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Enhancement of inhibitory control in a sample of preschoolers from poor homes after cognitive training in a kindergarten setting: Cognitive and ERP evidence

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ABSTRACT

Objective: Cognitive Control (CC) is a central aspect of self-regulatory development, which can be modulated by individual differences, the quality of experiences in several developmental contexts (e.g., home, school, community), and cognitive interventions. In particular, associations between childhood poverty and cognitive and neural aspects of CC have also been documented in recent years. Less evidence is available regarding the brain areas influence by cognitive intervention in children from poor homes. In the present study, we examined the impact of a computerized, cognitive training that was implemented at a kindergarten on inhibitory control performance by cognitive and EEG methods.

Methods: Children were trained weekly for 8 weeks and tested before and after the intervention using EEG recordings during a Go/NoGo task performance. Children in the intervention group (n = 24; 18 girls, mean age 5.32 ± 0.39 years) played games that tapped inhibitory control, working memory, and planning demands on a tablet, whereas those in the control group (n = 20; 7 girls, mean age 5.42 ± 0.27 years) played Internet free games with the same schedule.

Results: Electrophysiological measures related to performance of inhibitory control showed improvements only in the intervention group, and no differences were found in cognitive performance. Specifically, only the intervention group showed in increase in the frontal N2-effect; that is, there was larger differentiation between the amplitude of N2-NoGo and N2-Go in the post-test stage.

Conclusions: These results show: (a) that the implemented intervention modulated the neural resources related to inhibitory control processes, and (b) it is possible to implement portable neural methodologies in school settings to enhance the evaluation of cognitive training interventions by adding an EEG component.

1. Introduction

Cognitive Control (CC) is a central aspect of children's self-regulatory development that depends significantly on individual differences and the quality of early experiences. Broadly defined, CC refers to a complex set of cognitive processes associated with conscious inhibitory control and conflict monitoring [1]. These processes underlie adaptive, goal-directed behaviors that enable individuals to override more automatic or established thoughts and responses [2], and determine what is essential for self-regulatory development, academic learning, and social behavior [3–6]. CC is related to certain networks of brain structures, such as the fronto-parietal and the cingulo-opercular

Abbreviations: CC, Cognitive control; EFF, Efficiency scores; ERP, Event-Related Potential; EA, Executive Attention; FA, False alarms; RTs, Reaction Times; SES, Socioeconomic Status; TOL, Tower of London Task; UBN, Unsatisfied Basic Needs

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networks [7]. Higher efficient control processing is supported by small-world, control network architecture, that involves distributed brain nodes and short cuts that connect such nodes [8]. Specifically, control processes are implemented by a large set of distributed brain regions that communicate through long-range connections that involve the executive attention (EA) network and other frontal and posterior brain networks involved in the processing of cognitive and emotional processes [2,9,10]. The efficiency of CC is associated with the growth and development of involved brain networks. Despite important changes in both functional and structural connectivity of the EA network that take place during childhood, before age 9 children still show many local (short-range) connections [11,12], which suggests an organization related to their anatomical proximity [13]. This pattern is associated with children's performance in conflict tasks, which changes before the age of 7, and reach stability in late childhood (after the age of 10).

Likewise, the processing involved in CC differs greatly between individuals. Individual differences can be measured by different methods and instruments [14–17] at different levels of analysis (i.e., molecular, brain networks, cognition, behavioral). In particular, event-related potentials (ERP) can be used as a measure for exploring neural mechanisms that underlie individual differences in CC during development. For example, inducing conflict in inhibitory control tasks engaged EA and altered an electrophysiological response named N2 that occurred as early as 200 ms following the presentation of the stimuli [1,2]. This response has been associated with the activation of the EA network, and it is recorded on a set of scalp electrodes at the frontal midline. The amplitude of changes in the N2 component is related to performance in inhibitory control tasks from age 3 [1,11,18]. In particular, the N2 is larger when inhibition is correctly applied to the dominant incorrect response that can be produced, for example, by distracting information or a prepotent or automatic response.

Even though CC efficiency is associated with the development of specific brain networks, it can also be influenced by other factors related to individual differences and environmental experiences associated with the quality of the micro- and mesosystemic developmental contexts (e.g., homes and school). Because environmental factors are associated with family, and social contexts interact with individual factors to modulate cognition and behavior, it would be possible to develop specific training methods that can be used to influence/optimize underlying brain networks. Several training methods that target CC development have been designed and evaluated in the fields of developmental cognitive neuroscience. For instance, Rueda and colleagues [19] trained 4- 6-year-old children during five sessions over 2–3 weeks using different CC tasks. The trained group of children showed more adult-like responses in N2 and a distribution of the ERP effects during a flanker task similar to those expected during development. In a new study, the authors extended the training intervention by adding several new exercises, and they increased the number of sessions [20]. This experiment allowed them to replicate their results and showed that some of the training-induced changes remained 2 months after the completion of the training. In both studies, trained children showed higher performance in non-trained cognitive abilities such as fluid intelligence, which suggested that CC training was transferred to related higher-level abilities that were different from applied exercises. Further evidence emerged from a study that used a single commercial computer game based on the Go/No Go paradigm with preschool children. The intervention involved 12 sessions over 3 weeks. The N2 effect of the Go/No-go task was enhanced after training only for girls in the intervention group. In summary, the available evidence from EEG studies suggested that CC training influences the underlying brain networks and performance, and that gains can be achieved in a relatively short time and through the implementation of a single training task [20].

