing at. For the HP group, the stimulus position was randomly established. This was done in order to extend the time to which the LP group was exposed to inhibitory control trials before facing the mixed condition, giving a smoother difficulty slope for the LP group than for the HP group. For the LP group, the stimulus was displayed for 9000 ms in the first level, and then diminished gradually to 3000 ms. For the HP group, the stimulus was displayed for 9000, and decreased gradually to 3000 ms between levels 1 and 3, while it was presented for 4000 ms and decreased to 2000 ms between levels 2 and 4. In both groups, distractors were presented in levels 3 and 4.

For the working memory activity, two training menus were designed. A set of trials with growing difficulty was defined for each performance group considering the number of items to recall, their complexity, and the number of possible chunks. Children in both performance groups were instructed in the use of memory strategy by the research assistant. For the LP group, the items comprised two features, i.e., the background color (six different themes) and a character (five different themes).

The background color was considered the grouping feature for the clustering strategy. The increasing difficulty was organized in levels. The first one consisted of two items with the same color where, if the child responded four consecutive trials correctly, he or she would advance to the next level with 3 stimuli, one of them of color A and the other two of color B, providing the chance to advance in the number of items to recall while still using the "assistance" of the clustering strategy. The next level had three stimuli to recall with three different background colors. This sequence was repeated for the next levels with a growing number of items and number of chunks. If two consecutive errors were committed, the activity regressed by one level. Overall, the scheme involved recalling 2 to 6 items. For the HP group, the items comprised three features, including color (6), shape (6), and a character (five different themes). The shapes chosen were complex (e.g., octagons and pentagons), which were intended to be much more difficult to name and give meaning to than the background colors. Increasing difficulty levels were steeper for the HP group compared to LP group. For example, in the LP group, levels with four stimuli went from an A-A-B-B color sorting to an A-A-A-B configuration and then to A-B-C-D; in the HPG there was only one level with four stimuli, meaning that children did not have intermediate configurations between levels with four and five stimuli. In addition, children in the HP group were required to complete five trials to level up. This scheme involved recalling 2 to 7 stimuli.

For the planning activity, two training menus were designed, each with different difficulty levels composed of some of the problem parameters mentioned in the previous section. For the LP group, difficulty levels were based on the path length, the number of possible moves in the first movement, the use of the diagonal, the search depth, and whether the first movement was anti-intuitive or not. All difficulty levels were ordered based on the path's length. For example: for trials of three movements, five levels were created by combining each parameter of the problem and were ordered according to the literature (Klahr, 1985), from easiest to most difficult. For the HP group, difficulty levels were based only on the path length, leaving only six levels for each phase.

Data Analysis

All statistical procedures were carried out using MATLAB (version R2016a).

Preliminary Analysis Data of each dependent variable were subjected to normality and homoscedasticity analysis, via the Kolmogorov–Smirnov test and Levene's test, respectively.

Baseline Homogeneity Analysis. Between-group contrast analyses were performed between the study groups (i.e., CTL-LP, CTL-HP, INT-LP, and INT-HP) in the pre-intervention session, regarding (1) neural activity (i.e., ΔN2 and ΔERN for ERP and ERSP), (2) cognitive performance (i.e., RT go, RT after error, false alarms, and efficiency), and (3) sociodemographic characteristics (i.e., SES variables and UBN indicators). For this analysis, the nonparametric Kruskal–Wallis test was applied, which is used for comparing two or more independent samples (i.e., the four study groups). Chi-square analyses were conducted when the sociodemographic variables were not continuous. The performance groups were formed based on a different cognitive task (i.e., Stroop) than the one employed for training impact evaluation (i.e., Go/NoGo). Thus, the proportion of correct trials performed in the Stroop task and the cognitive variables of the Go/NoGo task were used to compare baseline CC abilities between HP and LP groups. For this analysis, the nonparametric Mann–Whitney U-test was applied. Also, effect sizes were calculated. The *r* value was used for the Mann–Whitney U-test, the Epsilon-squared (E^2_r) was calculated for the Kruskal–Wallis test, and Cramer's *V* was used for chi-square statistics (Tomczak & Tomczak, 2014).

Analysis of Training Progression Eventual training-induced changes were analyzed in function of the training progression level in the inhibitory control activity. Children were classified into two groups, i.e., low- and high-increasing, according to their final performance in the training activity. Children performing between levels 1 and 2 were assigned to the low-increasing group, while children performing between levels 3 and 4 were assigned to the high-increasing group. Additionally, the standardized gain scores ((post—pre) / sd pre) were calculated for the low-increasing and high-increasing groups within each intervention group (i.e., INT-LP, INT-HP), in order to compare the size of training-related gains across all significant measurements. For this analysis, the nonparametric Mann–Whitney U-test was applied.

Results

Normality and Homoscedasticity Assumptions

The Kolmogorov–Smirnov test indicated that 27 dependent variables did not meet the normality assumption (i.e., $p < 0.05$; see Tables 1 and 2), whereas Levene's test for homogeneity of variance between study groups revealed that only two dependent measures did not meet the homoscedasticity assumption (i.e., $p < 0.05$; see Tables 3 and 4).

Descriptive Analysis of Sociodemographic Characteristics

The median values of the variables involved in the SES score show the presence of low education (incomplete high

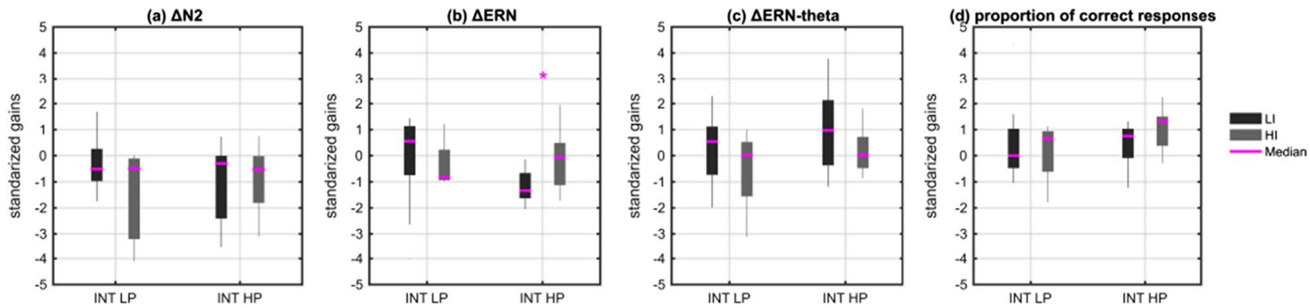

Fig. 7 Boxplots of standardized gains in the Go/NoGo task (**a**, **b**, **c**) and K-BIT (**d**) for each INT group (i.e., low-performing (LP) and high-performing (HP) groups) averaged by progression in the intervention phase (i.e., low-increasing (LI) and high-increasing (HI) groups). The asterisk denotes significant differences ($p < 0.05$) between LI and HI groups

school = 6) and occupation (skilled laborer = 4) levels in the sample. On the other hand, the medians obtained in housing (12) and overcrowding (1 to 2 people per room = 9) show maximum values (see Table 5).

Baseline Homogeneity Analysis

Stroop Task. The proportion of correct trials to total trials was significantly different between LP and HP groups (LP group: median = 0.46; min–max = 0.23–0.58; HP group: median = 0.66; min–max = 0.54–0.93; Mann–Whitney test; $Z = 7.37$; $p < 0.001$; $r = 0.83$). Additionally, the performance of LP and HP groups did not differ between study conditions (i.e., control vs. intervention) (Mann–Whitney test; LP group: $Z = 1.57$, $p = 0.11$; HP group: $Z = 0.28$, $p = 0.781$, $r = 0.01$).

Go/NoGo Task. The results of contrasts between performance groups showed significant differences for the variable efficiency (HP group: median = 0.47; min–max = -0.10–0.72; LP group: median = 0.33; min–max = -0.22–0.66; Mann–Whitney test; $Z = 2.66$, $p = 0.008$, $r = 0.29$) and RT Go (HP group: median = 579.68; min–max = 410.83–719.10; LP group: median = 604.79; min–max = 479.27–774.89; Mann–Whitney test; $Z = 2.17$, $p = 0.030$, $r = 0.24$), which suggested that the HP group was faster and more efficient than the LP group in the Go/NoGo task. Not significant differences were observed for false alarms (HP group: median = 0.34; min–max = 0.09–0.82; LP group: median = 0.37; min–max = 0.02–0.73; Mann–Whitney test; $Z = 0.53$, $p = 0.597$, $r = 0.06$) and relative RT after error (HP group: median = 1.06; min–max = 0.76–1.28; LP group: median = 1.05; min–max = 0.93–1.27; Mann–Whitney test; $Z = 1.29$, $p = 0.197$, $r = 0.14$).