Additionally, it is well documented that adverse environmental experiences associated with poverty and low-socioeconomic status (SES) are related to changes in the development of different aspects of CC at different levels of analysis [21–30]. Several EEG studies have verified differences in ERP that were associated with different processes involved in CC demanding tasks in children from different SES backgrounds [31]. Electrophysiological patterns of children from poor or low-SES homes have been associated with reduced efficiency in abilities that require control over the interference in perception and to detect conflicts [32–36]. In some cases, ERP evidence showed associations between poverty or low-SES and neural processing even when behavioral differences did not emerge [32,33]. In other cases, disparities in control-related activity in childhood poverty were associated with performance in higher-cognitive domains, such as fluid intelligence [35]. For instance, Isbell and colleagues showed larger fronto-central differences between the amplitudes of responses associated with attended and unattended stories during an auditory attentional control task, which were also related to higher nonverbal IQ scores in children from low-SES families. The importance of this type of result is that it provides evidence from at least two levels of analysis (i.e., neural activation and cognitive performance) [36].

In addition, there is preliminary evidence that brain activity that underlies CC processes in children from poor or low-SES backgrounds can be modified through individual and two-generation intervention strategies. For instance, Neville and colleagues [37] applied an ERP auditory attentional paradigm to evaluate the impact of an 8-week, two-generation intervention (PCMC); this paradigm combined self-regulatory parental training with individual attentional intervention of children that optimized processes of CC in preschoolers from low-SES homes. Children who participated in PCMC groups had more gains than children who participated in the other two groups that were compared (individual attentional training alone and Head Start curriculum alone). Specifically, children in the PCMC intervention not only showed higher scores in both non-verbal intelligence and receptive language tasks, but also showed an increase in the neural response to relevant information in a task that involved processes linked to control attention. Preliminary evidence showed that the electrophysiological changes were related to polymorphic variations in a serotonin transporter [38]. In addition, reports by parents showed that their children exhibited greater social skills and had fewer behavioral problems, and the parents experienced less stress.

We found no previous studies that examined cognitive interventions aimed at optimizing CC performance for poor or low-SES children that used EEG technologies in a context other than the laboratory (e.g., school settings). Without diminishing the importance of laboratory-based interventions, there are advantages of carrying out interventions in the school context and by using instruments that allow the evaluation of their impact at different levels of analysis (i.e., neural, cognitive). Two of these advantages are: (1) the partial maintenance of the environmental conditions in which children develop their daily activities (i.e., partial naturalistic or ecological approaches); and (2) the possibility of implementing studies that require complex technology of neural evaluation with lower economic and logistical costs, which are important determinants in developing countries with financial instability for the scientific efforts. The goal of the present study was to design, implement, and evaluate a 2-month, 12-session intervention with individual activities aimed at promoting CC performance in 5-year-old children from poor homes. The impact evaluation included both neural and cognitive measures (i.e., an ERP Go/No Go paradigm), which were collected at the school using portable EEG methods. The proposed hypotheses are that CC training would: (1) promote participants' ability to suppress pre-potent or automatic responses, and (2) lead to changes in brain activity associated with CC processes, as indicated by the N2 signal.

2. Materials and methods

2.1. Study design

The data included in this manuscript are part of a larger study in which we implemented a computerized cognitive intervention based on games aimed at optimizing inhibitory control, cognitive flexibility, working memory, and planning processes [39,40]. We present here an evaluation of the impact of such intervention at the cognitive performance and EEG levels for a Go/No-go paradigm. A longitudinal quasi-experimental design was used in which a sample of kindergartners from poor homes was randomly assigned to control or intervention groups.

2.2. Participants

A total of 69 5-year-old children (40 girls, mean age in years: $M = 5.36$, SD = 0.33) participated in this study. Seven children were excluded from the analysis because of their history of neurological diseases, change of school before the end of the study, or high rate of absenteeism. Participants attended a public kindergarten in Buenos Aires and belonged to poor homes (poverty criteria: Unsatisfied Basic needs, see operational definitions below). Children had a full-time school schedule (8:45 a.m./04:00 p.m.), which included nap time and three meals (breakfast, lunch, and an afternoon snack). Parents or legal caregivers gave written consent to participate in the study. All procedures described in this manuscript followed national and international research procedures and norms, and they were reviewed and approved by the institutional IRB (CEMIC, Protocols N° 682, and 961).

2.3. Procedures

2.3.1. Sociodemographic and children information

A questionnaire used in previous studies by our research team [17,22] was administered to each mother or father at schools to identify home socioeconomic and living conditions. A total socioeconomic (NES) score was determined based on the following criteria: (1) higher parental educational level (values between 0 and 12 based on the following scale: no studies = 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 and more = 12); (2) higher parental occupation level (values between 0 and 12 based on the following scales: 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); (4) overcrowding (values between 0 and 9 based on the amount of people and rooms: 1–2 people per room = 9; 2.01–4 people per room = 6; 4.01–6 people per room = 3; and ≥ 6.01 per room = 0). A home was considered poor if at least one of the following indicators of Unsatisfied Basic Needs (UBN) were verified: (1) inappropriate dwelling (housing); (2) absence of waste discharge system in household; (3) overcrowding (more than 3 people per room); (4) presence of school-aged children who do not attend any educational system; and (5) head of household with incomplete secondary school, with more than four dependents. The questionnaire also included items aimed at identifying indicators of children´s general health condition and history of developmental disorders, sleep quality, physical activity, and nutrition. Sleep quality scores were 1–5 (5 = highest) based on onset, maintenance, somnolence, and breathing problems [41]. Nutrition score was computed using information about type of nutrients (i.e., energy, proteins, vegetables, fruits, and dairy) and amount of daily intake (i.e., breakfast, lunch, snack, dinner, and three snacks per day). Finally, physical activity was computed in a dichotomous way with the information about the presence or absence of sport activity outside of school practice (presence = 1; absence = 0).