Training Impact by Progression in the Intervention Stage

Contrast analyses were conducted on variables and groups with significant differences between intervention stages (Fig. 7). The variable ΔN2, which had shown differences in both INT-LP and INT-HP groups, showed similar gains in both groups regardless of the final performance (INT-LP—low-increasing group: median = -0.50, min–max = -1.75–1.69, $n = 15$; high-increasing group: median = -0.49, min–max = -4.11–0.01, $n = 3$; Mann–Whitney test; $U = 18$, $p = 0.654$, $r = -0.20$; INT-HP—low-increasing group: median = -0.29, min–max = -3.56—0.73, $n = 9$; high-increasing group: median = -0.52, min–max = -3.10–0.75, $n = 12$; Mann–Whitney test; $U = 52$,

Table 1 Tests of normality of the sociodemographic information (NES score variables and no. of UBN indicators) for each study group

DV	Group	Statistic	df	p*
Education	CTL-LP		21	
	CTL-HP		20	
	INT-LP		19	
	INT-HP		24	
Occupation	CTL-LP		21	
	CTL-HP		20	
	INT-LP		19	
	INT-HP		24	
Housing	CTL-LP		21	
	CTL-HP		20	
	INT-LP		19	
	INT-HP		24	
Overcrowding	CTL-LP		21	
	CTL-HP		20	
	INT-LP		19	
	INT-HP		24	
NES score	CTL-LP		21	
	CTL-HP		20	
	INT-LP		19	
	INT-HP		24	
No. UBN indicators	CTL-LP		21	
	CTL-HP		19	
	INT-LP		18	
	INT-HP		22	

*Lilliefors significance correction

Table 2 Tests of normality of all measures of the tasks (Go/NoGo, Stroop, and K-BIT) for pre- and post-intervention phases and for each study group

		Pre-intervention			Post-intervention		
Task DV	Group	Statistic	df	p	Statistic	df	p*
Go/NoGo task							
False alarms	CTL-LP	0.090	21	0.926	0.197	21	0.031
	CTL-HP	0.227	20	0.008	0.110	20	0.746
	INT-LP	0.154	19	0.270	0.160	19	0.216
	INT-HP	0.163	24	0.094	0.146	24	0.203
Efficiency	CTL-LP	0.098	21	0.864	0.141	21	0.325
	CTL-HP	0.153	20	0.246	0.075	20	0.994
	INT-LP	0.126	19	0.585	0.120	19	0.665
	INT-HP	0.152	24	0.155	0.123	24	0.437
RT Go	CTL-LP	0.172	21	0.102	0.109	21	0.735
	CTL-HP	0.126	20	0.547	0.141	20	0.359
	INT-LP	0.098	19	0.901	0.144	19	0.360
	INT-HP	0.102	24	0.743	0.101	24	0.757
RT after error	CTL-LP	0.100	21	0.836	0.129	21	0.473
	CTL-HP	0.215	20	0.017	0.127	20	0.529
	INT-LP	0.145	19	0.359	0.284	19	<0.001
	INT-HP	0.146	24	0.200	0.100	24	0.762
ΔN2	CTL-LP	0.145	21	0.281	0.093	21	0.909
	CTL-HP	0.132	18	0.550	0.145	18	0.393
	INT-LP	0.196	18	0.063	0.137	18	0.486
	INT-HP	0.105	21	0.780	0.145	21	0.287
ΔN2-theta	CTL-LP	0.114	21	0.669	0.097	21	0.871
	CTL-HP	0.157	18	0.279	0.114	18	0.768
	INT-LP	0.148	18	0.362	0.143	18	0.410
	INT-HP	0.128	21	0.481	0.123	21	0.543
ΔERN	CTL-LP	0.147	19	0.338	0.163	19	0.197
	CTL-HP	0.145	18	0.391	0.078	18	0.992
	INT-LP	0.095	17	0.950	0.146	17	0.429
	INT-HP	0.129	23	0.404	0.128	23	0.409
ΔERN-theta	CTL-LP	0.099	19	0.892	0.138	19	0.427
	CTL-HP	0.120	18	0.691	0.115	18	0.763
	INT-LP	0.153	17	0.352	0.153	17	0.354
	INT-HP	0.096	23	0.840	0.119	23	0.532
Stroop task							
Proportion of correct trials	CTL-LP	0.159	16	0.338	0.169	16	0.250
	CTL-HP	0.118	18	0.723	0.126	18	0.620
	INT-LP	0.137	15	0.626	0.173	15	0.257
	INT-HP	0.089	20	0.947	0.094	20	0.914
K-BIT							
Raw score	CTL-LP	0.167	20	0.143	0.140	20	0.374
	CTL-HP	0.175	14	0.282	0.169	14	0.333
	INT-LP	0.157	18	0.275	0.165	18	0.214
	INT-HP	0.123	19	0.618	0.178	19	0.110
Errors	CTL-LP	0.092	20	0.932	0.144	20	0.325
	CTL-HP	0.195	14	0.157	0.272	14	0.005
	INT-LP	0.162	18	0.236	0.141	18	0.437
	INT-HP	0.193	19	0.060	0.166	19	0.173

Table 2 (continued)

Task DV	Group	Pre-intervention			Post-intervention		
		Statistic	df	p	Statistic	df	p*
Proportion of correct responses	CTL-LP	0.093	20	0.922	0.148	20	0.289
	CTL-HP	0.121	14	0.829	0.134	14	0.704
	INT-LP	0.149	18	0.356	0.116	18	0.748
	INT-HP	0.174	19	0.131	0.244	19	0.004

*Lilliefors significance correction

Table 3 Tests of homogeneity of variance between study groups for the sociodemographic information (SES score variables and no. of UBN indicators)

DV	Statistic	df1	df2	*p*
Education	0.261	3	76	0.853
Occupation	1.873	3	76	0.141
Housing	0.805	3	75	0.495
Overcrowding	2.772	3	76	0.047
SES score	1.143	3	75	0.337
No. of UBN indicators	2.531	3	76	0.063

$p=0.915$, $r=0.04$). Thus, the changes shown by the children in the ΔN2 may not be associated with the level of progress obtained during the intervention. The variable ΔERN, which had shown differences in the INT-HP group, showed increased gains in children with a lower increasing level during the intervention (INT-HP—low-increasing group: median = -1.34, min–max = -2.05–0.15, $n=11$; high-increasing group: median = -0.07, min–max = -1.72–1.95, $n=12$; Mann–Whitney test; $U=28$, $p=0.021$, $r=0.58$). Hence, the change shown by the children in the ΔERN could be associated with the level of increase in the intervention. Specifically, children with a lower level of increase (i.e., low-increasing group) were those who evidenced a greater proportion of change. The variable ΔERN-theta, which had shown differences in the INT-HP group, did not show gain differences between low-increasing and high-increasing groups (INT-HP—low-increasing group: median = 0.97, min–max = -1.78–3.78, $n=11$; high-increasing group: median = 0.02, min–max = -0.86–1.81, $n=12$; Mann–Whitney test; $U=44$, $p=0.186$, $r=-0.33$). Thus, the change in ΔERN-theta may not be associated with the final performance. Finally, the variable proportion of correct responses of the K-BIT test, which had shown differences in the INT-HP group, showed similar gains between low-increasing and high-increasing groups, suggesting that the training effect observed in the proportion of correct responses would not be associated with the progress reached in the training activity (INT-LP—low-increasing group: median = 0, min–max = -1.03–4.32, $n=9$; high-increasing group: median = 0.66, min–max = -1.78–1.13, $n=10$; Mann–Whitney test; $U=23$, $p=0.071$, $r=0.41$).

Table 4 Tests of homogeneity of variance between study groups in all measures of the tasks (Go/NoGo, Stroop, and K-BIT) for pre- and post-intervention phases

Task DV	Pre-intervention				Post-intervention			
	Statistic	df1	df2	*p*	Statistic	df1	df2	*p*
Go/NoGo task								
False alarms	0.864	3	80	0.464	0.978	3	80	0.407
Efficiency	0.332	3	80	0.802	0.664	3	80	0.577
RT Go	0.787	3	80	0.505	0.138	3	80	0.937
RT after error	0.496	3	80	0.686	0.153	3	80	0.927
ΔN2	1.414	3	74	0.246	0.510	3	74	0.677
ΔN2-theta	0.135	3	74	0.939	2.435	3	74	0.071
ΔERN	0.275	3	73	0.843	0.738	3	73	0.533
ΔERN-theta	0.296	3	73	0.828	1.131	3	73	0.342
Stroop task								
Proportion of correct trials	3.490	3	65	0.021	1.265	3	65	0.294
K-BIT								
Raw score	0.663	3	67	0.577	0.804	3	67	0.496
Errors	0.567	3	67	0.639	0.731	3	67	0.537
Proportion of correct responses	0.469	3	67	0.705	0.639	3	67	0.592

Appendix 2

Table 5 Sociodemographic characteristics of participants (SES score variables)

Variables	*N*	Median	Min–Max
SES score	80	28	17–40
Education	81	6	1–12
Occupation	81	4	1–10
Housing	80	12	6–12
Overcrowding	81	9	0–9

N sample size, *Min* minimum score, *Max* maximum score

Appendix 3

Table 6 Sociodemographic characteristics of participants (SES score variables and UBN indicators) and assessment measurements (Go/NoGo, Stroop, and K-BIT) in the pre-intervention phase, according to study groups