2.3.2. Cognitive and EEG measures

The Go/NoGo task involved inhibitory control processes that were assumed to tap the ability to suppress pre-potent or automatic responses [40]. The task consisted of not responding to a particular stimulus in a context of rapid responses to similar frequent stimuli. The processes involved in this task have been associated with the EA network. The stimuli were two pairs of pictures of the *Pacman* and *Angry Birds* games in which *Pacman/Bird* were “Go” stimuli and *Ghosts/Porks* the “NoGo” stimuli. They were created using five colors for the bodies (RGB values; Pacman/Bird: Yellow = 253, 217, 47; Ghosts/Porks: Blue = 47, 140, 253; Green = 48, 253, 72; Orange = 253, 135, 48; and Magenta = 250, 47, 253). Stimuli were presented in the center of the screen and occupied a visual angle of 8.84 vertically and horizontally on a gray background (RGB values, Gray = 150, 150, 150). Every trial was initiated with the presentation of the stimulus that was displayed for 400 ms. Then, the stimulus was replaced immediately by a black arrow (2°) that was presented at the center of the screen for 800 ms. In each trial, the stimulus was either a Pacman/Bird (70% of the trials) or a Ghost/Pork (30% of the trials). Children were instructed to respond (press the “space” button) or not respond when the Pacman/Birds (Go), or Ghost/Pork (NoGo) were presented, respectively. The task duration was approximately 20 min, in which each participant completed a maximum of eight blocks of 90 trials (720 trials in total), which were distributed in two sections of 4 blocks (1-Pacman; 2-Angry Birds). Each section was preceded by three blocks of practice ($n = 20$ trials). For behavioral analysis, the mean reaction time, the mean proportion of correct responses (hits), the mean proportion of false alarms (i.e., giving a response when instructed not to respond), and the efficiency score (hits – false alarms) were computed.

Brain activity from participants was recorded with a portable Emotiv EPOCH + EEG system (see technical description below) that was performed in two different sessions of approximately 40 min. before and after the implementation of the intervention. During each session, children performed a Go/NoGo task. Each child was tested individually at school, in a quiet room, and seated in a chair 50 cm from a computer screen. The preparation of the EEG headset and electrodes took approximately 5 min. Stimuli were presented on a laptop monitor 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) [42] for Python programming language [43] (v2.7, Python Software Foundation, https://www.python.org/). The sampling rate of EEG recordings was 128 Hz, and signals were filtered using a band-pass of 0.16–43 Hz. This system has 14 electrodes placed in locations consistent with the 10–20 montage. Impedance was kept according to EPOC calibration at the threshold between YELLOW and GREEN. The presentation of the stimuli and the recording ran on the same computer. Recordings were retrieved from the same python program using our own functions [44].

2.3.3. Cognitive intervention

The cognitive intervention consisted of three games aimed at tapping inhibitory control, cognitive flexibility, working memory, and planning processes [40]. The 3 games were administered individually by a researcher in a quiet school room across 12 sessions of 15 min each, once a week. Every child in the intervention group played each game for 4 consecutive sessions. The *inhibitory/cognitive flexibility* game is based on Stroop-like tasks, such as the one designed by Davidson et al. [45]. In each trial, a plane or a rocket of different colors appeared at the right of left of the screen that pointed either to the right or to the left. The child needed to indicate the direction of the plane or the rocket by controlling different conditions. In the *congruent condition*, a blue plane or rocket appeared, and the child had to press the button that indicated which direction the planes or the rockets were pointing. In the *incongruent condition*, the plane or the rocket was red, and the child had to press the button to the opposite side to which the rocket pointed. In addition, the child had to control the interference of several distractors that appeared in some trials, for example, balloons, paper planes, or other flying objects. Every session started in the trial where the child left the game in the previous session.

The *working memory game* was designed to stimulate recognition memory for visual patterns and is based on the Self Ordered Pointing Task (SOPT) [46,47]. An array of items (i.e., cards with different drawings) was presented within a 4 × 3 squared grid. The child had to choose one of them, and after 1000 ms all the items disappeared and reappeared randomly with another order. Now, the child had to choose a different item than the one selected in the previous trial. In each trial, a constant number of items appeared. The trial ended when all the items had been selected or when the child selected an incorrect item (one that had been selected before). The number and complexity of the items increased as the child won more trials.