	CTL-LP	CTL-HP	INT-LP	INT-HP	X^2	*p*	Effect size
SES variables							
Education	9	9	6	6	2.37	0.500	0.127
Occupation	4	4	4	4	0.81	0.847	0.136
Housing	9	12	12	9	4.91	0.178	0.091
Overcrowding	6	9	9	9	4.70	0.195	0.165
SES score	28	31	28	28	5.40	0.145	0.184
UBN indicators							
1(x)	0.05	0.05	0.22	0.05	5.16	0.161	0.254
2(x)	0.05	0	0.06	0	2.18	0.536	0.165
3(x)	0.29	0.26	0.06	0.32	4.42	0.220	0.235
4(x)	0.48	0.05	0.17	0.32	10.48	0.015	0.362
5(x)	0.24	0.16	0.11	0.09	2.10	0.551	0.162
6(x)	1	0.89	1	0.86	5.24	0.155	0.256
No. of UBN indicators	2	1	1	1	2.04	0.565	0.072
Go/NoGo							
False alarms	0.38	0.30	0.31	0.35	2.16	0.539	0.035
Efficiency	0.33	0.49	0.38	0.46	7.63	0.054	0.219
RT Go	596.22	579.26	616.50	581.42	5.22	0.156	0.188
RT after error	1.06	1.08	1.01	1.05	5.02	0.170	0.117
ΔN2	-83.08	-112.78	-128.78	-97.03	0.95	0.813	0.144
ΔN2-theta	0.70	1.01	0.78	0.75	0.74	0.864	0.111
ΔERN	-58.69	-42.61	-61.10	-53.94	0.74	0.863	0.010
ΔERN-theta	2.24	2.46	1.71	4.21	1.56	0.669	0.021
Stroop							
Proportion of correct trials	0.47	0.66	0.44	0.66	55.15	<0.001	0.716
K-BIT							
Raw score	11	11	11.50	13	2.95	0.400	0.042
Errors	15	14	13	17	3.77	0.287	0.054
Proportion of correct responses	0.42	0.44	0.46	0.44	0.124	0.989	0.002

The medians of each variable for each study group are reported

1 head of the household with incomplete secondary schooling with more than four dependents, *2* school-aged children not attending any educational system, *3* inappropriate dwelling, *4* absence of a waste discharge system in the household, *5* overcrowding, *6* disadvantaged neighborhoods, *(x)* chi-square test for independence

Appendix 4

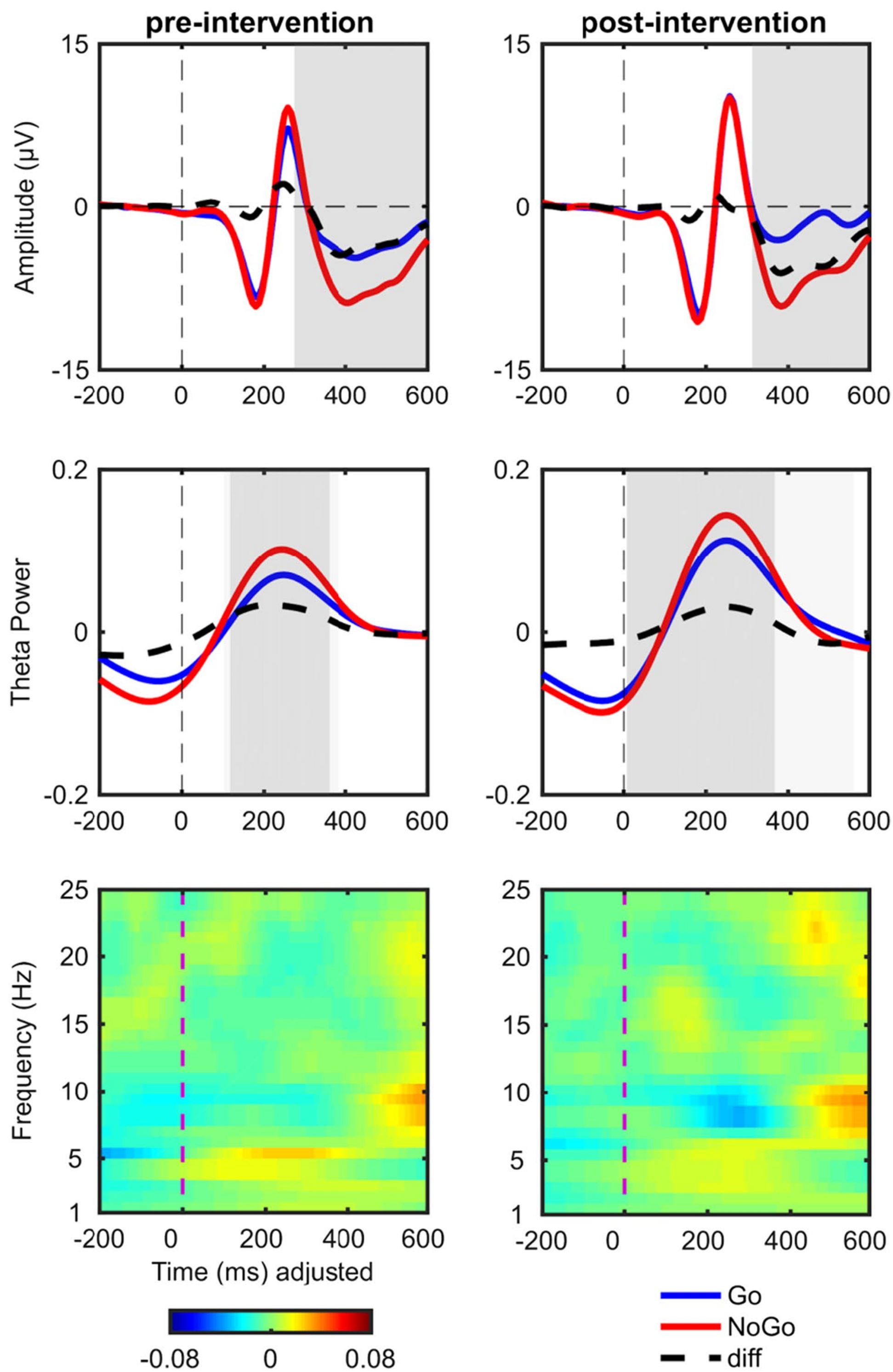

Fig. 8 Stimulus-locked for the ERP and ERSP domains in the Go/NoGo task from frontal electrodes (F3/F4), averaged by the entire sample and stage (i.e., pre- and post-intervention). Top graphs represent ERP for Go and NoGo trials and amplitude difference waveform between these conditions. Middle graphs represent ERSP in the theta band (4–7 Hz) for Go and NoGo trials and theta power difference between these conditions. Bottom graphs represent subtracted spectrograms between task conditions at all frequencies from 1 to 25 Hz. Nonparametric bootstrap permutation *t*-tests revealed significant differences in amplitude and power between Go and NoGo conditions for both intervention stages. Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p < 0.05$ light gray; $p < 0.01$ dark gray)