In a previous study with the same task [40], difficulty was defined by the number of items to remember. The task started with the demand to remember three trials and, if the child completed three consecutive trials correctly, the number of items was increased to four. If the child made incorrect choices in three consecutive trials, the number of items decreased by one. In the present study, we added complexity to the items as another difficulty parameter. According to Cragg and colleagues [48], adults and children commit more errors in the SOPT task when items are abstract than when they are objects with meaning. In our version of the task, the game started with simple and a low number of items to remember, and then it advanced to a larger number and more complex items. Every session started in the trial where the child left the game in the previous session.

The *planning game* [49] is based on the *dog, cat, mouse* task designed by Klahr et al. [50]. In the screen, a square with a diagonal appeared, and in 3 of the 4 corners were placed the "houses" of three characters (i.e., a boy, a girl, and a cat). These characters were also sorted each one on a different corner of the square, but not in their corresponding houses. In each trial, the task consisted of taking each character to their houses in a determined minimum number of moves. The child was given three rules: (1) the characters could be moved one at a time, (2) they could be moved only through the paths (sides and the diagonal of the square), and (3) they could not share a house. As the game progressed, the number of movements required to complete each trial increased. The use of the diagonal, the amount of possible paths, and the search depth (the number of moves necessary to get the first character to its house) were controlled across the trials. Two schemes of training were administered: (1) a *free exploration* stage, in which the trials were considered correct if the child had taken all characters to their houses regardless of the number of moves (this stage ended when the child completed all trials), and (2) a *restricted movement* stage, in which the child was given a number of movements in which the trial must be finished. Every session started in the trial where the child left the game in the previous session.

The control condition consisted of 3 games (*booble shooter, painting, dots*) available for free download in Google Play Store, which were not designed for cognitive training purposes. The administration scheme and procedures were identical to those administered to the intervention group. The *booble shooter* is a classic game in which the child had to destroy a bunch of bubbles placed in the top of the screen by directing and shooting a bubble of the same color from the bottom. In the *painting game,* the child painted a wide variety of animals, cars, and objects with her fingers. The *dots game* consisted of an array of colored circles that disappeared when the player connected the ones with the same color.

2.3.4. Data analysis

Analyses were oriented to investigate training effects on measures of children's brain activity and behavioral performance that support inhibitory control processes. Accordingly, between-group contrasts were performed to determine if children differed on measures of inhibitory control, depending on their study group (control compared to intervention) at both the time of pre-test and post-test. In addition, within-group contrasts were performed to investigate how much children in their study group tended to vary in measures of inhibitory control between pre-test and post-test stages. Statistical significance was assessed by performing Mann Whitney *U* Tests, Chi Square, and Wilcoxon Signed Rank Tests for between-group and within-group contrasts.

Analyses of EEG recordings were performed using EEGLAB (version 13.5.4b) [51] in MATLAB (version R2016a). For each participant the number of false alarms was calculated. Children that had more than 80% of false alarms were excluded from the EEG processing. The EEG activity was bandpass-filtered between 0.5 Hz (high pass) and 30 Hz (low pass). Then, continuous signals were segmented into 1000 ms epochs, with 200 ms before and 800 ms after the onset of the stimulus. Baseline activity, which was defined as the mean activity in the interval [−200 ms, 0 ms], was subtracted from each epoch. Independent Components Analysis (ICA) that used the *InfoMax* algorithm was implemented to identify blink and saccade components in the epoched EEG recordings and to remove them from the data [51]. Epochs that contained artifacts that exceeded a threshold of +/− 100 μV were removed automatically. Additionally, segments with residual artifacts were removed manually from the data set. ERP waveforms were re-referenced offline to the algebraic average of the P7 and P8 channels (the closest electrodes to the right and left mastoids). Finally, separate ERP average waveforms were computed for each condition (i.e., Go versus NoGo). The critical analyses were carried out on separate ERP waveforms for each condition (Go vs. NoGo) over a ROI located on frontal scalp sites (F3 and F4 electrodes), and we included only trials associated with the correct responses. This procedure left an average of Go: 279 ± 90, 312 ± 83, NoGo: 98 ± 42, 107 ± 37 trials per participant for *pre-test* and *post-test*, respectively.

A denoising algorithm that used a wavelet decomposition of the single-trial waveform was used to obtain clean, single-trial ERPs [52–54]. They were reconstructed using only the wavelet coefficients that were related to the evoked responses, which were identified automatically using four scales and the NZT algorithm proposed by Ahmadi and and co-workers [53]. The set of wavelet coefficients selected to denoise the single-trial waveforms was kept constant for all conditions and participants. As shown previously, this method improves the estimation of the single-trial ERPs significantly compared with the non-denoised, single-trial waveforms. The single-trial P2 responses were identified as the local maximum between 270 ms and 320 ms. The peaks for each participant were measured by automatic selection of the EEGLAB function "findpeaks.m" [MATLAB (version R2016a) and Statistics Toolbox Release 2013a] within that time-window. Then, single-trial waveforms were shifted by the corresponding P2 latency, which aligned the single-trial waveforms by the P2 peak. The latencies were defined initially as the time from the onset of stimulus to the peak of interest, and the amplitudes were defined from the baseline. Finally, time-corrected ERP (tcERP) were estimated by averaging across trials for each participant and condition, and baseline activity was re-subtracted from each average segment.