Appendix 5

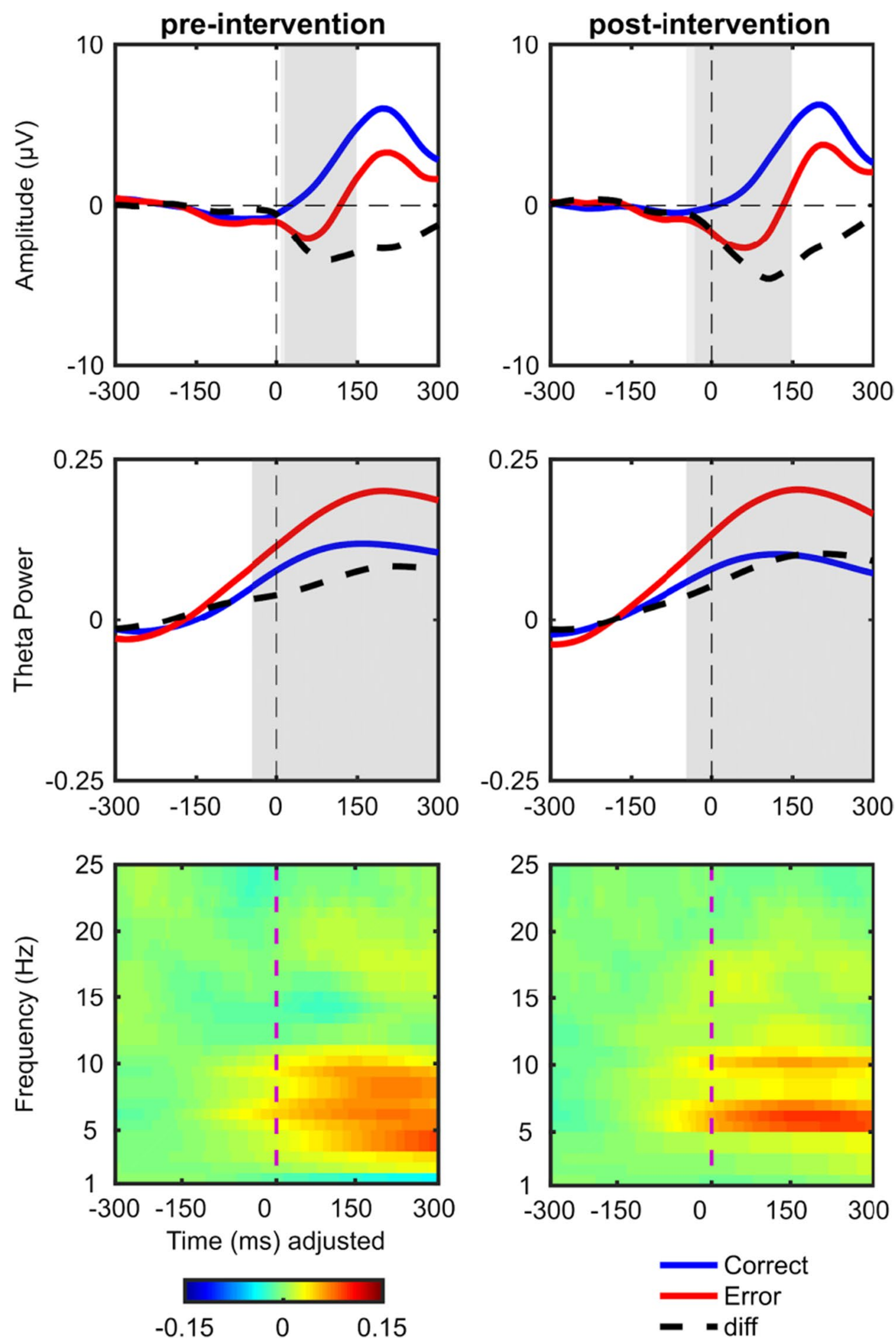

Fig. 9 Response-locked for the ERP and ERSP domains in the Go/NoGo task from frontal electrodes (F3/F4), averaged by the entire sample and stage (i.e., pre- and post-intervention). Top graphs represent ERP for correct and error trials and amplitude difference waveform between these conditions. Middle graphs represent ERSP in the theta band (4–7 Hz) for correct and error trials and theta power difference between these conditions. Bottom graphs represent subtracted spectrograms between task conditions at all frequencies from 1 to 25 Hz. Nonparametric bootstrap permutation *t*-tests revealed significant differences in amplitude and power between correct and error conditions for both intervention stages. Areas that showed a significant difference in amplitude in at least 5 consecutive samples (~40 ms) are shadowed ($p < 0.05$ light gray; $p < 0.01$ dark gray)

Appendix 6

Table 7 Descriptive statistics for pre- and posttest intervention phases for all the measures of interest (Go/NoGo, Stroop, and K-BIT) and for each study group