To identify significant differences between the two conditions (Go vs. NoGo), we applied a combination of the Monte Carlo test and non-parametric bootstrapping [55–57], by using the statcond.m function implemented in the EEGLAB toolbox [58]. The data were analyzed by applying 1000 permutation draws to generate a histogram, which is the Monte-Carlo approximation of the permutation distribution. To calculate the differences between our data and this distribution, we calculated the proportion of random partitions in which the observed test statistic is larger than the value drawn from the permutation distribution, which is the Monte-Carlo estimation of the permutation *p*-value. If this *p*-value is smaller than the critical alpha-level, then it is concluded that there is a significant difference between the two conditions. This method offers a straightforward solution for Gaussian assumptions about the probability distribution of the data [59]. This approach has been used in previous ERPs reports [46,60–62]. Previous ERP studies that used Go/NoGo tasks found larger amplitudes of the N2 component on frontal sites for successful responses to NoGo trials compared to Go trials, which reflected conflict monitoring and inhibition [63,64]. Thus, contrasts were carried out independently in N2 time-windows for each study group (*Control, Intervention*) in each test stage (*pre-test, post-test*) [P2 + 50 ms, P2 + 250 ms] over a ROI located on frontal scalp sites (F3 and F4 electrodes).

Finally, to perform between-group (*Control* vs. *Intervention*) and within-group contrasts (*pre-test* vs. *post-test*) across the two conditions (Go vs. NoGo), we used different amplitudes measures of P2 and N2 components. The P2 component was computed as the positive peak in the 270–320 ms window, for the average ERP response in both conditions together (P2-m), and for the subtraction of the NoGo–Go average ERP responses (P2-s). For each study group, we calculated the Delta value of the N2 component by the subtraction of N2 *post-test* – N2 *pre-test*.

3. Results

3.1. Sociodemographic analysis

To identify basal differences between groups (control compared to intervention), a Mann Whitney *U* Test or Chi Square was performed with the following variables: NES score, maternal education, nutrition, sleep, and physical activity. The results showed non-significant differences between Intervention and Control groups (NES score: $z = 0.09$, $p = 0.93$; maternal education: $z = 0.47$, $p = 0.64$; nutrition: $z = 1.93$, $p = 0.05$; sleep: $z = 0.23$, $p = 0.82$; physical activity: $\mathrm{Chi}^2 = 2.92$; $p = 0.09$) (Table 1). The entire sample (100%) of children belonged to homes with at least one indicator of poverty (UBN).

3.2. Go/NoGo performance

There were no significant difference in RTs in pre versus post-test between control and intervention groups (pre-test: $z = 1.40$, $p = 0.16$; post-test: $z = 1.70$, $p = 0.09$). That is, groups did not differ between pre and test in how quickly they made responses to Go trials. Nonetheless, there were significant differences in RTs between pre-test and post-test within each study group (control: $z = 3.53$, $p < 0.01$; intervention: $z = 3.34$, $p < 0.01$). These differences were due to factors other than the implemented intervention. The children's scores on Go/NoGo tasks, t were not significantly different in hits between groups in either pre or post-test (pre-test: $z = 0.32$, $p = 0.75$; post-test: $z = 1.85$, $p = 0.06$) or between pre and post-test in each group (control: $z = -0.13$, $p = 0.89$; intervention: $z = 1.14$, $p = 0.26$). That is, the groups were equally accurate when they responded to Go stimuli in both stages of the study, and they did not differ after training. False alarms (FA) and efficiency (EFF) scores were different in pre-test between study groups (FA-pre-test: $z = 2.19$, $p = 0.03$; post-test: $z = 1.52$, $p = 0.13$; EFF-pre-test: $z = 2.05$, $p = 0.04$; post-test: $z = 0.19$, $p = 0.85$) and between pre-test and post-test within the control group (FA-Control: $z = 2.26$, $p = 0.02$; intervention: $z = 1.63$, $p = 0.10$; EFF-control: $z = -2.87$, $p < 0.01$; intervention: $z = 1.14$, $p = 0.26$). In particular, children in the control group made significantly more false alarms and were less efficient than those in the intervention group in pre-test performance . However, children in the control group committed fewer false alarms and were more efficient after training (Fig. 1).

Table 1
Descriptive statistic of sociodemographic variables for children from homes with at least one indicator of poverty.

	Control group			Intervention group			
	Mean	SD	Median	Mean	SD	Median	Significance
NES score	29.35	3.91	28	29.24	5.13	29	0.93
Maternal education	7	2.8	9	6.76	2.68	6	0.64
Nutrition	0.7	0.07	0.7	0.66	0.09	0.67	0.05
Sleep	1.79	0.46	1.75	1.82	0.48	1.73	0.82
Physical activity	0.34	0.48	N/A	0.16	0.37	N/A	0.09

Note. SD: Standard Deviation; NES: socioeconomic status.

3.3. Go/NoGo ERP

The automated artifact screening and paired samples procedures resulted in a final sample of 44 participants (25 girls) who were tested. First, for Go and NoGo conditions, ERP segments obtained for both groups in pre and post-test were compared to investigate traditional, conflict-related effects (i.e., control pre-test, intervention pre-test, control post-test, and intervention post-test). Data from both task conditions for frontal ROIs (F3/F4) were permuted by applying 1000 permutation draws using a non-parametric bootstrap method [statcond.m function from MATLAB (version R2016a)]. As expected, there were significant differences between Go and NoGo conditions at the N2 time-window over the frontal ROI ($p < 0.01$) for each study group at both pre and post-test. Closer inspection of the waveforms revealed that the above effects were driven by larger amplitudes of the N2 component in the NoGo condition relative to the Go one.

Then, we examined whether the intervention was related to eventual brain functions that supported inhibitory control processes that were associated with the task. The mean amplitude of NoGo–Go ERP of each group [intervention: $n = 24$ (6 girls); control: $n = 20$ (13 girls)], and stage were compared. There were not significant group differences in the amplitude of P2 and N2 in both test stages (P2-pre-test: $z = 1.40$, $p = 0.16$; post-test: $z = 0.44$, $p = 0.66$; N2-pre-test: $z = 0.44$, $p = 0.66$; post-test: $z = 0.81$, $p = 0.42$). That is, both groups showed similar conflict-related modulation. However, analysis of the amplitude of P2 and N2 components revealed within-group differences from the pre-test to post-test (P2-control: $z = 2.46$, $p = 0.01$; intervention: $z = 0.54$, $p = 0.59$; N2-control: $z = 0.67$, $p = 0.50$; Intervention: $z = 2.94$, $p < 0.01$). In particular, children in the intervention group showed significant changes in the N2 component after training, but children in the control group showed significant changes in the P2 component from pre-test to post-test. These data showed that only children in the intervention group displayed improvements in neural activity associated with inhibitory control processing between pre- and post-training stages (Fig. 2).

4. Discussion

The goal of this study was to investigate whether a training program aimed at optimizing CC could have an effect on the efficiency of inhibitory control performance and its underlying brain mechanisms in kindergartners from poor homes. The neural mechanisms that were related to an inhibitory control showed improvement. Specifically, only the intervention group showed in increase in the frontal N2-effect; that is, there was larger differentiation between the amplitude of N2-NoGo and N2-Go in the post-test stage. This effect of cognitive training was similar to those reported in previous studies that showed a larger N2-effect after inhibitory control training in a Go/NoGo task in preschoolers [18]. Previous evidence showed that larger N2 amplitude between Go and NoGo trials was correlated with both inhibition success [63] and higher performance in inhibitory control tasks [65]. Therefore, it is plausible to expect facilitations in development of response inhibition after the implemented training program.

However, the effect observed in neural activity was not accompanied by significant changes in performance. Training-induced changes at the neural level, but not at the cognitive level, were also found by other studies with preschoolers [18,19]. Other ERP evidence also showed associations between poverty and neural processing event when behavioral differences do not emerge [1,29,30,66]. This could be one of the advantages of combining neural and behavioral measures.

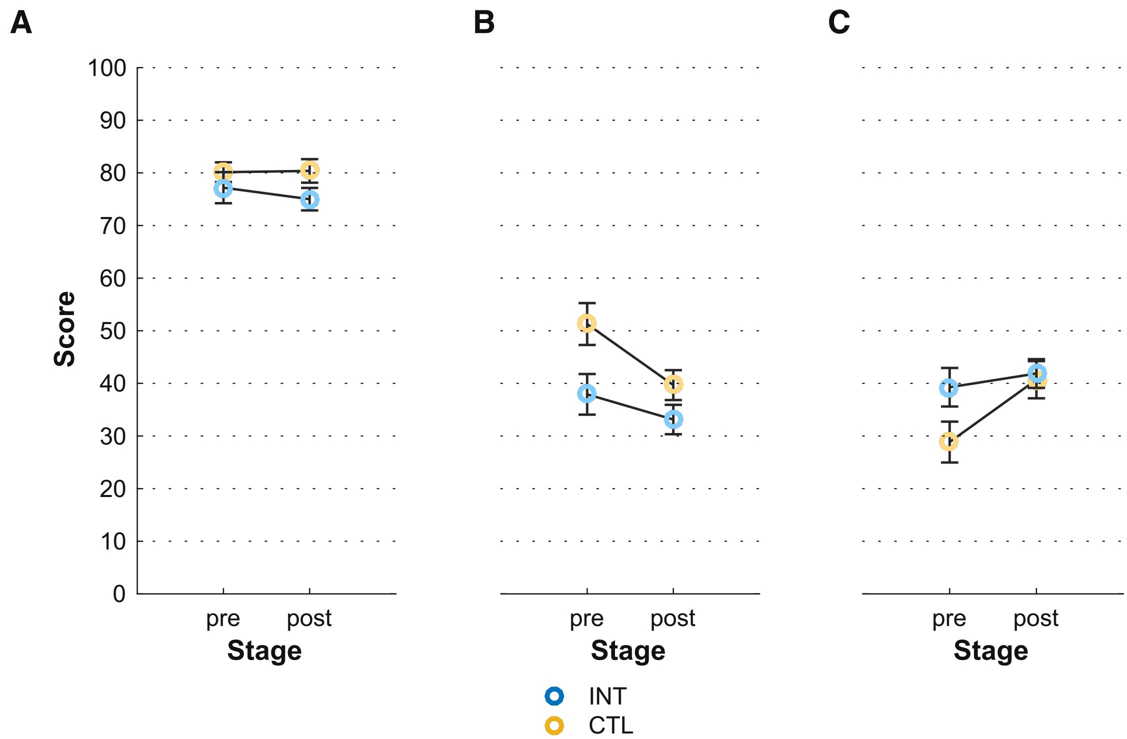

Fig. 1. Performance in the Go/NoGo task averaged by group (control, intervention) and stage (pre- and post-test). (A) Percentage of hits, (B) false alarms, and (C) efficiency scores. Error bars represent standard errors of the mean values.