			Pre-intervention					Post-intervention				
Task DV	Group	*n*	Mean	SD	Mdn	Q25	Q75	Mean	SD	Mdn	Q25	Q75
Go/NoGo task												
False alarms	CTL-LP	21	0.40	0.18	0.38	0.30	0.54	0.40	0.12	0.40	0.36	0.43
	CTL-HP	20	0.35	0.15	0.30	0.27	0.40	0.38	0.15	0.37	0.27	0.46
	INT-LP	19	0.33	0.19	0.31	0.15	0.47	0.33	0.15	0.37	0.21	0.43
	INT-HP	24	0.36	0.17	0.35	0.26	0.41	0.32	0.12	0.28	0.21	0.42
Efficiency	CTL-LP	21	0.30	0.20	0.33	0.15	0.46	0.26	0.19	0.32	0.11	0.38
	CTL-HP	20	0.43	0.20	0.49	0.30	0.57	0.42	0.22	0.44	0.24	0.54
	INT-LP	19	0.34	0.21	0.38	0.25	0.50	0.34	0.16	0.36	0.24	0.47
	INT-HP	24	0.43	0.18	0.46	0.29	0.57	0.43	0.19	0.45	0.31	0.58
RT Go	CTL-LP	21	611.4	59.7	596.2	565.6	657.7	567.4	57.6	571.8	532.3	614.8
	CTL-HP	20	572.9	50.9	579.3	530.3	610.7	510.5	63.6	495.8	471.8	554.6
	INT-LP	19	613.0	69.5	616.5	580.4	649.5	553.4	62.4	557.0	525.5	600.3
	INT-HP	24	581.7	73.5	581.4	539.8	637.7	538.5	62.4	549.1	498.1	576.2
RT after error	CTL-LP	21	1.07	0.08	1.05	1.02	1.11	1.03	0.08	1.03	0.99	1.12
	CTL-HP	20	1.07	0.11	1.08	1.04	1.14	1.05	0.08	1.05	1.00	1.08
	INT-LP	19	1.03	0.08	1.01	0.96	1.07	1.11	0.12	1.10	1.07	1.12
	INT-HP	24	1.06	0.07	1.05	1.03	1.11	1.11	0.09	1.10	1.04	1.15
ΔN2	CTL-LP	21	-114.0	142.1	-83.1	-221.2	-17.1	-137.7	131.7	-114.9	-239.0	-30.4
	CTL-HP	18	-137.3	107.5	-112.8	-216.8	-53.5	-155.4	121.5	-141.6	-268.6	-86.0
	INT-LP	18	-97.2	85.1	-128.8	-151.9	-50.0	-159.5	138.8	-170.8	-209.5	-85.6
	INT-HP	21	-109.0	128.5	-97.0	-181.9	-36.2	-209.9	108.1	-205.8	-263.3	-130.3
ΔN2-theta	CTL-LP	21	0.77	1.66	0.70	-0.66	1.64	0.630	2.11	0.57	-0.76	2.29
	CTL-HP	18	1.31	1.62	1.01	-0.26	2.93	0.51	1.63	0.80	-0.24	1.78
	INT-LP	18	0.87	1.97	0.78	-0.46	1.76	1.03	1.03	1.18	0.19	1.91
	INT-HP	21	0.94	1.59	0.75	-0.47	2.25	1.08	1.57	0.87	0	2.30
ΔERN	CTL-LP	19	-56.5	78.4	-58.7	-84.4	-10.0	-68.1	64.4	-46.3	-100.0	-24.5
	CTL-HP	18	-52.9	65.0	-42.6	-87.2	-22.7	-65.4	91.6	-59.4	-123.1	-15.6
	INT-LP	17	-60.5	68.8	-61.1	-100.3	-18.6	-69.7	70.1	-71.4	-100.4	-17.8
	INT-HP	23	-41.4	81.5	-53.9	-101.6	10.2	-91.0	75.2	-87.1	-135.2	-48.3
ΔERN-theta	CTL-LP	19	2.75	4.35	2.24	-0.74	5.84	2.74	3.94	3.31	-0.26	5.01
	CTL-HP	18	3.19	4.51	2.46	-0.30	7.26	3.12	4.86	3.30	-0.09	7.89
	INT-LP	17	1.85	5.67	1.71	-0.84	5.98	2.52	3.08	2.17	1.13	4.72
	INT-HP	23	3.39	4.38	4.21	0.99	6.40	5.84	4.13	5.74	3.10	9.18
Stroop task												
Proportion of correct trials	CTL-LP	16	0.46	0.09	0.47	0.40	0.52	0.58	0.14	0.62	0.47	0.66
	CTL-HP	18	0.68	0.12	0.66	0.58	0.75	0.70	0.16	0.70	0.63	0.82
	INT-LP	15	0.44	0.05	0.44	0.41	0.48	0.62	0.15	0.60	0.49	0.77
	INT-HP	20	0.66	0.08	0.66	0.62	0.71	0.66	0.10	0.66	0.60	0.73
K-BIT												
Raw score	CTL-LP	20	11.3	2.5	11.0	9.5	14.0	15.1	3.0	15.0	13.0	17.0
	CTL-HP	14	11.9	3.5	11.0	10.0	15.0	14.0	2.3	14.5	12.0	15.0
	INT-LP	18	11.1	3.6	11.5	10.0	13.0	13.9	3.4	13.5	12.0	18.0
	INT-HP	19	12.8	3.2	13.0	10.3	15.8	15.0	2.9	16.0	12.3	17.5

Table 7 (continued)

Task DV	Group	*n*	Pre-intervention Mean	SD	Mdn	Q25	Q75	Post-intervention Mean	SD	Mdn	Q25	Q75
Errors	CTL-LP	20	15.5	4.8	15.0	12.0	19.5	15.9	4.8	16.5	11.5	19.0
	CTL-HP	14	15.4	4.3	14.0	13.0	18.0	15.6	5.9	14.5	13.0	18.0
	INT-LP	18	14.0	3.7	13.0	11.0	17.0	16.4	5.9	16.0	12.0	21.0
	INT-HP	19	16.5	4.3	17.0	15.3	18.8	14.3	4.0	14.0	13.0	16.0
Proportion of correct responses	CTL-LP	20	0.43	0.09	0.42	0.38	0.49	0.49	0.07	0.50	0.45	0.53
	CTL-HP	14	0.44	0.12	0.44	0.37	0.52	0.48	0.09	0.48	0.41	0.52
	INT-LP	18	0.43	0.11	0.46	0.37	0.48	0.47	0.08	0.46	0.41	0.53
	INT-HP	19	0.44	0.10	0.44	0.39	0.47	0.52	0.09	0.53	0.47	0.55

Mdn median, *Q25* first quartile, *Q75* third quartile

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Data Availability The datasets analyzed during the current study data will be available upon publication in the GitHub repository (https://github.com/marcospietto/Piettoetal_Training-related-brain-activity-in-preschoolers).

Code Availability The code of the communication between the EMOTIV and the computer is available at https://github.com/mathigatti/Emotiv-Experiments.

Declarations

Ethics Approval All procedures included in the study followed national and international recommended research with children proceedings and norms and were reviewed and approved by the Institutional Review Board (CEMIC, Protocol Nos. 682 and 961).

Consent to participate Written informed consent was obtained from the parents.

Conflict of Interest The authors declare no competing interests.

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