Nevertheless, more sophisticated analyses are necessary to allow deeper explorations into the behavioral data in the future. For instance, diffusion models are able to combine response times and accuracy measures, and separate the variability between subjects into the parameters of the model, which is usually small. Eventually, this would enable the study of individual differences in performance [67,68] and to identify strategies for the same tasks in different stages of development [69]. In our study, no significant associations were found between N2 amplitude and behavioral measures of Go/NoGo task, which suggested that a neural training effect was not associated with inhibition of motor response. This result is consistent with previous evidence that showed little developmental progress in cognitive measures of inhibition control before the age of 10 [70,71]. Because increases in ERP amplitude are commonly associated with higher allocation to attention to a certain stimulus, the amplitude increase of the N2-effect after training may have been due to an increase in the efficiency of conflict monitoring. In this sense, the N2-effect was modulated by the presence of conflict in several cognitive control tasks (e.g., Flanker, Go/NoGo) [1,63,72], and it has been associated with control processes that arose in the anterior cingulate [73,74]. The observed training N2-effect might have reflected an increase in mental operations that were involved in the detection and resolution of conflict between trials in which the correct response corresponded to the prepotent response (GO) and between trials in which the correct response conflicted with the prepotent response (NoGo). Therefore, as other studies have also found [63,64,71,75], our results suggested that this effect was more associated with conflict monitoring processes than with inhibition response.

Successful evaluation of conflict necessarily precedes cognitive and behavioral inhibitory control in the processing-information stream, because this mechanism is particularly important in correctly responding to the task requirements. This finding is particularly important given the documented CC disparities among children from poor and low-SES backgrounds when considering different levels of analysis [24,31,76] and its contributing role to learning and memory abilities [77,78]. In the implemented cognitive training, although self-regulatory processes were targeted through a wide range of domains (i.e., inhibitory control/cognitive flexibility, working memory, planning), conflict monitoring mechanisms were aimed specifically at the inhibitory control game. However, the design of the present study did not allow us to assess the degree to which gains in the intervention group could be attributed to the targeted abilities involved in the inhibitory control game; our design allowed us only to assess results from the combination of the three games.

Notably, the control group showed changes in early stages of neural processing. In particular, this group showed lower differentiation between the amplitude of P2-NoGo and P2-Go (P2-s) in the post-test stage. The frontal P2 component has been associated with an index of stimulus evaluation [79,80] and it is enhanced in amplitude to task-relevant stimuli. Thus, less differentiation between the amplitude of P2 in controls may indicate a greater processing and evaluation of stimulus. That is, attentional resources may have been allocated more equally towards both Go and NoGo stimuli in the post-test stage.

The cognitive performance results did not reveal changes induced by the training. In particular, the percentage of correct detections were different between groups. This result is similar to those in previous intervention studies that were oriented to optimize inhibitory control processes in preschool children that showed no training-induced changes on scores in inhibitory control tasks [18,19]. Absence of training-induced changes at the cognitive level may be due to the relatively low sensitivity to change of performance in this task around the age of 5. Behavioral findings from developmental studies that involved Go/NoGo tasks indicated little development of response inhibition before the age of 10 [63,71]. In our study, the reaction times decreased in the post-test stage, but this effect was similar in both groups. This pattern of performance may be related to a practice effect and to individual changes in maturation. Although there is evidence suggesting that children 4–7 years old improved the speed of conflict solving considerably [81], both effects could be related to performance enhancements. Finally, the study groups showed differences in the percentage of false alarms and efficiency in the pre-test stage. In particular,

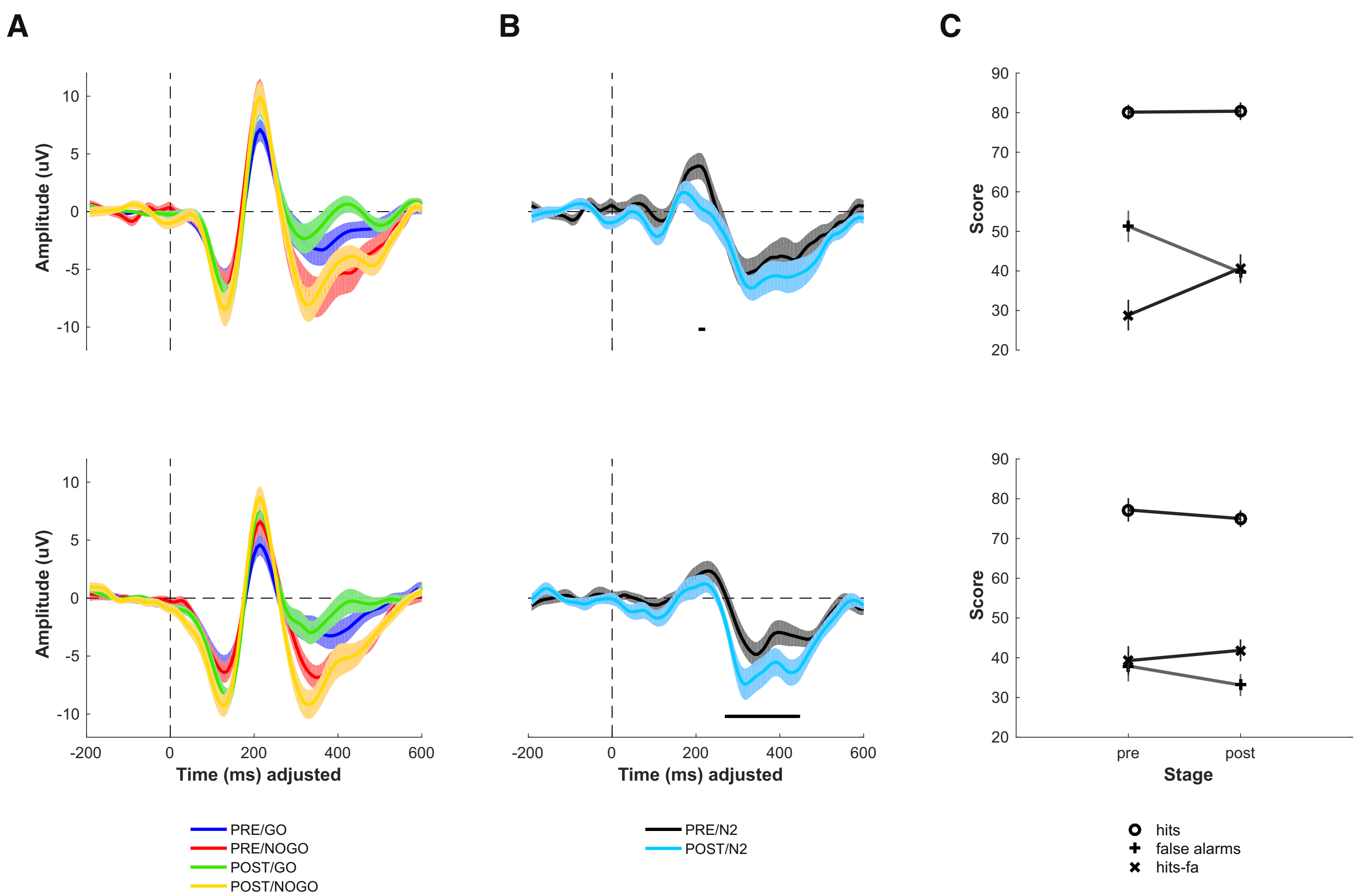

Fig. 2. Electrophysiological and cognitive performance in the Go/NoGo task. Top graph: data from Control group; Bottom graph: data from Intervention group. (A) All conditions ERP and (B) NoGo–Go ERP subtractions were averaged across all participants in each group by stage (pre- and post-training). (C) Percentage of hits, false alarms, and efficiency in each group at pre- and post-test. Significant increases in the N2 ERP were observed in children in the intervention group in waveforms from frontal electrodes F4/F7.

the intervention group had a higher level of performance than the control group. However, differences were not noticeable in the post-test stage. In fact, false alarms decreased and efficiency increased in the control group, but in the intervention group both remained constant.

Potential training-induced changes reported here cannot be explained by the collected sociodemographic information and sample characteristics. In this regard, it is necessary to address two limitations in future efforts: (1) the socioeconomic and sociodemographic measures, and (2) the sample size and composition. In future research, it will be necessary to add alternative measures of the same socioeconomic and sociodemographic factors and processes (i.e., adversity due to poverty, nutrition, physical activity, and sleep), to increase the sample size to implement analyses that have been applied commonly in recent studies of childhood poverty and cognition, such as mixed models [82] or multiple mediation models [83] and to balance the gender composition to verify its potential modulation such as was described in a previous study [20].

The present study was carried out in an educational setting. The advantages of this sort of approach has been indicated in previous studies [82,84]. Nonetheless, in our study, a portable EEG technology and method were added to contribute to a neural measure to complement information from the cognitive level for impact evaluation. Despite the fact that previous intervention studies have included EEG measures [18–20,37], to our knowledge this is the first time that a study assessed the neural impact of cognitive training of preschool children from poor homes outside a laboratory setting. This preliminary evidence should be followed by new studies that allow the implementation of alternative, validated EEG/ERP paradigms that are suitable to evaluate other aspects of interventions aimed at optimizing self-regulatory processes. Some of these limitations are being addressed in the larger study from which these data were obtained.

5. Conclusions

The results of this study indicate that cognitive interventions aimed at optimizing self-regulatory processes of young children from poor homes, and implemented in a school setting, could be effective to change aspects of the neural functioning of CC mechanisms. They also indicate that such types of interventions can have near-transfer effects from a combined set of cognitive, control-demanded games to a response inhibition activity. Finally, it supports the notion that the implementation of portable EEG technology could be useful for evaluating interventions in ecological settings.

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Authors contributions

M.L.P., F.G., M.S.S., M.L.R., J.E.K., and S.J.L. were involved in the design of the study. Data were collected by M.L.P., F.G., and the team of assistant researchers mentioned in *Acknowledgements* (2). Data analysis was performed by M.L.P., F.G., M.S.S., J.E.K., and S.J.L. M.L.M.B, A.P.G., and D.F.S. provided technical assistance. The manuscript was written by M.L.P., F.G., and S.J.L. with comments and edits from the other authors.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethical statement

All procedures described in this manuscript followed national and international research procedures and norms, and they were reviewed and approved by the institutional IRB (CEMIC, Protocols No. 682, and 961).

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